International Journal of Home Science

ISSN: 2395-7476
IJHS 2023; 9(3): 276-280

www.homesciencejournal.com
Received: 09-10-2023
Accepted: 27-11-2023

Dr. Hina Kausher
Research Scholar, University of Allahabad, Uttar Pradesh, India

Corresponding Author:
Dr. Hina Kausher
Research Scholar, University of Allahabad, Uttar Pradesh, India

Artificial neural network technique for prediction of relationships among body dimensions: An approach of artificial intelligence for apparel industry

Dr. Hina Kausher

Abstract
Purpose: While artificial intelligence has been extensively used in many fields; some research has been done on its applications in the apparel industry. The aim of this study to predict the relationships among the body dimensions using artificial neural network technique.
Design/methodology/approach: Two hundred data had been collected by an anthropometric survey undertaken over females between the ages of 16 to 80 years from the Uttar Pradesh, India by random sampling method. Artificial neural network technique was implemented to find out the relationships among the sizes of different body parts to be required for making ready-made garments.
Findings: In this study, drop value (the difference between the chest girth and the hip girth) had been taken as dependent variable and the age, height, weight, hip girth, abdomen girth are the input parameters under artificial neural network technique. Result shows most important variable is hip girth (100%) which affects the drop value and the second most important variable is round bust (95.8%). The percentage of importance of waist girth, round abdomen and age are 29.3%, 24.1% and 13.1% respectively.
Conclusions: Neural network is a type of artificial intelligence technique can predict the relationships among different body dimensions in a better way. Neural network has the capability to train itself on a sample population for finding the relationships among body dimensions and then can predict for the whole population which are to be importantly needed for making readymade garments.

Keywords: Anthropometric, artificial neural network, body dimensions, drop value, ready-made garments

Introduction
Artificial intelligence (AI) is a technique that makes machines and computers as capable as human brains. AI increases the efficiency of machines by bridging the gap between the theory and practical. Since there are many challenges before the apparel industry because of globalization and growing levels of international competition, many issues can be resolved by employing the artificial intelligence in apparel sector.
Artificial neural network (ANN) is a type of artificial intelligence. Nagi *et al*., 2014 [8] cited that ANN is computational models based on the structure and function of biological neural networks. Rather than using traditional computer algorithms, ANN provides answers using heuristics that are similar to the human brain.

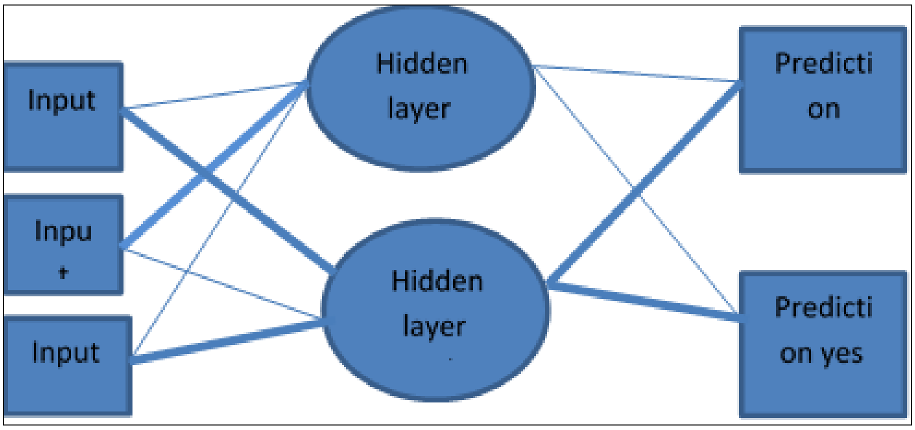

Fig 1: Artificial Neural Network (ANN) model

In this study, Multi-Layer Perceptron neural network (MLP) was used for analysing the data. The primary advantage of neural networks when compared to classical statistical technique is their flexibility and lack of distributional assumptions (SPSS Neural Connection, 2019) [9]. In this network value of inputs are taken and feeding them into the algorithm as an input layer. Hidden layers are created by using the input layers. Input layers contain nodes which are also known as units. Each node is some function of the input fields. The output layers contain the predictors. The network is continually rebuilt, so that the synaptic weights in the nodes correctly predict the outcome (SPSS Neural Connection, 2019) [9].

In this study, the effects of anthropometric variables (inputs) on the drop value are identified using ANN network. The drop value is the difference between bust girth and hip girth.

Literature review

Guo, Leung and Li (2011) [1] stated, the classical approaches use an appropriate mathematical description of the decision-making problem which is solved through a traditional mathematical method. AI is the branch of computer science focusing on creating machines that can engage in behaviours that human consider intelligent. Ai techniques exhibit heuristic and intelligent natures, which have the potential of providing superior solutions over classical techniques.

