PREDICTING THE EFFECT OF FABRIC PROPERTIES ON THE THERMAL INSULATION OF SPORTSWEAR BY USING ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION APPROACHES

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Abstract: *The study looks at two machine learning methods—multiple linear regression and artificial neural networks—to predict the thermal insulation value, known as CLO, of knit sportswear fabrics. The artificial neural network is created using feed-forward backpropagation and the trainlm training function in MATLAB. Its weights and basic values are adjusted using the Levenberg-Marquardt optimization method. The network uses the sigmoid transfer function to set the layer output and track its performance. When it comes to accuracy and how well it handles complex situations, the artificial neural network outperforms the multiple linear regression model. It better captures how thermal insulation values relate to fabric qualities. For the artificial neural network model, the mean absolute error percentage was 2.2771, the root mean squared error was 0.0017, and the coefficient of determination was 0.9268. The multiple linear regression model had a coefficient of determination of 0.8046 and mean absolute error percentages of 4.4170 and 0.0027. Compared to a time-consuming trial-and-error approach, the study shows that artificial neural networks are a better way to predict thermal insulation in textiles. This emphasizes how important these models are for creating energy-efficient designs and improving material engineering.*

Keywords: artificial neural network, multiple linear regression, sportswear, knit fabric, thermal insulation.

PREDVIĐANJE UTICAJA SVOJSTAVA TKANINE NA TOPLOTNU IZOLACIJU SPORTSKE ODEĆE POMOĆU VEŠTAČKIH NEURONSKIH MREŽA I VIŠESTRUKE LINEARNE REGRESIJE

Apstrakt: *Ova studija istražuje dve metode mašinskog učenja - višestruku linearnu regresiju i veštačke neuronske mreže - u cilju predviđanja vrednosti toplotne izolacije, poznate kao CLO, pletenih tkanina za sportsku odeću. Veštačka neuronska mreža je kreirana korišćenjem feed-forward backpropagation pristupa i trainlm funkcije za treniranje u MATLAB-u. Njene težine i osnovne vrednosti podešavaju se primenom Levenberg-Marquardt optimizacije. Mreža koristi sigmoidalnu transfer funkciju za određivanje izlaza sloja i praćenje performansi. Kada je reč o tačnosti i sposobnosti rešavanja složenih situacija, veštačka neuronska mreža nadmašuje model višestruke linearne regresije. Bolje hvata odnose između vrednosti toplotne izolacije i svojstava tkanine. Za model veštačke neuronske mreže, procenat srednje apsolutne greške iznosio je 2,2771, koren srednje kvadratne* *greške bio je 0,0017, a koeficijent determinacije 0,9268. Model višestruke linearne regresije imao je koeficijent determinacije 0,8046 i procente srednje apsolutne greške 4,4170 i 0,0027. U poređenju sa dugotrajnim pristupom „pokušaj i greška", studija pokazuje da su veštačke neuronske mreže efikasniji način predviđanja toplotne izolacije u tekstilu. Ovo naglašava značaj ovih modela za razvoj energetski efikasnih dizajna i unapređenje inženjeringa materijala.*

Ključne reči: veštačka neuronska mreža, višestruka linearna regresija, sportska odeća, pletena tkanina, toplotna izolacija.

1. INTRODUCTION

Sportswear has grown significantly recently as a result of improvements in textile and processing techniques. While shielding users from dangerous chemicals, these developments seek to offer special advantages and capabilities that satisfy the body, mind, and soul. The market for athletic wear is always looking for high-performance textiles for a range of sporting uses. The absorption of perspiration and moisture, heating and ventilation, and user comfort are all factors that impact the quality of sports materials [1-3]. The thermal insulation qualities of materials should be taken into account while designing clothing in order to provide comfort and shield the body from temperature fluctuations while being worn [4, 5]. The special qualities of thermal insulation fibres, which include both natural and synthetic fibres like polyester and nylon, restrict heat transfer. The utilisation of several layers and cutting-edge technology may improve a fabric's insulating ability, therefore fabric structure also affects thermal insulation [6]. Thermal insulation in sportswear improves an athlete's ability to tolerate changing weather conditions by minimising heat loss in cold weather and lowering heat absorption in hot situations. It retains body heat while protecting it from chilly temperatures, enabling for unrestricted temperature regulation in hot conditions. Thermal insulation also produces a comfortable environment, boosting attention on performance while minimising the negative impacts of temperature fluctuations [7]. Comfort, affordability, ease of manufacturing, variety of designs, and attractiveness are the main

in this situation than the Multiple Linear Regression (MLR) model because it is better at identifying reasons why knitwear has become so popular in recent years. Because of its exceptional air permeability, flexibility, and stretching, it may be used for a variety of clothing styles. Knitted clothing can swiftly spread body vapour, which makes it appropriate for casual wear, sportswear and knickers. The textile industry has an exciting opportunity to explore and develop the diversity and adaptability of knitted clothing. A thorough analysis of the thermal properties of these items is essential to enhancing performance and comfort. There are psychological, sensory, and thermophysiological components to the complicated idea of wearable comfort [8, 9].

The thermal insulation of cloth is gauged by its CLO value. It refers to the quantity of insulation needed to maintain a person's comfort level at 21°C (70°F) when they are in an otherwise active condition. The following formula [10] may be used to represent it:

$$\text{CLO value} = \frac{\text{h}}{0.155 \text{ x } \lambda \text{ x } 1000} \tag{1}$$

Where λ = thermal conductivity, h = fabric thickness.

When the rate of heat generation and loss is equal, the human body and its surroundings maintain thermal equilibrium. This relationship can be expressed using the following equation[11]:

Heat generation = Heat loss

Or,

$$M\text{-}W = C_v + C_k + R + E_{sk} + E_{res} + C_{res} \tag{2}$$

In this case, the metabolic rate is shown as M, measured in watts per square meter. The symbol W stands for external work, also measured in watts per square meter. Heat loss through convection, conduction, and radiation is represented by Cv, Ck, and R respectively, all in watts per square meter. Eres is the heat lost through respiration due to evaporation, also in watts per square meter. Esk is the heat lost through the skin by evaporation, measured in watts per square meter. Finally, Cres is the sensible heat loss connected to respiration, also in watts per square meter.

