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A COMPARISON OF THE THREE DIFFERENT TECHNIQUES IN PREDICTING BREAKING STRENGTH OF COTTON AND BLENDED WOVEN FABRICS

PAMUK VE KARIŞIM KUMAŞLARIN KOPMA MUKAVEMETİNİN TAHMİN EDİLMESİNDE ÜÇ FARKLI TEKNİĞİN KARŞILAŞTIRILMASI

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A COMPARISON OF THE THREE DIFFERENT TECHNIQUES IN PREDICTING BREAKING STRENGTH OF COTTON AND BLENDED WOVEN FABRICS

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ABSTRACT: The adaptation and utilization of artificial intelligence techniques for various demands of the textile and apparel industry has been gradually increasing. The use of such methods are particularly very useful when making predictions based on the past company data in the cases where statistical methods are likely to be insufficient. It is obvious that an accurate projection of both structural and performance properties of woven fabrics is extremely important in regard of fabric design. In this study, several models based on multiple linear regression, artificial neural networks and random forest algorithms were developed to predict the breaking strength of woven fabrics which is considered one of the most important performance characteristic. Industrial data comprising variables of 147 sets of pure cotton and 53 sets of polyester/viscose woven fabrics are used. Breaking strength of a fabric is very much effected by basic structural elements of the fabric. For the sake of revealing the best relationship between the breaking strength and variables of fabric, various explanatory variables influencing the fabric properties are taken into consideration and several models were developed by means of Minitab Statistics Program, Weka and R software and the overall results are compared. Among all the models created by the three different techniques, it was found that the regression and artificial neural networks models performed well in both cotton fabrics and blended fabrics, while random forest algorithms were not very accurate in estimating the breaking strength.

Keywords: Regression model, artificial neural networks, random forest algorithm, breaking strength, woven fabric

PAMUK VE KARIŞIM KUMAŞLARIN KOPMA MUKAVEMETİNİN TAHMİN EDİLMESİNDE ÜÇ FARKLI TEKNİĞİN KARŞILAŞTIRILMASI

ÖZ: Teknolojinin gelişmesiyle birlikte tekstil sektöründe yapay zeka uygulamaları giderek artmaktadır. İşletmelerin geçmişteki verilerinin doğru değerlendirilip analiz edilmesi ile gelecekteki durumlarının tahmin edilmesinde istatistiki yöntemlerin eksik kaldığı durumlarda bu yöntemlerin kullanılması oldukça iyi sonuçlar vermektedir. Kopma mukavemeti, dokuma kumaşların en önemli performans özelliklerinden biri olarak kabul edilmektedir. Çoğunlukla kumaşın yapısal elemanları tarafından belirlenir. Bu çalışmada, endüstriyel veriler kullanılarak istatistiksel ve stokastik analiz yapmak için çoklu doğrusal regresyon, yapay sinir ağları ve rastgele orman algoritmaları kullanılmıştır. Pamuklu kumaşlarda eğitim ve test verileri için çözgü ve atkı yönünde toplam 147 kumaş veri seti ve karışımlı kumaşlarda çözgü ve atkı yönünde 53 kumaş veri seti kullanılmıştır. Minitab İstatistik ve Matlab yazılımları kullanılarak uygun modeller oluşturulmuştur. Kumaşların hem çözgü hem de atkı yönünde kopma mukavemetini tahmin eden modellerde değişken olarak iplik doğrusal yoğunlukları, iplik üretim yöntemleri, büküm miktarları, kumaş sıklıkları, kıvrım oranları, birim alan ağırlıkları, çeşitli örgü faktörleri ve kumaş yapı faktörleri seçilmiştir. Bu faktörler ayrı ayrı modellere sokularak en iyi sonucu veren altküme seçilmiş ve modeller revize edilmiştir. Oluşturulan üç model için hem pamuklu kumaşlarda hem de karışım kumaşlarda yapay sinir ağlarına dayalı modellerin daha iyi performans gösterdiği, rastgele orman algoritmalarının ise kopma mukavemetinin tahmin edilmesinde çok doğru bir algoritma olmadığı görülmüştür.