Gupta and Zakaria (2014) [2], stated since 2010, a few more techniques have been introduced and explored for the development of sizing systems. For example, neural network which is a type of AI technique –has the capability to train itself on a sample population and then classify the population into their own groups.

There exists a variety of decision –making problems in the apparel industry, including optimization, forecasting, pattern recognition, classification, modelling, and control. Compared with other industries with higher automation levels, the apparel industry has attracted relatively little attention from the AI community. (Guo, Leung and Li, 2011) [1].

Advanced AI techniques such as artificial neural networks and genetic algorithms (GA) can be used to predict the sizes needed for a specific population accurately with low dependency on humans to make decisions about size classifications. Finding the right sizes for different body types is more sophisticated and can be done precisely and quickly using the artificial intelligence. (Gupta and Zakaria, 2014) [2].

According to Jain, Mao and Mohiuddin (1996) [5], ANNs which are inspired by biological neural network, are massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. ANN model attempts to use some “organizational” principles believed to be used in the human.

Methodology

For the purpose of this study, 500 data has been collected by an anthropometric survey undertaken over females between the ages of 16 to 80 years from the Uttar Pradesh, India through random sampling. After clipping the data cases that contained missing values and outliers, 426 were remained which is the 95% of the available data.

Building a neural network model

In this study, multilayer perceptron neural network, SPSS statistics 20 was used for analysing the data. For developing the network, the minimum no of training data cases should be ten times the total numbers of input variables (SPSS Neural Connection). 5 input variables were selected for making the network. These were round bust, round abdomen, round hip, round waist and age. The dependent variable is drop value of the respondents. Drop value is the difference between the bust girth and the hip girth of the respondent. Drop value was categorised into intervals as: (-12.1 to -9.0 = 1, -9.1 to -6.0 = 2, -6.1 to -3.0 = 3, -3.1 to 0 = 4, 0-3.0 = 5 and 3.1-6.0 = 6).

The number of neurons in the output layer was equal to the input variables (anthropometric variables). and the neurons of output layer contains the dependent variables (drop values).

Result and Discussion

Table 1 shows, ANN used 298 cases in the training phase in calculating the weights and then it treated this versus the remaining 128 cases. So it’s 70/30 division.

Table 1: Case processing summary

		N	Percent
Sample	Training	298	70.0%
	Testing	128	30.0%
Valid		426	100.0%
Excluded		0	
Total		426	