Artificial neural networks (ANNs) are software programs that replicate data on the model of the biological nervous system. Neural networks are composed of interconnected neurons, which work together to resolve intricate issues. ANNs gained huge popularity over the last 50 years because they can analyze and interpret intricate data, grow through optimization and parallelization, and perform intense mathematical calculations. Python, C++, Tensorflow, Theano, Matlab, and Spark are a few of the commonly accessible frameworks for the building of artificial neural networks. Because they are trained on a particular dataset, artificial neural networks (ANNs) are data modeling tools that may be used to derive meaning from difficult or ambiguous problems [12-14]. Optimization problems often require effective methods to either minimize or maximize objective functions. When these functions are not linear or polynomial, they can be challenging to solve. While evolutionary algorithms can be used to approximate solutions, other methods use derivatives - either fully or partially - to linearize these functions. To find an optimal solution, the derivative of the objective function should be a polynomial. Algorithms are used to optimize various aspects of neural networks, including weights, network structure, learning rules, neurons, activation functions, and biases. Another way to improve neural networks is by replacing traditional training methods with specialized optimizers, like the Levenberg-Marquardt algorithm. This review focuses on enhancing optimization techniques by adjusting neural network or training parameters to achieve a more efficient and accurate network structure for faster and better problem-solving [15, 16]. Neural networks are flexible instruments that can quickly identify patterns in vast amounts of data with intricate properties. They are helpful for industrial applications like as behavior prediction, anomaly detection, and image, sound, or picture detection. Their modeling methodology is rapid, adaptable, and simple to change in response to operator experiences. Because they keep their inputs in their networks rather on a database line, they are very good at solving complicated non-linear relationships [17].

The statistical method of multiple linear regression is employed in quantitative structure-activity relationship models (QSAR) because of its ease of use and simplicity. Researchers can use it to describe correlations between variables and evaluate individual predictors and their combined effects. When variables and several independent factors have linear correlations, MLR is very advantageous. However, in real-world scenarios, this may not always be the case because it presumes a straight link between the independent and dependent variables. Due to MLR's shortcomings in QSAR, researchers have looked at other techniques such principal component regression, polynomial regression, ANN, and partial least squares regression. Nonlinear multivariate methods are able to capture complex relationships and interactions between variables [18].

Hussain et al., calculated the color strength of viscose knitted fabrics using a fuzzy logic model that considered salt, dye, and alkali levels. They found that the dye concentration has a major impact on how strong the fabric's color appears. When they compared the two models, the Artificial Neural Network model performed better in terms of how accurately it predicted the color strength[19]. In another study, Akter et al. used both multiple linear regression and artificial neural networks to predict the thermal transmittance of plain-woven cotton fabric. The results indicated that the artificial neural network model worked better than the multiple linear regression model. It showed higher accuracy and was more reliable in understanding the complex connections between thermal transmittance and key fabric properties like thickness, picks per inch, and ends per inch [11]. Hung et al. studied how to forecast the color properties of denim textiles treated with lasers using Artificial Neural Networks (ANN) and Linear Regression (LR) techniques. After applying several laser processing scenarios, they carried out a comparison analysis. According to the findings, ANN performed better in terms of prediction accuracy than LR[20]. Fayala et al. used an optimum ANN system with four input parameters to accurately forecast the heat conductivity of knit textiles, obtaining a correlation value of 0.913[21]. Mandal et al. conducted a study comparing ANN and MLR models, finding that ANN outperforms MLR in prediction accuracy. They also analyzed seam strength prediction in 100% cotton plain weave structured woven fabric, considering thread density through polynomial regression, highlighting the effectiveness of ANN in predicting fabric properties [22].

This study's primary goal is to use ANN and MLR to anticipate and create a model for the impact of GSM, spirality, count, thickness, stitch length, and count on sportswear fabric's thermal insulation characteristics and make a comparison between the ANN and MLR models. Every sportswear fabric utilized in this study has 70% viscose and 30% polyester in it.

2. EXPERIMENTAL

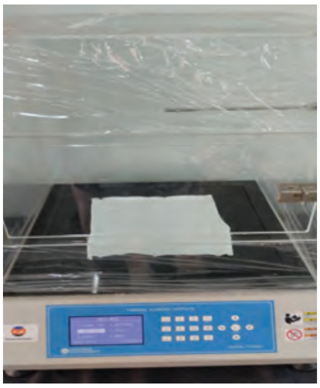
2.1. Fabric

This experiment was conducted using Sportswear's knit fabric, which consists of 70% viscose and 30% polyester, and includes parameters such as GSM 140-160, fabric thickness of 0.18-0.50 mm, stitch length of 2.5-3.0 mm, count of 28-40, and spirality ranging from 1% to 10%, all sourced from a renowned factory in Dhaka.

2.2. Fabric thickness

An AMES thickness gauge was used to measure the fabric's thickness for this experiment in accordance with ISO 5084:1996 at the textile testing lab of a reputable facility situated in Tejgaon, Dhaka. (Figure 1).

a



b

Figure 1: (a) Fabric thickness measurement with AMES thickness gauge and 1(b) Thermal insulation measurement with thermal guarded hotplate

2.3. Thermal insulation Measurement

The Bangladesh University of Textiles' Apparel Engineering Lab in Tejgaon, Dhaka, served as the site for the experiment's thermal insulation assessments. A guarded hot plate equipment was used in the procedure, which complied with ISO 8302:1991 requirements (Figure 1). The guarded hot plate method is a steady-state technique used to determine how much electrical energy a hot plate uses, which helps evaluate a material's ability to insulate against heat. It works by applying heat to one side of a sample using an electrically heated plate, making it simpler to measure how well heat is transferred through the material.

2.4. ANN modeling

Artificial Neural Networks (ANNs) are data modeling tools with input, hidden, and output layers that are modeled after the human nervous system. Backpropagation, non-linearity, and optimization techniques like gradient descent and Levenberg-Marquardt are used to achieve precision.

In case of steepest descent method, weight update rule can be expressed as:

$$w_{k+1} = w_k - \alpha g_k \tag{3}$$

Here, represents the updated weight vector after the kth iteration, and is the weight vector before the update. “α” is the learning constant (step size) and “g”