Anahtar Kelimeler: Regresyon modeli, yapay sinir ağları, rastgele orman algoritması, kopma mukavemeti, dokuma kumaş

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1. INTRODUCTION

The tensile properties of textile materials are always considered an important parameter in the selection of appropriate materials or in designing an acceptable fabric construction. It is therefore useful and in some cases essential to predict or calculate these parameters even before the fabric is manufactured. Breaking strength is one of the most important features that determine the usage performance of woven fabrics [1]. The breaking strength of a woven fabric is identified as the largest force exposed to the fabric sample right at the breaking point of a tensile test. It is well known that the breaking strength of a woven fabric is not determined by only the strength of the component yarns. It's also affected by particular fibre properties (i.e., fineness, type, strength, and length), yarn properties (i.e., linear density, twist rate, and ply number) as well as construction and density of the fabric together with the final finishing processes [2].

In the technical literature, there are three common ways of predicting fabric properties such as breaking strength [3].

- mathematical models based on geometric and physical properties derived from the model,
- empirical models based on experimental data and statistical analysis,
- stochastic models based on artificial intelligence

In practice, the selection and application of an appropriate model is of critical importance. It is, therefore, crucial to understand the basic principles of these models and their compatibility with the relevant case. For an accurate prediction of fabric properties through nonlinear and complex fabric parameters, a reliable and decent model is required [3]. In this study, three different methodologies, namely regression analysis, artificial neural network and random forest technique are applied to predict the breaking strength of woven fabrics.

It is possible to use various geometric or dynamic mathematical models based on the dimensional and physical variables of the fabric and the interrelation between them to identify and predict basic parameters and fabric behaviour. However, in practice, the use of such models in fabric design, which were developed to predict fabric structural properties, is quite limited. This is because mathematical models are often very complicated and limited to certain cases. They are mostly based on certain idealized assumptions which may cause significant prediction errors. These models are usually generated based on a particular fabric construction and require new analysis and new solutions in the case of any change in the fabric structure.

Currently, empirical models based on statistical analysis or experimental assumptions are widely used to predict fabric properties. In this context, regression analysis is one of the most common statistical tools which are used to estimate the relationship between two or more variables.

Artificial intelligence systems are also capable of making decisions toward the prediction of basic parameters based on current knowledge. The knowledge provided for the analysis must be related to the problem which is required to solve and represent the entire pile. Such systems can generate predictions about possible consequences by learning from past events using the provided information. An artificial neural network as an artificial intelligence model, is a computer-based system developed which automatically deduce possible solution in a similar way to the human brain such as deriving new information, and creating and discovering new knowledge through learning, without any help [4]. The real power and advantage of artificial neural networks depend on their ability to represent both linear and nonlinear relationships and also to derive these relationships directly from the data entered into the system [5].

Artificial Neural Networks (ANN) appear to deduce useful information for most issues with less inaccuracy than mathematical and regression-based modelling methods ANN has the advantage of approximating any functional relationship between a large number of input-output (independent and dependent variables) parameters. There is no need to make any prior assumptions about the statistical nature of the variables because ANN is non-parametric in nature. ANN requires a much smaller dataset than that of regression analysis to capture nonlinear relationships between input and output parameters. Even with a small training data set, the network is able to generalize a reliable relationship [3].

The method of machine learning which is a relatively new branch of artificial intelligence is also used in this study. This method is called Random forest (RF) and, it is a tree-based ensemble consisting of trees connected to a collection of random variables. RF can be applied to both regression and classification problems, trained faster in comparison to other methods, and has a higher prediction speed. It draws attention due to its features such as less number of parameters and direct application to multidimensional problems [6]. RF is a community learning method. Differential classification and regression decision trees form the decision forest community. The results acquired by the decision forest formation are combined and the final estimate is made accordingly [7].

It appears that there are many studies in the literature, which have employed the ANN method to predict fabric properties. Most of them are focused on the fabric handle which is often evaluated subjectively. In 2004, Hui et al. tried to predict fabric handle by using a multilayer feed-forward backpropagation artificial neural network model in a study [8]. In another study, Pattanayak et al. tried to estimate the drape parameters from the fabric sample using a feed-forward backpropagation model [9]. It is interesting to note that those studies were conducted with fewer samples including certain weaves of specific fabric types. Almost all researchers agreed that the ANN technique is likely to produce better results in the case of removing the constraints and increasing the number of samples.

