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DEPENDENCE OF SOFTNESS PERCEPTION ON TISSUE PHYSICAL PROPERTIES AND DEVELOPMENT OF NEURAL MODEL FOR PREDICTING SOFTNESS




V. K. Rastogi *H. Großmann* *A. K. Ray* *I. Greiffenberg*

Summary :

Tissue papers are distinguished and graded specifically based on several properties, but softness is the most desirable one for the customer. Several efforts are still being made for the accurate prediction of softness, but till date its evaluation is difficult. Hence, the development of a standard assessment procedure for the softness evaluation of tissue products is an absolute necessity for manufacturers, converters and consumers alike.

This study mainly focuses on development of a neural model for softness prediction. By using the Artificial Neural Network (ANN) the impact of tissues physical properties on tissue softness were determined. Neural network was trained properly with the given set of inputs and outputs values to find the appropriate weights which minimizes the error of the network and after which new inputs were given to trained network for finding out the predicted softness through simulation. This model was able to predict the facial tissue softness very well and a high degree of correlation was achieved for predicted softness and panel softness.

1. INTRODUCTION

Today the worldwide tissue market is large and estimated to be around $58 billion turnover annually. The consumption growth of tissue products is tremendous, therefore, tissue market is really tough and competitive which is the only reason for strong motivation for tissue manufacturers to improve tissue product quality even though many technological hurdles have already been achieved [1]. To make tissue with finest quality, one or more tissue properties must be improved including strength, bulk and water absorptive capacity. However, softness is the most desirable and demanding property favoured by customers [2], and must given prior importance by producers. Softness and good hand feel are outstanding in inducing a positive attitude towards all tissue products such as paper handkerchiefs, toilet paper, serviette and medical products.

Softness is a multifaceted and psycho-physical property which is manifested by multidimensional perception involving sight, sound and touch of the tissue [3, 4, 5, 6]. Softness evaluation has been carried out by many researchers and tissue industries [7, 8], but still its determination is challenging. According to the present state-of-the-art, the softness of tissue product is evaluated more or less by "panel test". It is believed that softness is perceived because of the combined effect of the surface softness and bulk softness [9]. Surface softness is perceived by brushing the fingers over the tissue product that is laid out flat on a table. Bulk softness is perceived by folding and/or crumpling of tissue into the hands.

Many previous studies on softness related ground suggested that softness is dependent on various tissue physical properties like, basic properties, strength properties and surface properties. Basic properties like, thickness, grammage, bulk (specific volume) and apparent bulk density have been shown to correlate with softness [10]. Some researchers have attempted to correlate the strength properties with bulk softness, properties like tensile stiffness by taking into account tensile strength and modulus of elasticity [9, 11] and compressibility [10] which is believed to be the reason for tissue cushion [12], which correlate well with bulk softness. Surface properties have been correlated to surface softness, properties like surface roughness determined by stylus profilometry [11, 13, 14, 15] and surface friction [11] measurement by determining the coefficient of friction which was found to correlate strongly with surface softness. Several mathematical and statistical models have been built comprising the effect of either bulk softness, surface softness or both [9, 11, 12]. Recently, the softness of tissue was predicted online by using the Artificial Neural Network model, with the need to improve the prediction accuracy [16]. These neural networks have been continuously proving to be quite superior over the conventional methods used in the different areas of paper making industry [16, 17, 18, 19].

In this study, Artificial neural networks (ANNs) are used to develop a neural model, which infer the predicted softness from various measured parameters. Each parameter was used to predict a weight factor that shows the influence of that parameter on overall predicted softness. More the weight assigned, more will be the impact of that parameter on the predicted softness. Softness determined from neural model compared with the softness determined from that of panel test showed a high degree of correlation. There is not much published work reported to evaluate the softness by the Artificial neural networks except Sarimveis and Retsina [16] and Sarimveis et al [20]. Therefore, in this study we have chosen ANN and attempted to refine the past results for softness with high degree of correlation.