Table 1: Thermal insulation experimental results

SL.	GSM	Thickness (mm)	Stitch Length (mm)	Count (Ne)	Spirality (%)	Actual Thermal Insulation (CLO)
1	145	0.25	2.8	35	4	0.049
2	150	0.3	2.7	32	5	0.062
3	160	0.3	2.9	28	5	0.054
4	142	0.22	3	32	3	0.042
5	155	0.28	2.6	30	4	0.052
6	148	0.32	2.7	38	4	0.065
7	153	0.29	2.8	34	5	0.062
8	146	0.24	2.5	36	4	0.042
9	140	0.23	2.6	39	3	0.044
10	149	0.31	2.9	33	5	0.063
11	150	0.29	2.8	32	4	0.057
12	155	0.28	2.7	37	4	0.050
13	158	0.31	2.6	40	5	0.063
14	160	0.29	3	28	5	0.053
15	147	0.2	2.8	34	4	0.042
16	144	0.27	2.7	36	4	0.051
17	152	0.27	2.7	36	4	0.051
18	148	0.3	2.8	38	4	0.062
19	150	0.32	2.6	32	3	0.059
20	155	0.28	2.7	30	5	0.050
21	146	0.25	2.8	39	4	0.049
22	148	0.29	2.7	34	5	0.058
23	149	0.3	2.6	31	3	0.062
24	151	0.32	2.8	37	4	0.061
25	156	0.3	2.9	33	5	0.062
26	154	0.27	2.7	36	4	0.056
27	149	0.28	2.8	30	4	0.055
28	153	0.3	2.9	35	5	0.055
29	145	0.27	2.7	34	4	0.054
30	150	0.26	2.8	38	3	0.054
31	160	0.3	2.8	29	4	0.054
32	152	0.27	2.7	36	5	0.050
33	153	0.26	2.6	33	4	0.052
34	155	0.27	2.7	38	5	0.051
35	148	0.28	2.6	34	4	0.058
36	151	0.3	2.8	36	5	0.059
37	150	0.28	2.6	37	4	0.056
38	160	0.3	2.8	35	5	0.062
39	155	0.27	2.7	36	4	0.051
40	158	0.32	2.5	37	4	0.065

is gradient, which is defined as the first-order derivative of total error function.

For the gauss newton method, update rule will be

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k \quad (4)$$

Here, is the Jacobian matrix and is the residual (error) vector at the kth iteration. is the transpose of the Jacobian matrix.

Update rule for the Levenberg–Marquardt (LM) algorithm can be presented as

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \quad (5)$$

Here, I is the identity matrix and μ is the positive combination coefficient. During training, the Levenberg-Marquardt (LM) algorithm switches between Gauss-Newton and the steepest descent techniques. The Gauss-Newton technique is employed when μ is small, while the steepest descent method in which μ serves as the learning coefficient is utilized when μ is big [23].

2.5 MLR modelling

The MLR model is a commonly used and successful technique for evaluating the link between several explanatory factors and a response variable since it may be difficult to identify these correlations. Fitting a linear equation (vi) to the data accomplishes this. One way to summarize the formulation is as

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots\dots\dots + \beta_k x_k + \varepsilon \quad (6)$$

The coefficients β_i show how a one-unit change in each independent variable influences the dependent variable Y, assuming all other variables stay the same. Using statistical techniques to calculate these coefficients, multiple linear regression offers a clear way to understand and predict how different factors affect the dependent variable. This method is commonly used in various areas like economics, finance, social sciences, environmental studies, and medical research to make informed predictions and uncover intricate patterns in data.

2.6 Analysis of Predictions Performance

The coefficient of determination (R^2), root mean square, and mean absolute error percentage were analyzed to assess how well the predictions worked. These assessments' equations are given in Equations (7) through (9).

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{i=1}^{i=N} (E_a - E_M)^2} \right) \quad (7)$$

$$\text{Root mean square} = \sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}} \quad (8)$$

$$\text{Mean absolute error percentage} = \frac{1}{N} \sum_{i=1}^{i=N} \left(\frac{|E_a - E_p|}{E_a} \times 100 \right) \quad (9)$$

N are distinct patterns, E_M is the average, E_p is the expected outcome, and E_a is the actual outcome. The root mean square decreases for accurate predictions until it is nearly zero, even though the coefficient of determination (R^2) is most likely employed to compare a model's accuracy to that of a pointless benchmark model. The difference between the actual and anticipated values is represented by the mean absolute error percentage, which ought to be zero.

3. RESULTS AND DISCUSSION

3.1. Prediction of ANN model

An artificial neural network model was developed to predict the thermal insulation performance of sportswear. The fabric used for manufacturing the sportswear is a knitted material made from 70% viscose and 30% polyester yarn. The neural network was created using MATLAB's neural network fitting tool, version 9.14. Several fabric properties were included as input data, such as GSM ranging from 140 to 160, fabric thickness between 0.18 and 0.50 mm, stitch length from 2.5 to 3.0 mm, count between 28 to 40, and spirality from 1% to 10%. These inputs were used to predict the thermal insulation value, measured in

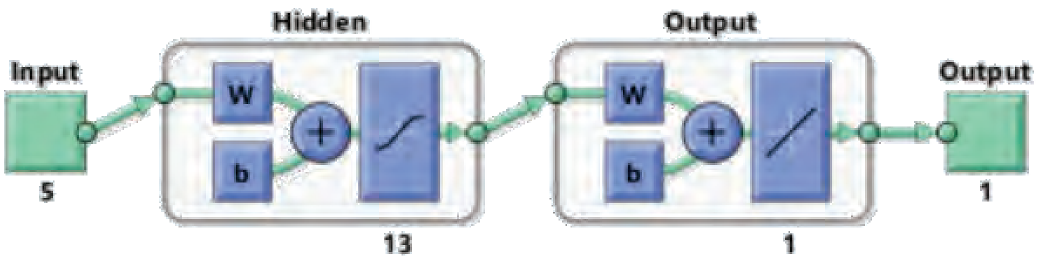


Figure 2: ANN with activation function and network tropology, Where 'b' indicates bias and 'W' indicates weight

CLO units. The model has a structure of 5-13-1, which means it has five neurons in the input layer, thirteen in the hidden layer, and one in the output layer. Figure 2 illustrates the setup, showing that a linear activation function (purelin) is used in the output layer, while a sigmoid activation function (tansig) is applied in the hidden layer.

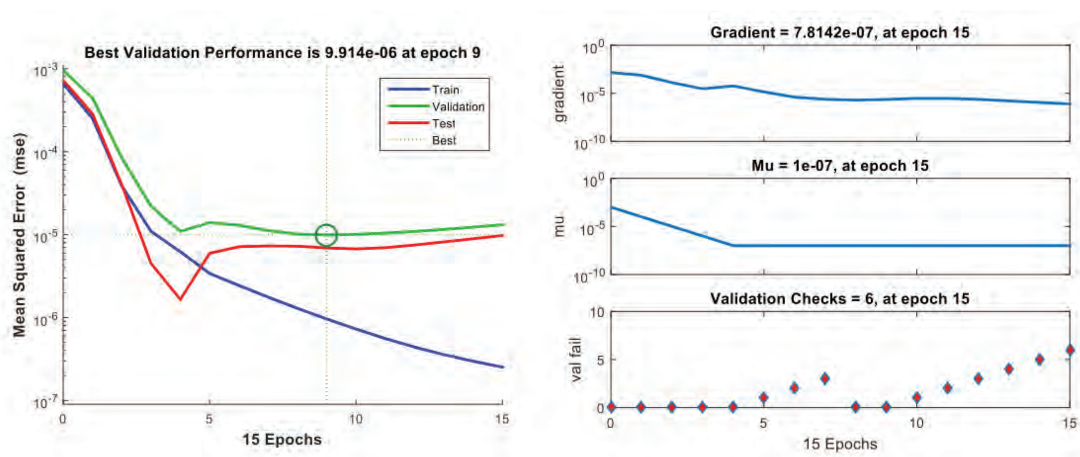
The model was created using 40 datasets, with 12 of them chosen at random for testing (6 samples) and validation (6 samples), while the remaining 28 were used for training. The input layer didn't have any transfer function applied. To train the network, the Levenberg-Marquardt (trainlm) feedforward back-propagation method was used, which is a typical approach for small datasets. During training, the network changes its weights and biases to prevent overfitting and to make sure it works well with new data. Testing with separate data gives the final measure of how well the model performs. Table 2 shows how the training went. The bias values and weights were generated using MATLAB software.