On the other hand, regression models employed in several studies, especially those used in the estimation of the fabric breaking strength, were developed to make predictions in accordance with a single variable by means of simple regression model. As an example, Sankaran and Subramaniam calculated Morino's cross tightness factor (CFF), yarn float factor (FYF) and Milasius' fabric tightness factor (FFF) for 16 different weaves. This study revealed the effects of these factors on tensile, bending, shear, compression and surface properties [16]. Although there are a few studies using multiple linear regression models developed for fabrics with several weaves in consideration of the relationship between various weave factors and yarn properties, it was noticed that the range of weaves, yarn counts and the blend ratios were kept limited in these studies. For example; Malik et al. created regression models for 135 woven samples of plain and 3/1 twill weaves by incorporating yarn strength, yarn frequency and weave floating length as independent variable. They presumed that those variables affect the fabric strength in both warp and weft directions [10].

In the literature, no study was found with the random forest algorithm on the estimation of fabric properties. In this study, regression models were created with different independent variables (input variables) for the best estimation of the breaking strength of woven fabrics. Two groups of data are used including pure cotton and polyester/viscose blend fabrics woven at two different mills. In addition to regression models, artificial neural networks and random forest algorithms are developed with the variables which generated the best predictions in the regression analysis, and the results were compared.

2. MATERIALS AND METHODS

In consideration of the parameters affecting the breaking strength of woven fabrics, 32 models each for cotton and blended fabrics are developed based on different independent variables in both warp and weft directions.

The data set comprising the variables of 147 different cotton fabrics is obtained from a cotton weaving mill. It is actual industrial data and includes various fabric constructions of basic weaves and their derivatives woven with various yarn types, namely ring, combed, open-end rotor and compact. The linear density and twist values of yarns and the densities warp and weft are also varied Fabrics woven by several dobby weaves were not included in this sample set.

The other set of sample data includes certain variables of 53 woven blend fabrics with varying weave structures. These blended fabrics are woven by double-plied ring-spun yarns with different twists and counts at varied warp and weft densities.

In the breaking strength prediction models of cotton fabrics, warp yarn linear density (coz_tex), weft yarn linear densities (atk_tex), warp yarn production method (coz_ipl_ure_met), weft yarn production method (atk_ipl_ure_met), warp yarn twist amount (coz_ipl_buk_mik), weft yarn twist amount (weft_ipl_buk_mik), warp density(coz_sik), weft density (atk_sik), warp crimp (coz_kiv), weft crimp (atk_kiv) and finished fabric unit area weights (mam_kum_bir_ala_agi) are used as independent variables. Additionally, F (Ashenhurst's weave factor) [11], KL (Galceran's fabric structure factor)) [12], CFF (Morino's crossing-over firmness factor) [13] and FYF (Morino's floating yarn factor) [13], as fabric structure factors K (Peirce's cover factor) [14], TS (Seyam's fabric structure factor)) [15] and OG (Galceran's fabric structure factor) [12] are also used as weave factors.

Similar independent variables are also used for modelling the breaking strength of blend fabric except for the raw fabric unit area weights (raw_kum_bir_ala_agi) instead of the finished fabric unit area weight. In addition, a parameter called "average fiber strength coefficient" (avg_ely_muk_kat) has been defined in order to reveal the differences of the blend ratios of each type, since the fabrics are made from blended yarns. The strength values are taken 47 cN/tex, 18 cN/tex and 3,1 cN/tex for polyester fibre, viscose fibre and elastane, respectively and calculated in accordance with the fabric composition.

First of all, multiple linear regression equations were created by the Minitab package program for the predicted parameters. For each model, the T value, P value, and VIF value and the significance of the coefficients were checked by means of the T-Test, the standard error (s value) and the coefficient of determination (R-sq) of the model created. The model summary table were prepared, and finally the significance of the model was tested by the F- Test.

Patterns has been named Cwarp-model no. for cotton and warp-directional breaking strength, Cweftmodel no. for cotton and weft-directional breaking strength, and Bwarp-model no. for blend and warp-directional breaking strength. and finally Bweft-model no. for blend and weft directional breaking strength.