2. THEORY

2.1 Artificial Neural Networks (ANN)

ANNs are the computer generated mathematical black-box programs that mimic the response of the human brain for the given stimulus (inputs). ANNs are capable of creating and establishing the complex nonlinear relationship between the dependent variable (outputs) and the independent variables (inputs), and proving quite superior in comparison to the classical statistical technology. A simple ANN comprises of an input and output layer with the interconnection of a processing layer called hidden layer. Each layer is made up of several neurons and the number is dependent on number of inputs and outputs used to create the network, except the hidden layer neurons that are user-defined. In hidden layers as well as in output layer, the individual neuron acquires the information from neurons in former layer, and transforms the information via a transfer function with weights and bias, prior to output the result. As in nature, the network function is determined largely by the interconnections between neurons, which are not simple connections, but some non-linear functions. Each input to a neuron has a weight factor of the function that determines the strength of the interconnection and thus the contribution of that interconnection to the following neurons. ANNs can be trained to perform a particular function by adjusting the values of these weight factors between the neurons, either from the information from outside the network or by the neurons themselves in response to the input. This is the key to the ability of ANNs to achieve learning and memory. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process,

2. Inter-neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

2.2 ANN Methodologies

The basic methodologies with ANNs is to train the network with a given set of input-output data by using the various training algorithms, so as to predict and compare the resultant outputs for the new set of input-output data which trained network never seen before. ANN can also learn from its environment just like as human brain by adjusting the various parameters to the optimized value. During the working of ANN (Figure 1), all signals are first collected at their respective input nodes and a pre-initialized weight factor is assigned to them. All inputs values are multiplied with their corresponding weight factor and summed together, which later feed to the hidden layer where processing takes place according to the transfer function used. Finally, the resultant outputs are compared with the target outputs and weight factors are adjusted accordingly to obtain as near results to target values.

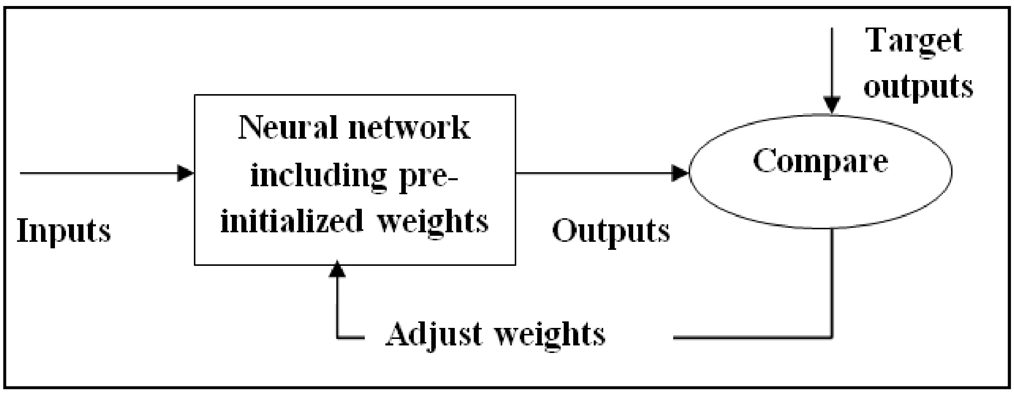

Figure 1: Flow chart describing the principle behind ANN in case of known target values.

The performance of the ANN can be determined by estimating the mean square error (MSE) between the predicted output of the model and the actual output. The main objective for the efficient training is to minimizing the MSE as much as possible.

3. EXPERIMENTAL

3.1 Sample selection

31 samples of facial tissues were obtained from the CORNET SOTIPA (European project), currently working on the softness of tissue papers. Samples include a mix of all the brands of facial tissues within the Europe. For evaluation of tissue softness by panel testing and calibration of test results, 3 Standards facial tissue (Hard, Middle, and Soft) of known softness score were also obtained from the same organization. All samples were conditioned in TAPPI standard environment.