Table 2: ANN training progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	15	1000
Elapsed Time	-	00:00:01	-
Performance	0.000662	2.52×10^{-07}	0.00
Gradient	0.00144	7.81×10^{-07}	1×10^{-07}
Mu	0.00100	1.0×10^{-07}	1×10^{10}
Validation Checks	0	6	6

The performance of the ANN model over 15 epochs is shown in Figure 3(a), including the MSE for the test, validation, and training datasets. The training MSE starts by dropping quickly and then slowly converges, causing some confusion and frustration. The test MSE is very similar to the validation MSE, showing good generalization, while the validation MSE stops improving early, suggesting little further progress. The 'Best' vertical line marks epoch 9, where the validation MSE reaches its lowest point without overfitting, showing the model is well-tuned and has good generalization, as seen by the close match between the errors. Figure 3(b) shows the gradient, damping factor (mu), and validation checks during the ANN training over 15 epochs. When the gradient reaches 7.8142×10^{-7}, the loss function stabilizes. By epoch 15, the number of validation checks increases to six, suggesting overfitting may not occur and more training might not improve results. The damping factor changes to help the model converge efficiently.

The error histogram for the ANN in Figure 4 shows how errors between the network's outputs and the target values are spread out across the training, validation, and test datasets. The line showing zero error, which is in orange, represents perfect predictions. Errors are grouped into different ranges, and the majority of the errors fall near zero, meaning the network's predictions are mostly correct. As you move further away from the zero line, you see more errors, which show where the predictions differ from the desired outcomes.



(a) (b)

Figure 3: (a) ANN training result over 15 epochs and (b) ANN with gradient, damping factor (mu), and validation check during training

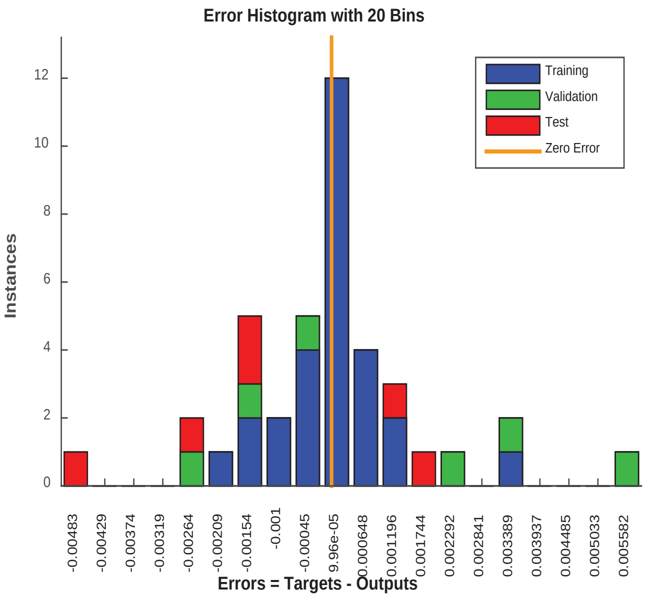


Figure 4: Histogram of errors in the ANN prediction model

The output values are plotted against the training, validation, test, and all data that the ANN has trained in Figure 5. The best-fit curve, which shows where outputs match targets, and data points (circles) demonstrate how accurate the model is. R = 0.98623 indicates a nearly perfect correlation in the training plot (top-left), but R = 0.9661 indicates high generalization in the validation plot (top-right). Indicating the accuracy and strong generalization of the ANN, the test data plot (bottom-left) exhibits robust performance (R = 0.94577), while the whole dataset plot (bottom-right) displays consistent performance (R = 0.96126).

The projected values of thermal insulation based on the input variables by the created ANN model are displayed in Table 3, along with the absolute and squared errors.