Whenever the coefficients were found insignificant with the aid of T-test in the first step models, the Mallow's Cp test was carried out to find valid subsets that would reveal the best predictive power score with these inputs. Then, those with the lowest “Cp” and “s” values were selected among the first step models to create the second step models with these input values. These models have been named Cwarp-model-variant no. for cotton and warp-directional breaking strength, Cweft-model-variant no. for cotton and weft- directional breaking strength, and Bwarp-model-variant no. for blend and warp-directional breaking strength and finally, Bweft-model-variant no for blend and weft directional breaking strength.

Since the number of samples for both types of fabrics is limited, the data in the models are not separated into two groups as test and training data. Hence, K-Folds Cross Validation analysis is carried out to test the model by dividing the data into 10 different subsets, and the average of the specificity coefficient “R-sq” and standard error “s” values of each cluster separately revealed the predictive power of the model.

3. RESULTS AND DISCUSSION

The models created for the breaking strength along the warp in cotton fabrics, the explanatory variables included in the model, the “R-sq” coefficients of determination and the R correlation coefficient are given in Table 1.

When Table 1 is examined, it may be seen that the predictive power of the Cwarp2-1 model is higher than the other models with an R-sq value of 96.86%. The regression equation (1) for Cwarp2-1 is given below. Breaking strength in the warp direction according to the regression model for cotton fabrics;

The second step models were created with the same explanatory variables to compare the Cwarp2 and Cwarp2-1 variation by means of the artificial neural network and random forest algorithms under the same conditions. A data set including the variables of 147 woven fabrics used for the model Cwarp2-1 is given in the Table 2.

The models created for the breaking strength along the weft in cotton fabrics, the explanatory variables included in the model, the R-sq coefficients of determination and the R correlation coefficient are given in Table 3.

When Table 3 is examined, it is seen that the predictive power of Cweft5-1, Cweft6-1, Cweft7-1 and Cweft 8-1 models is higher than the other models with 94.48% R-sq value. The regression equation (2) for Cweft5-1 is given below. Breaking strength in the weft direction according to the regression model for cotton fabrics;

The new models were created with the same dependent variables to compare the Cweft5 and Cweft5- 1 variation with artificial neural network and random forest algorithms under the same conditions. A sample of 147 fabric data used for Cweft5-1 is given in Table 4.

kop_muk_coz = (0,3212*coz_tex) + (1,638*coz_ipl_ure_met) - (0,4713*atk_tex) + (0,1708*coz_sik) -(0,832*coz_kiv) + (0,2501*mam_kum_bir_ala_agi)	(1)
kop_muk_atk = - (0,673*coz_tex) + (2,61*atk_ipl_ure_met) - (0,5458*coz_sik) - (1,914*K2) + (0,2024*mam_kum_bir_ala_agi)	(2)