3.2 Panel test

In this process, standard samples were arranged from hard "softness score 2" to the soft "softness score 8" on the flat large laboratory table. Each sample then directly compared by the standards starting form hard to soft and a suitable softness score (from 1 to 10) based on its surface roughness, bulk softness and stiffness were given to that sample. The panelist determined the softness by feeling or running the fingertips of the preferred hand over the surface of tissue, by gently pressing or squeezing the folded tissue, by bending it, gently crumpling it and noting the sound produced after crumple. For each sample, the softness score was the average of the all the panels of participating organization in the SOTIPA project for softness evaluations of tissue products. All the hand feel determinations were made on samples conditioned in TAPPI standard environment.

3.3 Determination of tissue surface texture

Surface texture was determined by using Infinite-Focus (Alicona Imaging GmbH, Austria) an optical profiler. Surface texture of the tissues were examined for the sake of surface roughness determination. The data in the form of 3D images were obtained for all samples and were analysed by the surface roughness parameters by the help of Alicona's software. Tissues were firmly gripped by the concentric rings made so as to prevent any fold or waviness and placed on the vacuum plate under the beam of light measuring the surface texture. The total scanned area was 3.32 mm2. Vertical and lateral resolutions were fixed to 0.444 µm and 1.6 µm, respectively. The maximum height-range was 1.2 mm with a magnification of 5x. After setting the necessary process parameter, start button was clicked and 3D images were stored in the database of software for further analysis. The three dimentional images of the surface obtained, in Figure 2 were then treated with a filter with a cut-off frequency of 200 µm, to determine the roughness at fiber level. After filtering, surface roughness parameters Sa (arithmetic mean surface roughness, µm) and Sq (root mean square surface roughness, µm) were computed using Eqs. 1 and 2, respectively.

$$Sa = \frac{1}{A}\int_0^A |z(x,y)|dxdy \qquad ..... (1)$$

$$Sq = \sqrt{\frac{1}{A}\iint_0^A |z^2(x,y)|dxdy} \qquad ..... (2)$$

where A is the scanned area, mm2, and Z(x,y) is the z direction height over the mean surface line.