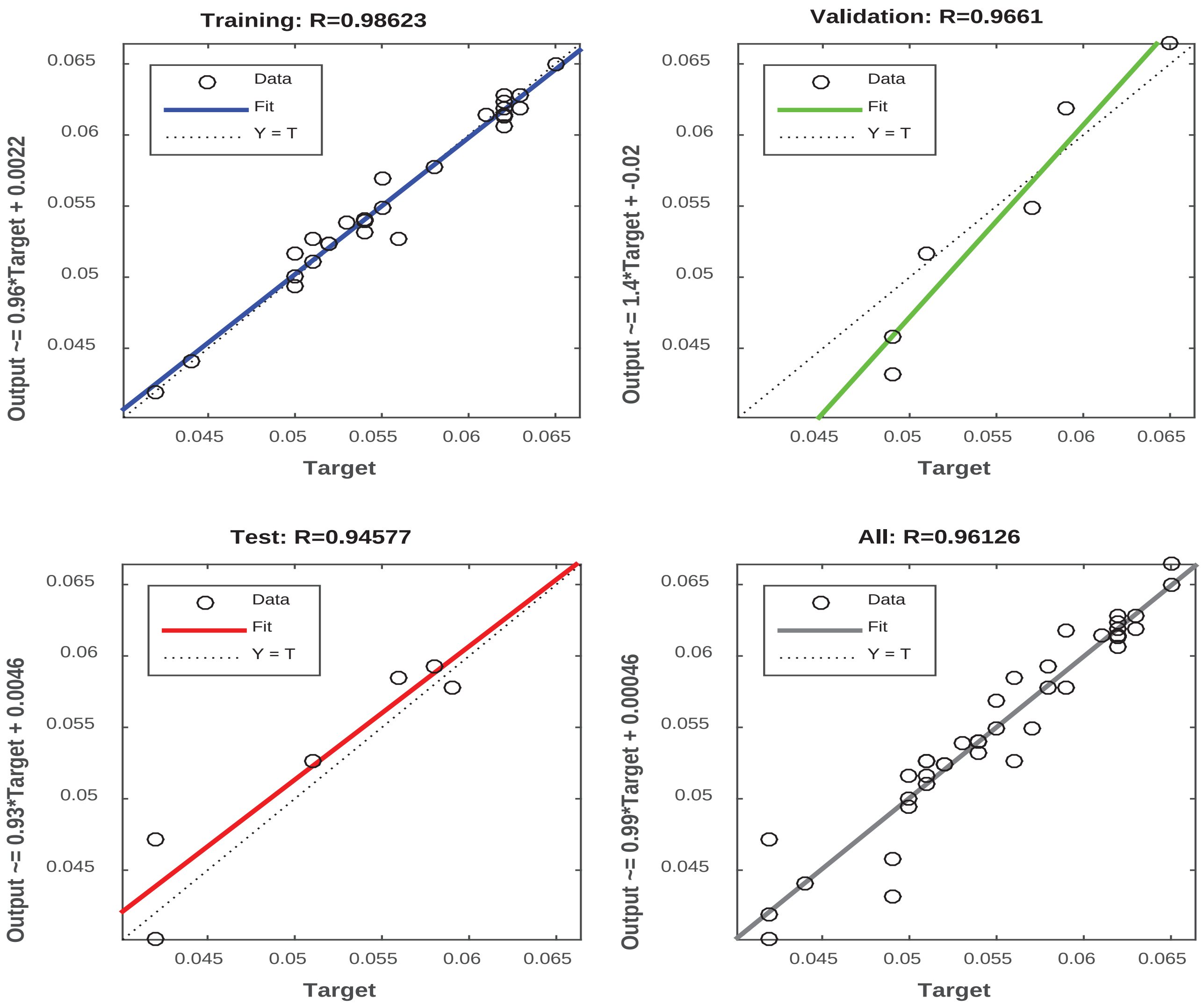


Figure 5: Output value scatter plots with training, validation, test, and correlation coefficient objectives for all data

Table 3: Prediction of thermal insulation by ANN with error

Trial	Actual Thermal Insulation	ANN Predicted Thermal Insulation	Absolute Error ANN	Squared Error ANN
1	0.049	0.046	6.33665582	9.592E-06
2	0.062	0.063	0.61298505	1.4647E-07
3	0.054	0.053	1.07271697	3.3262E-07
4	0.042	0.042	0.44549693	3.4587E-08
5	0.052	0.052	1.5203107	6.1572E-07
6	0.065	0.066	2.93104847	3.5759E-06
7	0.062	0.061	1.70555336	1.1314E-06
8	0.042	0.047	12.5692326	2.7668E-05
9	0.044	0.044	1.03269659	2.0313E-07
10	0.063	0.062	1.0107835	3.991E-07
11	0.057	0.055	3.19251232	3.2762E-06
12	0.050	0.052	2.90323994	2.1223E-06
13	0.063	0.063	0.49307551	9.497E-08
14	0.053	0.054	0.72630124	1.5074E-07
15	0.042	0.040	3.59376724	2.2376E-06
16	0.051	0.052	0.77249803	1.5664E-07
17	0.051	0.053	2.7996164	2.0573E-06
18	0.062	0.061	2.85584353	3.1792E-06
19	0.059	0.062	4.81012028	8.0503E-06
20	0.050	0.049	1.51412161	5.7726E-07
21	0.049	0.043	11.7269813	3.2852E-05
22	0.058	0.059	1.41479844	6.8426E-07
23	0.062	0.062	0.20971713	1.7144E-08
24	0.061	0.061	1.12229266	4.644E-07
25	0.062	0.062	0.95351368	3.5441E-07
26	0.056	0.053	6.22983711	1.2254E-05
27	0.055	0.055	0.30227076	2.7379E-08
28	0.055	0.057	2.86426573	2.5088E-06
29	0.054	0.054	0.71369108	1.5093E-07
30	0.054	0.054	0.25963933	1.9738E-08
31	0.054	0.054	0.43266373	5.411E-08
32	0.050	0.050	0.49386505	6.0415E-08
33	0.052	0.052	0.12044069	3.9859E-09
34	0.051	0.051	0.3409948	3.0521E-08
35	0.058	0.058	0.9048048	2.78E-07
36	0.059	0.058	1.40161865	6.7579E-07
37	0.056	0.058	3.54751615	4.0105E-06
38	0.062	0.061	1.57642171	9.6873E-07
39	0.051	0.053	2.77900999	2.0272E-06
40	0.065	0.065	0.79299175	2.6174E-07

3.2. Prediction of MLR model

For the current study, an MLR model was developed using fabric thickness, stitch length, GSM, thickness, count, and spirality (%) as input or independent variables, and thermal insulation as the dependent variable (Table 4). The model was developed using the minitab program, accounting for all 40 experimental datasets.

The results of the analysis carried out are presented in Table 4. Based on the findings derived from the study conducted in accordance with the data presented in Table 4, the MLR equation of thermal insulation for the sportswear's knit fabric samples is:

$$Y = 0.002613092 - (0.000149187 \times X_1) + (0.219988592 \times X_2) + (0.00131883 \times X_3) + (0.000231903 \times X_4) + (0.000354029 \times X_5)$$

where Y is the prediction of thermal Insulation, X_1 is GSM, X_2 is thickness, X_3 is stitch length, X_4 is count and X_5 is spirality. Table 5 displays the forecasting results for thermal insulation that take into account GSM, thickness, stitch length, count, and spirality and are derived from the statistical MLR model's execution along with its performance indicators.

Table 4: MLR model parameters

Model Parameters	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.002613092	0.024474303	0.106769	0.9156	-0.04712	0.052351
GSM	-0.000149187	0.000129521	-1.15184	0.257423	-0.00041	0.000114
Thickness(mm)	0.219988592	0.020937188	10.50707	3.24E-12	0.177439	0.262538
Stitch Length(mm)	0.00131883	0.004495105	0.293392	0.771006	-0.00782	0.010454
Count(Ne)	0.000231903	0.000172704	1.342776	0.188241	-0.00012	0.000583
Spirality(%)	0.000354029	0.000915395	0.386749	0.701352	-0.00151	0.002214