Table 1. Warp breaking strength regression models and results for cotton fabrics

COTTON FABRICS NO.	coz_tex	atk_tex	coz_sik	atk_sik	coz_kiv	coz_ipl_ure_met	atk_ipl_ure_met	coz_ipl_buk_mik	mam_kum_bir_ala_ag	F1	KL1	CFF	FYF	K1	K	T1	TS	OG1	OG	Regression R^2	Correlation R
Cwarp-1	x	x	x	x	x	x	x	x	x	x										57,11	75,57
Cwarp1-1	x	x	x		x				x											96,71	98,34
Cwarp-2	x	x	x	x	x	x	x	x	x		x									59,17	76,92
Cwarp2-1	x	x	x		x	x			x											96,86	98,42
Cwarp-3	x	x	x	x	x	x	x	x	x			x								57,06	75,54
Cwarp3-1	x	x	x		x				x											96,71	98,34
Cwarp-4	x	x	x	x	x	x	x	x	x				x							57,06	75,54
Cwarp4-1	x	x	x		x				x											96,71	98,34
Cwarp-5		x		x	x	x		x	x	x				x						55,49	74,49
Cwarp5-1					x	x		x						x						46,65	68,30
Cwarp-6		x		x	x	x		x	x		x			x						55,61	74,57
Cwarp6-1					x	x		x	x					x						46,65	68,30
Cwarp-7		x		x	x	x		x	x			x		x						55,43	74,45
Cwarp7-1					x	x		x	x					x						46,65	68,30
Cwarp-8		x		x	x	x		x	x				x	x						55,43	74,45
Cwarp8-1					x	x		x	x					x						46,65	68,30
Cwarp-9					x	x		x	x	x					x					49,38	70,27
Cwarp9-1					x	x		x	x						x					96,11	98,04
Cwarp-10					x	x		x	x		x				x					49,45	70,32
Cwarp10-1					x	x		x	x						x					96,11	98,04
Cwarp-11					x	x		x	x			x			x					49,42	70,30
Cwarp11-1					x	x		x	x						x					96,11	98,04
Cwarp-12					x	x		x	x				x		x					49,42	70,30
Cwarp12-1					x	x		x	x						x					96,11	98,04
Cwarp13		x		x	x	x		x	x							x				54,89	74,09
Cwarp13-1		x			x	x		x	x											52,16	72,22
Cwarp-14					x			x	x								x			43,34	65,83
Cwarp14-1									x								x			40,71	63,80
Cwarp-15		x		x	x	x		x	x									x		54,94	74,12
Cwarp15-1		x			x				x											51,42	71,71
Cwarp-16					x	x		x	x										x	43,35	65,84
Cwarp16-1					x	x			x											40,56	63,69

Table 2. A sample of cotton fabric data for Cwarp2-1

coz_tex (tex)	coz_ipl_ure_met	atk_tex (tex)	coz_sik tel/cm)	coz_kiv (%)	Mzm_kum_bir_ala_agi (g/m2)	kop_muk_coz (kgf)
14,767	3,000	14,767	49,800	13,000	126,000	32,000
29,533	1,000	29,533	40,925	11,500	217,000	47,000
14,767	3,000	14,767	41,209	8,000	115,000	26,000
11,813	3,000	11,813	47,872	12,000	105,000	31,000
29,533	1,000	29,533	40,876	11,000	198,000	45,000
36,917	1,000	36,917	40,423	12,000	229,000	32,000

Table 3. Weft breaking strength regression models and results for cotton fabrics

COTTON FABRICS NO.	coz_tex	atk_tex	coz_sik	atk_sik	atk_kiv	coz_ipl_ure_met	atk_ipl_ure_met	atk_ipl_buk_mik	mam_kum_bir_ala_ag	F2	KL2	CFF	FYF	K2	K	T2	TS	OG2	OG	Regression R^2	Correlation R
Cweft-1	x	x	x	x	x	x	x	x	x	x										67,8	82,34
Cweft1-1	x	x	x	x					x											94,34	97,13
Cweft-2	x	x	x	x	x	x	x	x	x		x									68,02	82,47
Cweft2-1	x	x	x	x					x											94,34	97,13
Cweft-3	x	x	x	x	x	x	x	x	x			x								67,92	82,41
Cweft3-1	x	x	x	x					x											94,34	97,13
Cweft-4	x	x	x	x	x	x	x	x	x				x							67,92	82,41
Cweft4-1	x	x	x	x					x											94,34	97,13
Cweft-5	x		x		x		x	x	x	x				x						68,43	82,72
Cweft5-1	x		x				x		x					x						94,48	97,20
Cweft-6	x		x				x	x	x		x			x						68,62	82,84
Cweft6-1	x		x				x		x					x						94,48	97,20
Cweft-7	x		x				x	x	x			x		x						68,63	82,84
Cweft7-1	x		x				x		x					x						94,48	97,20
Cweft-8	x		x				x	x	x				x	x						68,63	82,84
Cweft8-1	x		x				x		x					x						94,48	97,20
Cweft-9					x		x	x	x	x					x					54,31	73,70
Cweft9-1							x		x	x										52,51	72,46
Cweft-10					x		x	x	x		x				x					53,72	73,29
Cweft10-1					x		x		x											52,92	72,75
Cweft-11					x		x	x	x			x			x					54,1	73,55
Cweft11-1					x		x		x											52,92	72,75
Cweft-12					x		x	x	x				x		x					54,1	73,55
Cweft12-1					x		x		x											52,92	72,75
Cweft13	x		x		x		x	x	x							x				65,4	80,87
Cweft13-1	x				x		x		x							x				63,94	79,96
Cweft-14					x		x	x	x								x			54,69	73,95
Cweft14-1							x		x								x			53,79	73,34
Cweft-15	x		x		x		x	x	x									x		64,81	80,50
Cweft15-1	x		x				x		x											93,86	96,88
Cweft-16					x		x	x	x										x	55,28	74,35
Cweft16-1							x		x										x	54,02	73,50