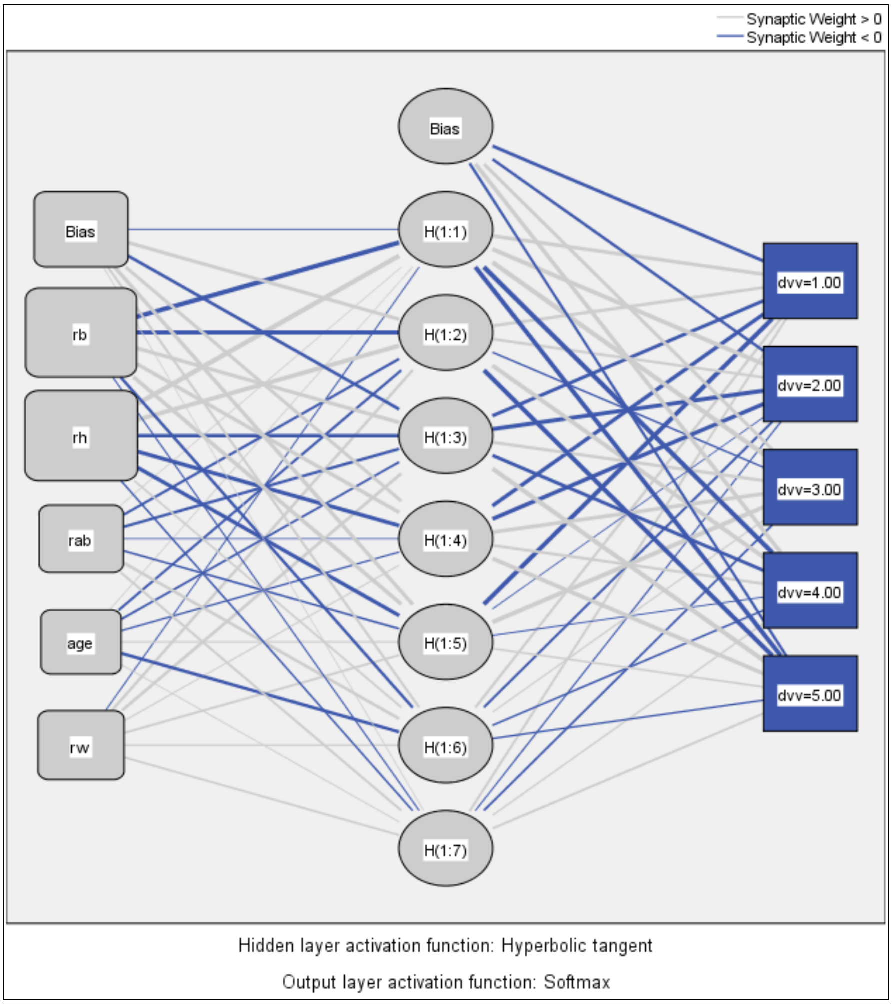

Fig 2: Hidden layer and output layer activation function

The network (fig 1) was generated with selection of 7 nodes, 7 units in the one hidden layer. The lines of synaptic weights shows the estimated relationship. The darker blue lines and the fatter lines show the stronger relations. Outcome nodes determines the intervals of drop values of respondents, e.g. if respondent is assigned to class 1, then her drop value lies between -12 to -9. This is basically impacts whether respondent is assigned to class 1 or other classes. Besides the 5 input factors, there is also error term of the bias in both parts: the input layer and the output layer.

Table 2: Parameter estimates

Predictor		Predicted											
		Hidden Layer 1							Output Layer				
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	[dw=1.00]	[dw=2.00]	[dw=3.00]	[dw=4.00]	[dw=5.00]
Input Layer	(Bias)	-.101	1.742	-1.399	1.634	2.274	.501	.014					
	rb	-6.704	-2.902	2.027	2.181	2.341	-.889	-.137					
	rh	7.024	3.223	-1.813	-2.359	-2.289	.291	-.252					
	rab	.021	-.634	-.859	-.077	-.293	.913	.493					
	age	.026	-.512	-.368	-.184	.145	-1.573	.098					
	rw	-.122	.811	.952	.126	.396	.175	.317					
Hidden Layer 1	(Bias)								-1.573	-.877	1.657	2.519	-.692
	H(1:1)								1.757	3.087	5.551	-6.567	-3.641
	H(1:2)								1.129	.744	-.242	2.899	-4.202
	H(1:3)								-1.707	-2.860	1.083	-1.694	4.191
	H(1:4)								-2.321	-2.560	2.222	.787	2.614
	H(1:5)								-3.873	-.033	3.588	-.110	.271
	H(1:6)								.657	-.496	.144	-.252	-.196
	H(1:7)								.452	-.142	-.317	.156	.433

In table 2, there are two parameter estimates, which are actually the values calculated for all the synaptic weights. It shows the amount of importance of the relationship. The upper left part that is from the input factors to the hidden layer and the second part that is from the hidden layer to the output. quality of the model can be checked by model summery table 3. During the training phase an error percentages of 0.3% occurred which is very little.in case of testing the error chance of performing well a suitable prognosis is slightly larger. So, in testing phase, the percentage of incorrect prediction is 1.6%.

Table 3: Model summary

Training	Cross Entropy Error	13.616
	Percent incorrect	0.3%
	Prediction	
	Stopping rule used	1 consecutive step (s) with no decrease in error[a]
	Training time	0:00:00.61
Testing	Cross entropy error	8.824
	Percent incorrect	1.6%
	Predictions	

Dependent variable: dw
a. Error computations are based on the testing sample

Table 4: Classification

		Predicated					
Sample	**Observed**	**1.00**	**2.00**	**3.00**	**4.00**	**5.00**	**Percent correct**
Training	1.00	4	0	0	0	0	100.0%
	2.00	0	13	1	0	0	92.9%
	3.00	0	0	128	0	0	100.0%
	4.00	0	0	0	132	0	100.0%
	5.00	0	0	0	0	20	100.0%
	Overall percent	1.3%	4.4%	43.3%	44.3%	6.7%	99.7%
Testing	1.00	4	0	0	0	0	100.0%
	2.00	2	3	0	0	0	60.0%
	3.00	0	0	55	0	0	100.0%
	4.00	0	0	0	57	0	100.0%
	5.00	0	0	0	0	7	100.0%
	Overall percent	4.7%	2.3%	43.0%	44.5%	5.5%	98.4%

Dependent variable: dw

Classification scheme shows, where the different wrong assignments actually occurred.in the testing phase table 4. There are 2 misplacements. It brings the error part of 0.6%.