Table 5: Prediction of thermal insulation by MLR with error

Trial	Actual Thermal Insulation	MLR Predicted Thermal Insulation	Absolute Error MLR	Squared Error MLR
1	0.049	0.049	0.67043513	1.0737E-07
2	0.062	0.059	5.52814835	1.1913E-05
3	0.054	0.057	5.69961052	9.39E-06
4	0.042	0.042	1.2450081	2.7013E-07
5	0.052	0.053	2.47057855	1.626E-06
6	0.065	0.065	0.31445347	4.1158E-08
7	0.062	0.057	8.71295153	2.9527E-05
8	0.042	0.047	11.5713598	2.3449E-05
9	0.044	0.046	5.07811357	4.9118E-06
10	0.063	0.062	1.07486674	4.513E-07
11	0.057	0.057	0.2373317	1.8106E-08
12	0.050	0.055	8.89618094	1.9928E-05
13	0.063	0.062	1.25888668	6.1906E-07
14	0.053	0.055	2.43848779	1.6992E-06
15	0.042	0.038	9.48862556	1.5598E-05
16	0.051	0.054	5.11213193	6.8598E-06

17	0.051	0.053	2.78260104	2.0324E-06
18	0.062	0.060	3.17746678	3.9357E-06
19	0.059	0.063	6.0304347	1.2653E-05
20	0.050	0.053	6.36666165	1.0206E-05
21	0.049	0.050	2.26309271	1.2235E-06
22	0.058	0.058	1.57690563	8.5005E-07
23	0.062	0.058	7.00593565	1.9133E-05
24	0.061	0.064	5.68230807	1.1905E-05
25	0.062	0.059	6.16794111	1.483E-05
26	0.056	0.052	6.81744801	1.4675E-05
27	0.055	0.054	1.26784074	4.8168E-07
28	0.055	0.059	7.58747809	1.7605E-05
29	0.054	0.053	2.19702614	1.4303E-06
30	0.054	0.051	5.74961707	9.6792E-06
31	0.054	0.057	5.22715475	7.8978E-06
32	0.050	0.053	6.51695393	1.052E-05
33	0.052	0.049	5.6028971	8.626E-06
34	0.051	0.053	3.50531914	3.2252E-06
35	0.058	0.055	5.85638431	1.1646E-05
36	0.059	0.060	2.11888491	1.5444E-06
37	0.056	0.055	2.11564339	1.4264E-06
38	0.062	0.058	6.59210366	1.694E-05
39	0.051	0.052	1.90902695	9.566E-07
40	0.065	0.063	2.76623541	3.185E-06

3.3 Comparative analysis of ANN and MLR model

To check how well two different methods work for figuring out the thermal insulation of knit fabrics used in sportswear, a statistical comparison was done. The methods used both real experimental data and predictions from ANN and MLR models. The accuracy of these models was tested using the same experimental data. The error from both ANN and MLR models is shown in Table 6. To compare the models, statistical measures like R^2, RMSE, and MAPE were used. When looking at the correlation coefficients (R) for both models, the ANN model has a value of 0.9627, which is closer to 1 than the MLR model's value of 0.8970. This suggests that the ANN model has a stronger linear relationship between its predictions and the actual values, meaning it might be better at finding patterns in the data.

Table 6: Performance evaluation of ANN and MLR models

Model	MAEP	RMSE	Coefficient of determinants (R^2)	Correlation coefficient (R)
ANN	2.2771	0.0017	0.9268	0.9627
MLR	4.4170	0.0027	0.8046	0.8970

Figures 6 and 7 show how well the experimental data matches the predictions made by the ANN and MLR models, using correlation curves. In Figure 6, each number is very close to the straight line that best fits the data, which means there is a strong connection between what was expected and what was actually observed. There are no unusual data points, and the R^2 value is 0.92683560, showing that the model fits the data very well. However, in Figure 7, there is an outlier, and the R^2 value is lower at 0.804641188, meaning the experimental and predicted values do not match as closely.

The ANN model has fewer errors when looking at the statistical performance results in Table 6. The ANN model's error measurements, MAPE and RMSE, are 2.2771 and 0.0017 respectively, which are much lower than the MLR model's values of 4.4170 and 0.0027. Based on this error analysis, the ANN model is better at predicting thermal insulation parameters than the MLR model.

Figure 8 displays how the real experimental results from testing compare with the thermal insulation predictions made by the Artificial Neural Network (ANN) model, presented in a clear and easy-to-understand graph. Upon closer look, it's clear that the curve showing the model's predicted values closely matches the actual experimental data curve. This is quite different from the Multiple Linear Regression (MLR) model,

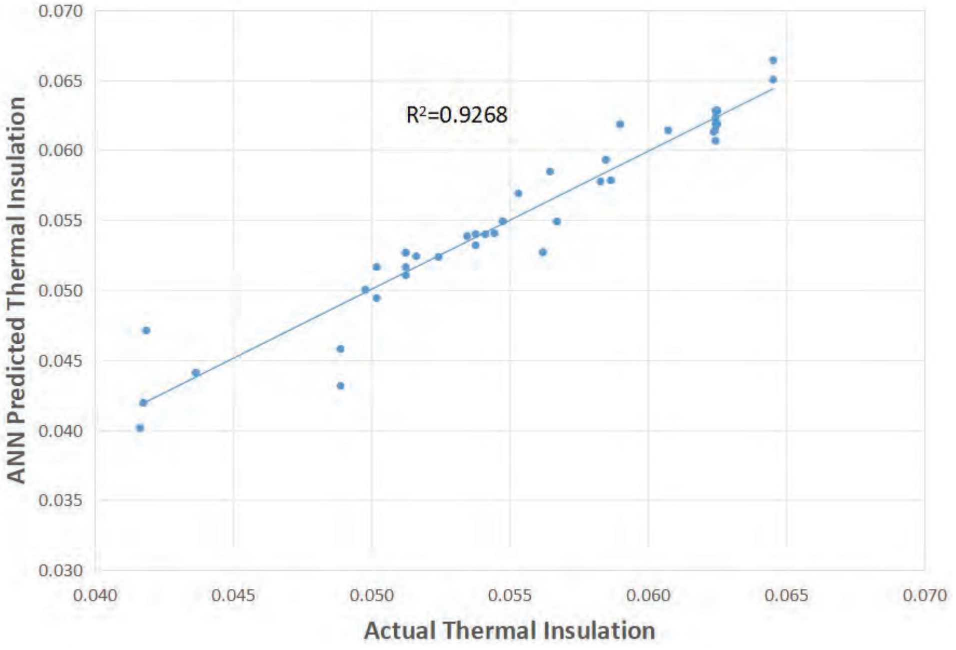


Figure 6: Actual and predicted thermal insulation for the ANN model.