Table 4. A sample of cotton fabric data for Cweft5-1

coz_tex (tex)	atk_ipl_ure_met	coz_sik (warp/cm)	K2	mam_kum_bir_ala_agi (g/m^2)	kop_muk_atk (kgf)
14,767	3,000	49,800	11,245	126,000	16,000
29,533	1,000	40,925	14,767	217,000	25,000
14,767	3,000	41,209	10,643	115,000	15,000
11,813	3,000	47,872	10,776	105,000	17,000
29,533	1,000	40,876	11,359	198,000	21,000
36,917	1,000	40,423	11,430	229,000	46,000

The models created for the breaking strength along the warp in blended fabrics, the explanatory variables included in the model, the R-sq coefficients of determination and the R correlation coefficient are given in Table 5.

When Table 5 is examined, it is seen that the predictive power of models Bwarp9-1, Bwarp10-1, Bwarp11-1, and Bwarp12-1 is higher than the other models with an R-sq value of 93.03%. The regression equation (3) for Bwarp9-1 is given below. The regression model of the breaking strength in warp direction for blended fabrics;

The second step models were created with the same dependent variables to compare the Bwarp9 and Bwarp9- 1variation with artificial neural networks and random forest algorithms under the same conditions. A sample of 53 fabric data used for Bwarp9-1 is given in Table 6.

The models created for the breaking strength along the weft in blended fabrics, the explanatory variables included in the model, the R-sq coefficients of determination, and the R correlation coefficient are given in Table 7.

When Table 7 is examined, it is seen that the prediction power of the Bweft1-1, Bweft2-1, Bweft3-1, and Bweft4-1, model is higher than other models with 92.85% R-sq value. The regression equation (4) for Bweft1-1 is given below. The regression model of the breaking strength in weft direction for blended fabrics;

New models were created with the same dependent variables to compare the Bweft1 and Bweft1- 1 variation with artificial neural networks and random forest algorithms under the same conditions. A sample of 53 fabric data used for Bweft1-1 is given in Table 8.

ANN and RF algorithms were created by using the independent variables (input variables) of regression models with high R-sq values. The models created and their results are as given in Table 9. According to Table 9, ANN has higher R values in all models compared to the RF algorithm.

kop_muk_coz = - (0,1102*coz_ipl_buk_mik) - (1,850*coz_kiv) + (8,78*K)	(3)
kop_muk_atk = (1,223*atk_tex) + (2,096*atk_sik) - (1,545*atk_kiv)	(4)

Table 5. Warp-breaking strength regression models and results for blended fabrics