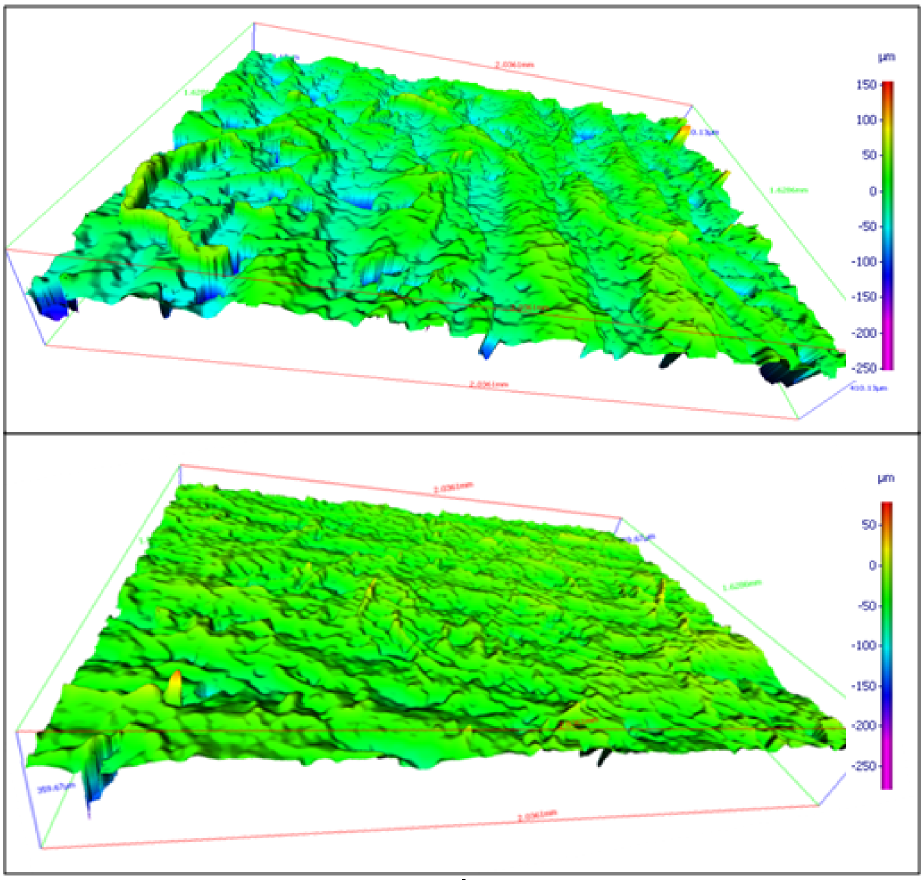

Figure 2: 3D images of hard and soft tissue showing irregularities (Top to bottom)

3.4 Determination of Coefficient of friction

The coefficients of friction of tissue samples were measured using Tribometer (CETR UMT Multi-specimen testing instrument, USA). Here, the dynamic coefficient of friction was determined by sliding the pin of diameter 6.3 mm against the tissue that was laid on the flat plate. A normal force of 1 N was used to scan 23 mm of distance of tissue surface in 11 seconds. Once the test was completed, the data was analyzed by software called "VIEWER" for the corresponding values of coefficient of friction against time (Figure 3). The dynamic coefficient of friction, μ, for the surface of tissues were determined by applying the normal force, N, and frictional force, f, and is given by Eqs. 3:

$$\mu = \frac{f}{N} \quad \text{..... (3)}$$

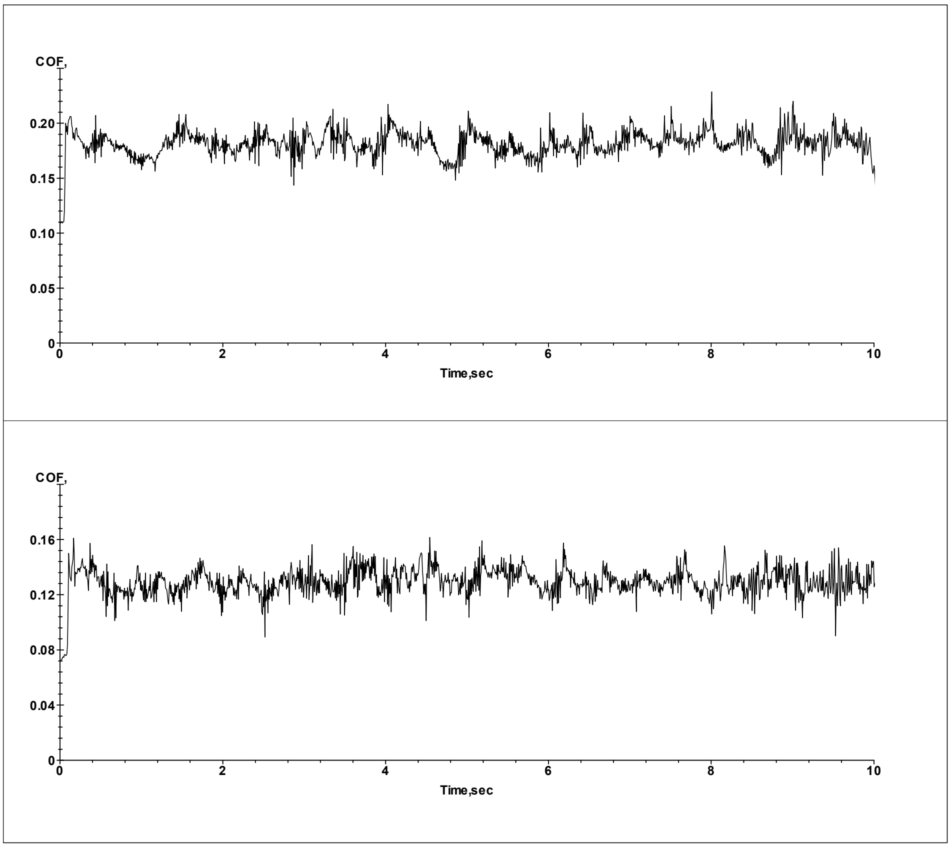

Figure 3: Coefficient of friction vs time curve for hard and soft tissues of known softness score (top to bottom)

3.5 Determination of strength properties

Several strength properties like, tensile strength, tensile index, tensile energy absorption (TEA) index, E-modulus and elongation were measured by Tensile tester (Lorentzen & Wettre group, Sweden). For each tissue sample, 5 test specimens in machine direction were cut with the width of 50 ± 2 mm and length of 100 ± 2 mm. The test strips were free of wrinkles and creases. The specimen was first aligned horizontally between the jaws of the tensile tester and strength properties were recorded when the strip was broken.

3.6 Thickness measurement

Tissue thickness was measured using an Electronic Thickness Tester (Model F16502, FRANK- PTI) based on the standards DIN EN ISO 12625-3. The thickness tester was capable of measuring tissue at various pressures by altering the tester's pressure foot and weights. The diameter and area of pressure foot were 3.57 cm and 10 cm2, respectively. The electronic bulk tester was calibrated by pressing the "ZERO" button. For each sample, the thickness of ten sheets was measured.

We also determined the values for compressibility (Eqs. 4) by measuring the tissue thickness at low pressure of 2KPa and a high pressure of 20KPa.

$$\text{Compressibility} = \left[\frac{\mathrm{T_L} - \mathrm{T_H}}{\mathrm{T_L}}\right] \times 100 \quad \text{... (4)}$$

Where TL is thickness at low pressure and TH is thickness at high pressure.

Tissue bulk (specific volume) which is the ratio of bulk thickness to grammage (Eqs. 5) was also obtained by measuring the bulk thickness at 2KPa, which is the thickness of a single sheet determined from thickness of thick pad of 7 tissues.

Bulk (cm3/gm) = Bulk thickness (μm) / Grammage (gsm) ... (5)

3.7 Softness prediction using Artificial Neural Network model

A Neural model was established for evaluating the relationship between various physical properties and the softness sensation. This process was divided into four parts: first, data collection (inputs), second, formation of network by using necessary parameters, third, to train the network with set of inputs and their corresponding target outputs, forth, to simulate the network by the sets of inputs which network never seen before and finally to compare the simulated outputs with target outputs.

3.7.1 Data collection

For the prediction of tissue papers softness, 8 physical properties as input data were used that were measured initially, as indicated in previous sections and follows as: surface roughness, coefficient of friction, compressibility, tensile index, TEA index, elongation, E-modulus and bulk.

3.7.2 Network configuration and training

Feed forward back propagation networks were created using MATLAB 2008 nntool. A network of 8-10-1 nodes was configured for prediction of softness as shown in Figure 4. The Bayesian regularization algorithm was used as training algorithm for predicting the output with appropriate weights. The Bayesian regularisation algorithm assumed the weights for each input at each node to be random variables with particular distributions [21]. Gradient descent with momentum weight and bias learning function (learngdm) was used along with the tan-sigmoid (tansig) function at hidden layer and linear (purelin) transfer function at output layer for the training of the ANN. The maximum number of desired iterations and the number of cross validation errors allowed were set to 1000 and 50, respectively.

We divide the total 31 samples randomly into two parts, one of 21 samples used for training the network and remaining 10 for simulating the network. Inputs to the network in turn further divided into 3 parts, 70% were used for training, 15% for validation and remaining 15% for testing.