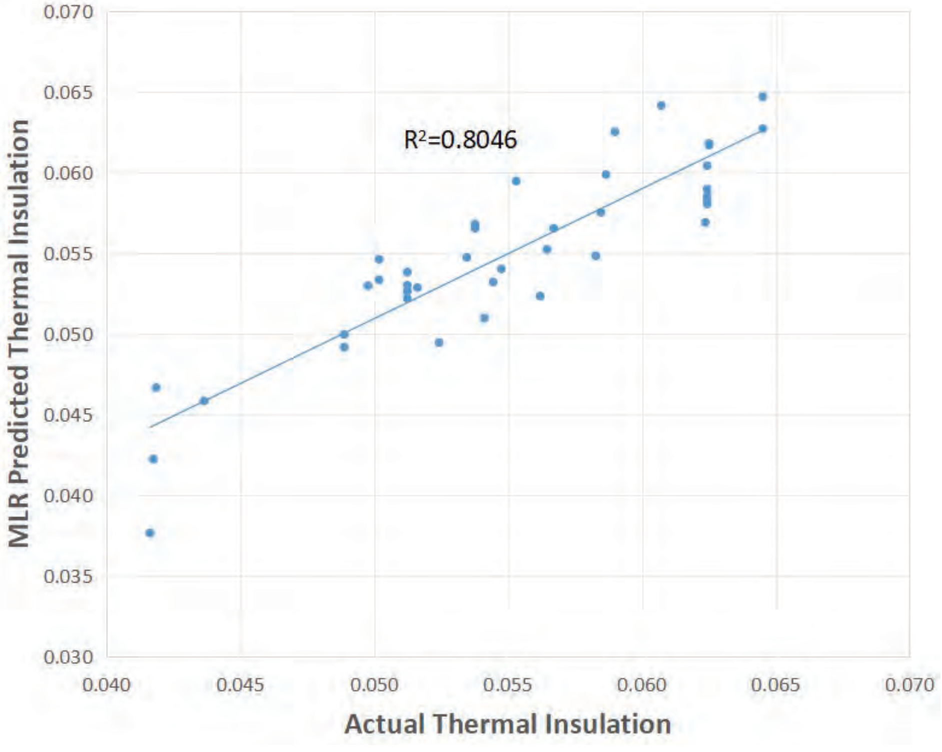


Figure 7: Actual and predicted thermal insulation for the MLR model.

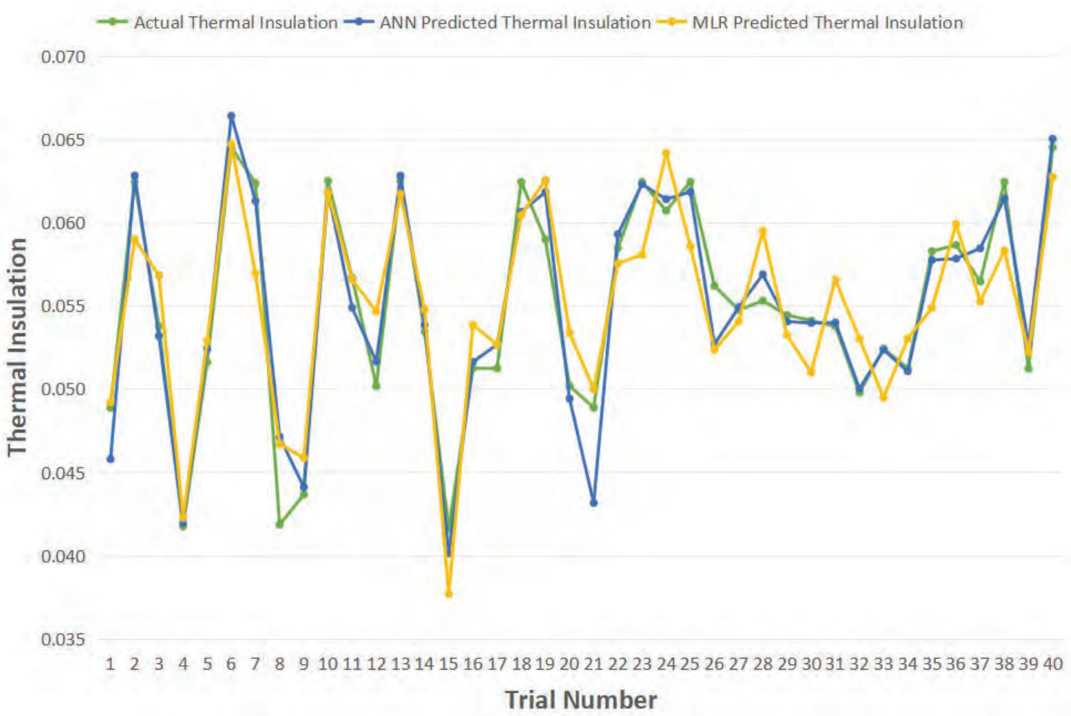


Figure 8: ANN and MLR predicted values comparison with experimental values for thermal insulation

which doesn't match the experimental results as accurately. It's important to highlight that the ANN model is more suitable and accurate for this task compared to the MLR model. This performance is due to the inherent qualities of ANNs. They are very good at finding and capturing nonlinear relationships in data, which is something linear models like MLR struggle with. Additionally, ANNs are flexible and can adapt well to different datasets and environments without overfitting, a problem that can reduce the accuracy of machine learning models. ANNs are more useful in real-world situations because they can generalize well to new, unseen data, improving their predictive power. They can also detect and explain complex relationships between features that aren't easily found using traditional methods. These features, along with their ability to handle various types of data, show how effective ANNs are for predictive modeling and data analysis.

4. CONCLUSION

Sportswear made from knit fabric was studied to predict its ability to provide thermal insulation. Two different methods were used: a statistical model called MLR and a machine learning model called ANN. This allowed the researchers to compare which method works better for predicting thermal insulation in textiles. Both models clearly showed how the input factors relate to the output and how these factors influence thermal comfort. The results suggested that machine learning models are very good at predicting thermal insulation. The ANN model performed better than the MLR model. For example, the R^2 score for the ANN model was 0.9268 compared to 0.8046 for the MLR model. The correlation coefficient was 0.8970 for MLR and 0.9627 for ANN, which shows the ANN model is better at capturing the relationship between input and output. The ANN model also had a lower MAPE of 2.2771 compared to 0.8970 for MLR. Its RMSE was 0.0017, which is lower than the MLR model's RMSE of 0.0027. All these results show that the ANN model gives more accurate predictions with fewer errors and higher precision. The findings suggest that the ANN model is a better choice for modeling and predicting data patterns related to thermal insulation. Industry professionals can use this model to help decide the best production settings for plain-woven textiles. The study used several input factors like GSM, fabric thickness, count, stitch length, and spirality for both models. Future studies might explore different fabric types, input variable ranges, and other factors to develop new prediction models that are useful in various industry situations.

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CONFLICTS OF INTEREST

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Nomenclature

ANNs	Artificial Neural Networks
MLR	Multiple linear regression
RMSE	Root mean squared error
MAPE	Mean absolute error percentage
MSE	Mean squared error

REFERENCES

[1] Ma, L., & Li, J. (2023). A review on active heating for high performance cold-proof clothing. International *Journal of Clothing Science and Technology,* 35(6), 952-970.