BLENDED FABRICS NO.	coz_tex	atk_tex	coz_sik	atk_sik	coz_kiv	coz_ipl_buk_mik	ort_ely_muk_kat	ham_kum_bir_ala_ag	F1	KL1	CFF	FYF	K1	K	T1	TS	OG1	OG	Regression R^2	Correlation R
Bwarp-1	x	x	x	x	x	x	x	x	x										51,4	71,69
Bwarp1-1			x		x	x		x											34,48	58,72
Bwarp-2	x	x	x	x	x	x	x	x		x									51,69	71,90
Bwarp2-1			x		x	x		x											34,48	58,72
Bwarp-3	x	x	x	x	x	x	x	x			x								52,06	72,15
Bwarp3-1			x		x	x		x											34,48	58,72
Bwarp-4	x	x	x	x	x	x	x	x				x							52,06	72,15
Bwarp4-1			x		x	x		x											34,48	58,72
Bwarp-5		x		x	x	x	x	x	x				x						51,72	71,92
Bwarp5-1					x	x							x						37,5	61,24
Bwarp-6		x		x	x	x	x	x		x			x						52,05	72,15
Bwarp6-1					x	x							x						37,5	61,24
Bwarp-7		x		x	x	x	x	x			x		x						52,35	72,35
Bwarp7-1					x	x							x						37,5	61,24
Bwarp-8		x		x	x	x	x	x				x	x						52,35	72,35
Bwarp8-1					x	x							x						37,5	61,24
Bwarp-9					x	x	x	x	x					x					48,51	69,65
Bwarp9-1					x	x								x					93,03	96,45
Bwarp-10					x	x	x	x		x				x					49,02	70,01
Bwarp10-1					x	x								x					93,03	96,45
Bwarp-11					x	x	x	x			x			x					49,59	70,42
Bwarp11-1					x	x								x					93,03	96,45
Bwarp-12					x	x	x	x				x		x					49,59	70,42
Bwarp12-1					x	x								x					93,03	96,45
Bwarp13		x		x	x	x	x	x							x				49,16	70,11
Bwarp13-1					x			x											34,9	59,08
Bwarp-14					x	x	x	x								x			46,9	68,48
Bwarp14-1					x			x											34,9	59,08
Bwarp-15		x		x	x	x	x	x									x		50,28	70,91
Bwarp15-1					x			x											34,9	59,08
Bwarp-16					x	x	x	x										x	48,74	69,81
Bwarp16-1					x			x											34,9	59,08

Table 6. A sample of blended fabric data for Bwarp9-1

coz_ipl_buk_mik (tour/m)	coz_kiv (%)	K	kop_muk_coz (kgf)
650,000	8,333	20,372	98,460
700,000	7,692	24,644	161,070
700,000	8,333	24,560	139,96
700,000	7,407	24,745	112,700
700,000	7,692	25,090	138,650
700,000	7,692	25,152	149,800

Table 7. The breaking strength regression patterns and results along weft for blended fabrics

BLENDED FABRICS NO.	coz_tex	atk_tex	coz_sik	atk_sik	atk_kiv	atk_ipl_buk_mik	ort_ely_muk_kat	ham_kum_bir_ala_ag	F2	KL2	CFF	FYF	K2	K	T2	TS	OG2	OG	Regression R^2	Correlation R
Bweft-1	x	x	x	x	x	x	x	x	x										32,91	57,37
Bweft1-1		x		x	x														92,85	96,36
Bweft-2	x	x	x	x	x	x	x	x		x									34,84	59,03
Bweft2-1		x		x	x														92,85	96,36
Bweft-3	x	x	x	x	x	x	x	x			x								35,27	59,39
Bweft3-1		x		x	x														92,85	96,36
Bweft-4	x	x	x	x	x	x	x	x				x							35,27	59,39
Bweft4-1		x		x	x														92,85	96,36
Bweft-5	x		x		x	x	x	x	x				x						28,33	53,23
Bweft5-1					x								x						28,11	53,02
Bweft-6	x		x		x	x	x	x		x			x						29,97	54,74
Bweft6-1					x								x						28,11	53,02
Bweft-7	x		x		x	x	x	x			x		x						30,35	55,09
Bweft7-1					x								x						28,11	53,02
Bweft-8	x		x		x	x	x	x				x	x						30,35	55,09
Bweft8-1					x								x						28,11	53,02
Bweft-9					x	x	x	x	x					x					27,38	52,33
Bweft9-1					x			x											26,31	51,29
Bweft-10					x	x	x	x		x				x					28,88	53,74
Bweft10-1					x			x											26,31	51,29
Bweft-11					x	x	x	x			x			x					29,38	54,20
Bweft11-1					x			x											26,31	51,29
Bweft-12					x	x	x	x				x		x					29,38	54,20
Bweft12-1					x			x											26,31	51,29
Bweft13	x		x		x	x	x	x							x				26,55	51,53
Bweft13-1					x			x											26,31	51,29
Bweft-14					x	x	x	x								x			28,55	53,43
Bweft14-1					x			x											26,31	51,29
Bweft-15	x		x		x	x	x	x									x		29,67	54,47
Bweft15-1					x			x											26,31	51,29
Bweft-16					x	x	x	x										x	30,81	55,51
Bweft16-1					x			x											26,31	51,29