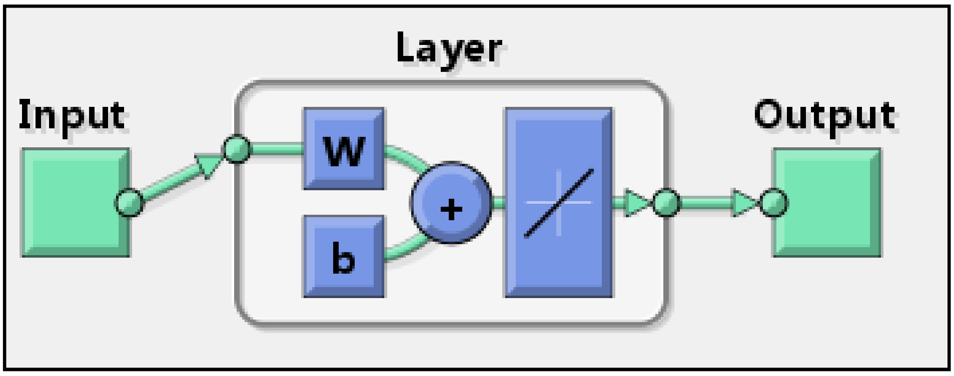

Figure 4: Neural network for softness prediction

4. RESULTS AND DISCUSSION

In this study, an artificial neural network model was developed for evaluating the relationship between various measured tissue physical properties with the predicted softness. The predicted softness of the model was then compared with that of target softness (panel softness score) to check the performance and validity of the model formed.

During the formation of neural model, 8 physical properties were measured by using the above explained methodologies and based on that a input matrix of 8x21 elements and a target output (softness) matrix of 1x21 elements were used for training the network. During training, several optimization algorithms were used to minimize the error between the predicted and actual values along with the continuous adjustment of several neural network parameters, like weights, bias, number of hidden layers etc. After training, performances curve (Figure 5) and regression curves (Figure 6) were generated, providing the indication to determine whether the network has been properly trained. If these plots are well trained, the network may used for simulation. As indicated in Figure 5, the mean square error of the network reached its minimum value for the samples used to train, validate and test the network. This is the first indication towards the formation of well-trained network. The second and the final indication was achieved by following the regression plots as in Figure 6, showing the regression coefficients (R) values close to 1, after training (0.96), validation (0.55), testing (0.79), and for the combination (0.85).

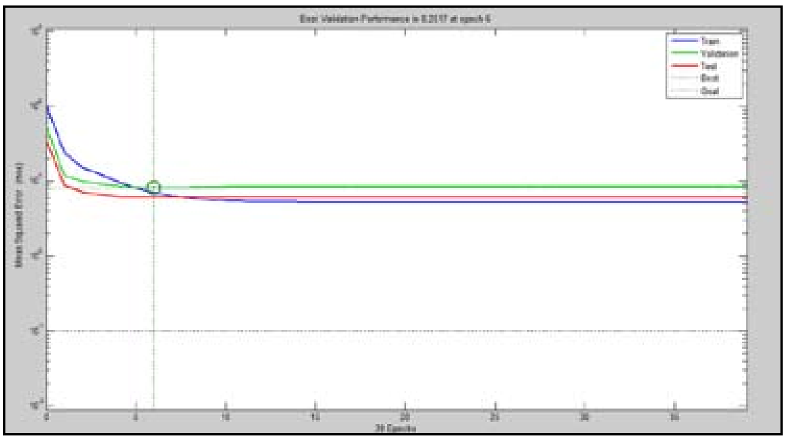

Figure 5: Performance plot produced after training the network

After the formation of well-trained network, each property was assigned a unique weight factor value, which decides the impact of that property on the overall softness as shown in Table 1.