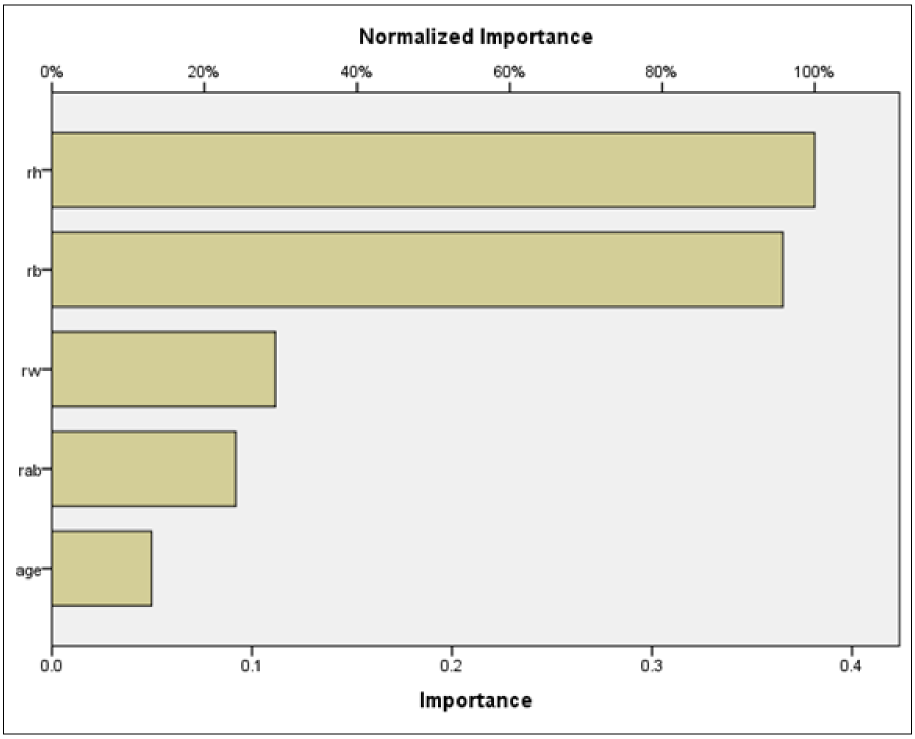

Fig 3: Normalized importance

Table 5: Independent variable importance

	Importance	**Normalized importance**
Round bust of the respondent	.365	95.8%
Round hip of the respondent	.381	100.0%
Round abdomen of the respondent	.092	24.1%
Age of the respondent	.050	13.1%
Round waist of the respondent	.112	29.3%

Fig 3. shows a normalized importance graph. All the independent variables are represented with a percentage figure indicating their level of importance in affecting the output. In this case, most important variable is hip girth (100%) which affects the drop value and the second most important variable is round bust (95.8%). Since the drop value is defined as the difference between bust girth and hip girth, there is a linear relationship among drop value, hip girth and bust girth. Round hip and round bust are the variables which actually make up the drop value.

Conclusion

A neural network model for identifying the effect of different anthropometric variables on the drop value was successfully developed using multi-layer perceptron (MLP) algorithm. This study has demonstrated that a neural network can be used to recognize the relationships among the different body dimensions. Moreover, artificial neural network (ANN) can be used to classify the anthropometric data accurately and more precisely.

Artificial intelligence in apparel sector is still new and has not been extensively applied. Artificial intelligence approach can be useful in apparel designing, apparel manufacturing, apparel retailing, and supply chain management and most importantly, for classifying anthropometric data and developing systematic size charts for Indians which can be a boon for readymade industry.

References

1. Guo ZX, Wong WK, Leung SYS, Li M. Application of artificial intelligence in the apparel industry: a review. Textile Research Journal. 2011;0(00):1-22.
2. Gupta D, Zakaria N. Anthropometry, apparel sizing and design; c2014.
3. Ha H, Stenstrom MK. Identification of land use with water quality data in stormwater using a neural network. Water Research. 2003;37(17):4222-4230.
4. IBM. SPSS Neural Networks. 5/23/2019.
5. Jain AK, Jianchang Mao, Mohiuddin KM. Artificial neural networks: a tutorial. Computer. 1996;29(3):31-44.
6. Liao S. Expert systems methodologies and applications - a decade review from 1995-2004. Expert Systems with Applications. 2004;28(1):1-11.
7. Minsky M. Steps toward Artificial Intelligence. Proceedings of the IRE. 1961;49(1):8-30.
8. Nagi EWT, Peng S, Alexander P, Moon KKL. Decision support and intelligent systems in the textile and apparel supply chain: an academic review of research articles. Expert Systems with Applications. 2014;41(1):81-91.
9. SPSS Neural Connection 2.0 User's Guide Inc. and Recognition Systems Inc. and Inc., Chicago, IL. 1997.
10. Uno Y, Prasher SO, Lacroix R, Goel PK, Karimi Y, Viau A, Patel RM. Artificial neural networks to predict corn yield from Compact Airborne Spectrographic Imager Data. Computers and Electronics in Agriculture. 2005;47(2):149-161.