Table 8. A sample of blended fabric data for Bweft1-1

atk_tex (tex)	atk_sik (weft/cm)	atk_kiv (%)	kop_muk_atk (kgf)
43,470	19,500	7,500	115,290
30,430	28,000	5,521	115,550
43,470	26,000	6,667	126,130
30,430	29,000	7,975	46,850
30,430	28,000	4,706	28,610
30,430	28,000	8,537	114,320

Table 9. Artificial neural networks and Random Forest models and their results

MODELS	Hidden Layer Size	Number of Neurons	Transfer Function	Learning Function	ANN R	RandomForest R
Cwarp-2	1	4	logsig	trainlm	88,613	69,470
Cwarp2-1	1	5	logsig	trainlm	89,138	70,160
Cweft-5	1	5	logsig	trainlm	96,567	78,460
Cweft5-1	1	4	logsig	trainlm	93,689	79,710
Bwarp-9	1	4	logsig	trainlm	97,907	54,720
Bwarp9-1	1	5	netinv	trainlm	92,433	49,210
Bweft-1	1	5	elliotsig	trainlm	98,653	32,140
Bweft1-1	1	5	logsig	trainlm	89,473	33,310

4. CONCLUSIONS

In the study, many regression models were created with different independent variables to estimate the breaking strength of cotton and polyester/viscose blended fabrics along the warp and weft direction. The models generating the highest predictive power (according to the R-sq coefficient of determination) were also tested using artificial neural networks and random forest algorithms. The comparison of the outcomes of these three models with reference to the R correlation coefficients for cotton and blended fabrics is given in Table 10.

Table 10. %R-correlation coefficients of Regression, Artificial Neural Networks and Random Forest models

MODELS	Regression	ANN R	Random Forest R
Cwarp-2	76,920	88,613	69,470
Cwarp2-1	98,420	89,138	70,160
Cweft-5	82,720	96,567	78,460
Cweft5-1	97,200	93,689	79,710
Bwarp-9	48,510	97,907	54,720
Bwarp9-1	93,030	92,433	49,210
Bweft-1	57,370	98,653	32,140
Bweft1-1	98,420	89,473	33,310

As a summary of the table, it is clearly seen that ANN models appear to provide the highest prediction power overall. The raw models of Cwarp-2, Cweft-2, Bwarp-9, and Bweft-1 which were developed by variables known to effect breaking strength produce the highest prediction power in the pursuit of artificial neural network models. However, the highest predictive power score of 98,42 is achieved in the case of regression models of Cwarp2-1 and Bweft1-1. It is also seen that the models generated by regression analysis for two other subsets of Cweft5-1 and Bwarp9-1 appear to provide the highest estimates in comparison with other methods. When the R correlation coefficients are compared, it is found that random forest algorithms fail to provide acceptable models for estimating the breaking strength of fabrics.

Among the regression models with the best results, the correlation between the measured weft breaking strength for cotton fabrics and the estimated weft breaking strength was 0.832 (Figure 1). This correlation was 0.766 in cotton warp breaking strength, 0.715 in blend warp breaking strength and 0.616 in blend weft breaking strength.

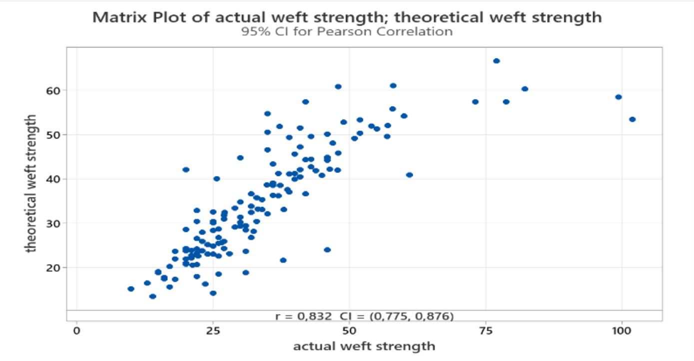

Figure 1 Highest predictive correlation graph

The analysis of the regression models revealed that the independent variables of weave and fabric structure factors are not decisive in the prediction of breaking strength. It was also confirmed that the number of data in prediction by means of the random forest algorithm is a critical factor to obtain higher predictive power. It is believed that increasing the quantity of data would improve the accuracy and prediction power of the results.

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