Table 1: Weights corresponding to each property

Property	Weight
Sa	-0.6832
Bulk	-0.33454
Compressibility	-0.11134
Tensile index	-0.0841
Elongation	0.076225
TEA index	-0.04514
Coefficient of friction	0.011857
E-mod	-0.00203

It is clearly observed from the obtained values of weight factor that surface roughness is the major parameter having the maximum impact on the perceived softness by consumers. After roughness, bulk comes out to be the second most important factor having a significant impact on softness evaluation by panelist. The possible reason for this behavior is the presence of bulk softness component in the overall softness evaluation [9]. Compressibility that gives the feel of cushion has a fair degree of impact on the softness, and it could be improved by selecting the appropriate pressures for thickness measurement [10]. Tensile properties shows minor impact on the overall softness and it is because of the fact that softness perceived by panelist were the combined effect of both bulk and surface softness. Surface softness is thought to play a major role during evaluation of softness that is why tensile properties were not showing much significance in comparison with the bulk softness [9].

The dynamic coefficient of friction had no significant impact on the softness, may be due to using very high pressure of 32.1KPa, which was generated by applying a normal force of 1 N with the pin of diameter 6.3 mm.

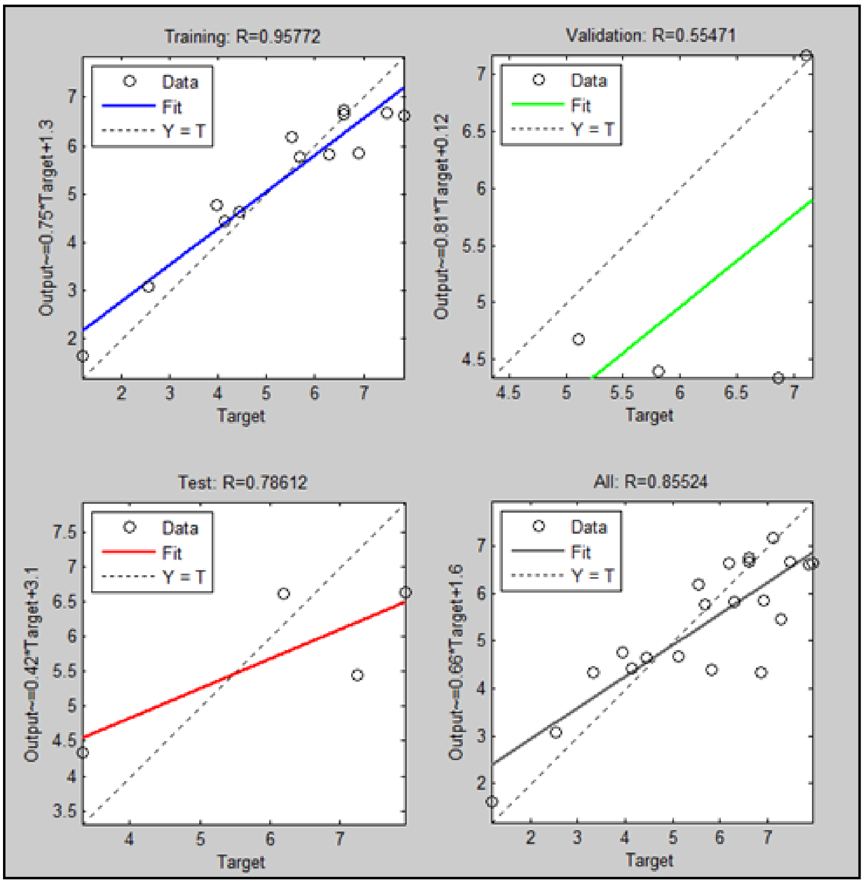

Figure 6: Regression plot produced after training the network

Finally, the trained network was used for validation of model by feeding the new set of input-output values to predict model softness. Figure 7 compares the softness of 10 new samples predicted by the neural model and softness determined by the panel test. It is clearly depicted that the model was well trained to predict the softness with high degree of accuracy. Figure 8 shows the high degree of correlation and percentage accuracy between the predictive softness by the neural model for the 10 new samples and those by the panelist with the R2 = 90.12 %.