[2] Kamal, M. S., Mahmoud, E., Hassabo, A., & Eid, M. M. (2020). Effect of some construction factors of bi-layer knitted fabrics produced for sports wear on resisting ultraviolet radiation. Egyptian Journal of Chemistry, 63(11), 4369-4378.

[3] Hassabo, A. G., Elmorsy, H., Gamal, N., Sediek, A., Saad, F., Hegazy, B. M., & Othman, H. (2023). Applications of nanotechnology in the creation of smart sportswear for enhanced sports performance: Efficiency and comfort. *Journal of Textiles, Coloration and Polymer Science*, *20*(1), 11-28. http://dx.doi.org/10.21608/jtcps.2022.181608.1147

[4] Abreu, M. J., Catarino, A., & Tama, D. (2018). Evaluating the effect of fabric type on thermal insulation properties of sports clothing. In *IOP Conference Series: Materials Science and Engineering,* 460, 012005. http://dx.doi.org/10.1088/1757-899X/460/1/012005

[5] Hassabo, A. G., Shaker, S. G., Abd El-Salam, N. A., Mohamed, N. A., Gouda, N. Z., Khalid, N., & Othman, H. (2023). Silica Aerogels and their Applications in Textile Industry. *Egyptian Journal of Chemistry*, *66*(12), 431-443. https://doi.org/10.21608/ejchem.2023.216963.8119

[6] Rossi, R. (2009). Comfort and thermoregulatory requirements in cold weather clothing. In Textiles for cold weather apparel (pp. 3-18). Woodhead Publishing.

[7] Atallah, H. A. A., Saleh, Y. D. M., Glal El-Den, R. E., Abdel Wahab, S. S. M., & Hassabo, A. G. (2025). Importance of Thermal Insulation in Sportswear Design. *Journal of Textiles, Coloration and Polymer Science*, *22*(2), 59-64. https://doi.org/10.21608/jtcps.2024.259733.1312

[8] Tabassum, S., Najib, I., Razzak Fera, R., Islam, S. M., Hasan, S. M. M., & Nahid-Ull-Islam, M. (2025). Evaluating the thermal properties of knit fabric made of 100% conventional cotton and BCI cotton.*Journal of Applied Research in Technology & Engineering,* 2025. 6(2): p. 1-10. http://dx.doi.org/10.4995/jarte.2025.23135

[9] Islam, M. M., Rokon, M. A. A., Rubel, M. M. C., Ahmed, M., & Islam, M. A. (2014). Investigation on Comfort Properties of Conventional Cotton and Organic Cotton of Knitted Fabric Structures. *Manufacturing Science and Technology,* 2(3), 62-66.

[10] Chen, H., Yue, Z., Ren, D., Zeng, H., Wei, T., Zhao, K., ... & Shi, X. (2019). Thermal conductivity during phase transitions. *Advanced Materials*, *31*(6), 1806518. http://dx.doi.org/10.1002/adma.201806518

[11] Akter, M., Khalil, E., Uddin, M. H., Chowdhury, M. K. H., & Hasan, S. M. M. (2024). Artificial neural network and multiple linear regression modeling for predicting thermal transmittance of plain-woven cotton fabric. *Textile Research Journal*, *94*(11-12), 1279-1296. DOI: http://dx.doi.org/10.1177/00405175241230082

[12] Jafarian, F., Taghipour, M., & Amirabadi, H. (2013). Application of artificial neural network and optimization algorithms for optimizing surface roughness, tool life and cutting forces in turning operation. *Journal of Mechanical Science and Technology*, *27*(5), 1469-1477. DOI: http://dx.doi.org/10.1007/s12206-013-0327-0

[13] Askarzadeh, A., & Rezazadeh, A. (2013). Artificial neural network training using a new efficient optimization algorithm. *Applied Soft Computing*, *13*(2), 1206-1213. http://dx.doi.org/10.1016/j.asoc.2012.10.023

[14] Zappone, A., Di Renzo, M., Debbah, M., Lam, T. T., & Qian, X. (2019). Model-aided wireless artificial intelligence: Embedding expert knowledge in deep neural networks for wireless system optimization. *IEEE Vehicular Technology Magazine*, *14*(3), 60-69.

[15] Abdolrasol, M. G., Hussain, S. S., Ustun, T. S., Sarker, M. R., Hannan, M. A., Mohamed, R., ... & Milad, A. (2021). Artificial neural networks based optimization techniques: A review. *Electronics*, *10*(21), 2689. https://doi.org/10.3390/electronics10212689

[16] Jiang, J., & Fan, J. A. (2020). Simulator-based training of generative neural networks for the inverse design of metasurfaces. *Nanophotonics*, 9(5), 1059-1069. http://dx.doi.org/10.1515/nanoph-2019-0330

[17] Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., ... & Gandomi, A. H. (2020). Data science in economics: comprehensive review of advanced machine learning and deep learning

methods. *Mathematics*, *8*(10), 1799. https://doi.org/10.3390/math8101799

[18] Luco, J. M., & Ferretti, F. H. (1997). QSAR based on multiple linear regression and PLS methods for the anti-HIV activity of a large group of HEPT derivatives. *Journal of chemical information and computer sciences*, *37*(2), 392-401.

[19] Hossain, I., Choudhury, I. A., Mamat, A. B., & Hossain, A. (2017). Predicting the colour properties of viscose knitted fabrics using soft computing approaches. *The Journal of the Textile Institute*, *108*(10), 1689-1699.

[20] Hung, O. N., Chan, C. K., Kan, C. W., Yuen, C. W. M., & Song, L. J. (2014). Artificial neural network approach for predicting colour properties of laser-treated denim fabrics. *Fibers and Polymers*, *15*(6), 1330-1336. http://dx.doi.org/10.1007/s12221-014-1330-5

[21] Fayala, F., Alibi, H., Benltoufa, S., & Jemni, A. (2008). Neural network for predicting thermal conductivity of knit materials. *Journal of Engineered Fibers and Fabrics*, *3*(4), DOI: http://dx.doi.org/10.1177/155892500800300407

[22] Mandal, S., Annaheim, S., Greve, J., Camenzind, M., & Rossi, R. M. (2019). Modeling for predicting the thermal protective and thermo-physiological comfort performance of fabrics used in firefighters' clothing. *Textile Research Journal*, *89*(14), 2836-2849, http://dx.doi.org/10.1177/0040517518803779

[23] Yu, H., & Wilamowski, B. M. (2018). Levenberg–marquardt training. In *Intelligent systems* (pp. 12-1). CRC Press.

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