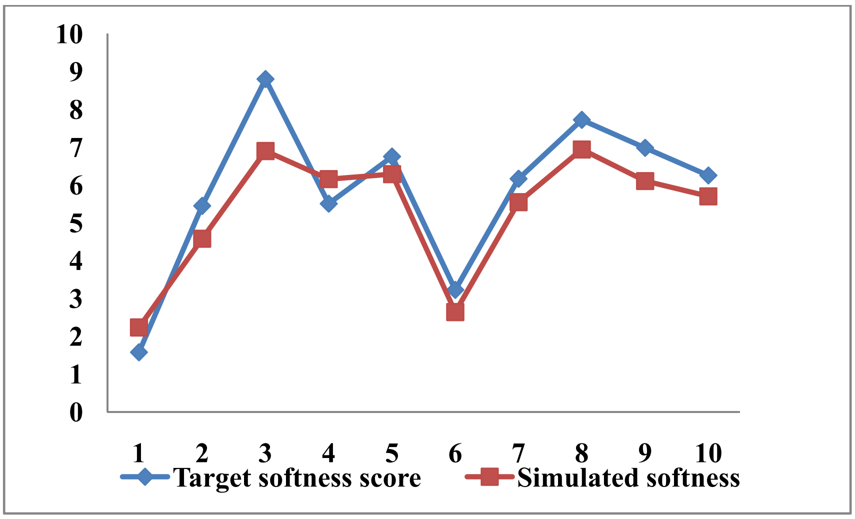

Figure 7: Comparison of tissue softness determined by panelist and by the neural model

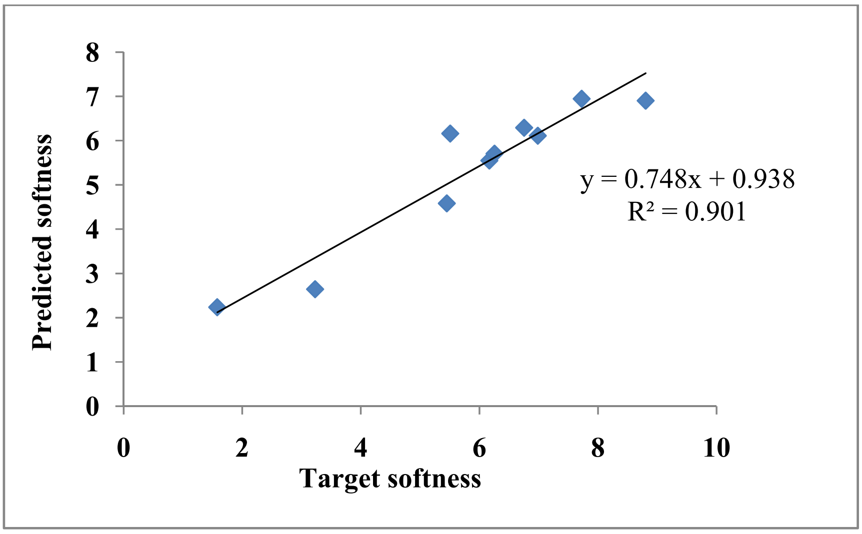

Figure 8: Linear correlation between Target softness (panel test) and Predicted softness (neural model).

5. CONCLUSIONS

In the present study, we proposed a new methodology based on artificial neural networks for prediction of tissue softness by using the tissue physical properties. This methodology proved quite promising in its approach, which infers the impact of various tissue's basic properties, strength properties and surface properties on the measured softness. Surface roughness was having major impact on the softness evaluation as indicated by the maximum value of the weight factor assigned after the network formation. Tissue bulk also came out with the substantial influence on the softness. Tensile properties and dynamic coefficient of friction had no significant impact on the softness. Neural model developed was able to predict the softness with a high degree of correlation and accuracy of about 90%. This model can be further improved by using more appropriate training and learning algorithms along with some noise filtering programs.

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