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RESEARCH ARTICLE

A THEORETICAL STUDY ON ESTIMATING BODY FAT PERCENTAGE BY USING A COMMITTEE MACHINE BASED ON GENETIC ALGORITHM OPTIMIZATION APPROACH

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ABSTRACT

Body fat is one of the most important parameters in determining one's health condition. The current study focuses on estimating body fat values from routine characteristics of adults with the use of artificial intelligent systems. The methodology applied here combines the results of the individual models in a committee machine with intelligent systems (CMIS) for estimating body fat percentage. The artificial neural networks (ANNs), fuzzy logic (FL), and adaptive neuro-fuzzy inference system (ANFIS) were utilized as intelligent experts of the CMIS. The NN models were developed with four different training algorithms (Levenberg–Marquardt (LM), scaled conjugate gradient (SCG), one step secant (OSS) and resilient back-propagation (RP)) and the best one was chosen as the optimal NN expert of the CMIS. The CMIS assigns a weight factor to each individual expert by the simple averaging and weighted averaging methods. A genetic algorithm (GA) optimization technique was used to derive the weighted averaging coefficients. The results indicated that the GA-optimized CMIS performed better than the individual experts acting alone for estimating the body fat percentage from one specific set of input characteristics.

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INTRODUCTION

If a person is overweight, it may not necessarily mean that he or she is not fit. If the reason for being overweight is due to muscle mass, it would not be considered as problem. However, if the reason for being overweight is due to body fat mass, then action is probably needed to lose weight. In this instance, body fat percentage can help to distinguish whether the overweight is due to increased muscle mass or due to body fat. Body fat, it's crucial role on the body as well as its evaluation methodologies are thoroughly presented in the existing literature. As an instance Bielemann *et al*. (2015) studied estimation of body fat in adults using a portable A-mode ultrasound which was based on anthropometric measurements of subcutaneous fat thickness (SFT) and muscle thickness (MT) in a group of Brazilian adults. However, to data, there has not been any study reporting the thorough usage of intelligent systems to obtain body fat information from routine body characteristics. On the other hand, the availability of all precious body fat information is challenged by the high measurement cost, desired precision of the experiments and measurements techniques, and the required time and efforts.

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Hence, there has always been a considerable desire aimed towards the acquirement of these valuable information with rather indirect methods. Among these attempts, Artificial Intelligence (AI) is currently playing a leading role. The most popular intelligent approaches include Fuzzy Logic (FL), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and the hybrid systems. The current research makes use of all the aforementioned techniques and represents a novel approach for obtaining body fat data from measurements of individuals' routine characteristics based on a committee machine approach.

Artificial intelligence: Artificial intelligence, or computational intelligence, is one of the best known modern approaches to deal with a wide variety of problems which own substantially differing natures. Medical sciences have shown a high level of broad-mindedness in adopting other branches of science, such as artificial intelligence, to deal with the new medical problems. AI mainly consists of artificial neural networks (ANNs), Fuzzy Logic (FL), adaptive neuro-fuzzy Inference Systems (ANFISs) and genetic algorithms (GA) which have made a meaningful contribution to the advances made in so many field of science. These techniques potentially can be used for the purpose of extrapolation, classification, and optimization. Therefore, wherever a particular medical problem offers the basic requirements of any of these techniques, that technique would be considered as a possible method of solving that problem. It's worth mentioning that artificial intelligence may not be an ideal choice in solving many medical problems, but it is a valuable approach that can satisfyingly solve the problem where the conventional methods fail to do so.

Artificial neural networks: Artificial neural networks are the simple mathematical formulation of the super-fast and over-complicated learning process which occurs in human brain. Mainly divided into the categories of supervised and unsupervised learning, these networks provide the rapid solution in many kinds of disciplines including function fitting, clustering, and pattern recognition problems (Golsanami *et al*., 2014, 2015). A human information processing system is composed of neurons switching at speeds about a million times slower than logical computer gates (Vemuri and V., 1988). Neural networks can be programmed to train, store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; and to control ill-defined problems. In summary, they estimate sampled functions when the form of the functions is not known (Kosko, 1992). In case of the artificial neural networks, the structure of the network plays the most significant role in the learning process of the network. This structures is composed of parallel processing elements called neurons (MATLAB, 2011) and their weighted input and output parameters. However, the knowledge of in an artificial neural network is not stored in a single neuron but inside all the neuron and their meaningful (weighted) connections with the neighboring neurons (Caudill, 1987). Even though the current study adopted the function fitting capability of neural networks, clustering and pattern recognition are also two powerful tools in dealing with many medical problems. Pattern recognition has got three major subdivisions which include the appropriate description of physical or conceptual objects in terms of representation space; the specification of an interpretation space; and the mapping process from the representation space into the interpretation space (Pao, 1989).

Fuzzy logic: Theory of fuzzy sets and following fuzzy logic was introduced by (Zadeh, 1965). While crisp logic takes only one of the 0 or 1states, i.e. a member would or would not belong to a particular class, fuzzy logic defines an infinite number of states in the range of [0-1]. This is possible through the membership functions that define how much a particular parameter belongs to a particular group. Fuzzy if-then rules make use of human knowledge and experience to behave in a manner similar to a human controller (Tanaka, 1997). Fuzzy logicis a perfect choice for solving problems associated with vagueness and uncertainty. While statistical methods try to minimize and even ignore this error, FLextracts useful information from this error and uses it as a powerful parameter for increasing the accuracy of the predictions. A fuzzy inference system (FIS) is the process of formulating from a given input space to an output space using fuzzy logic (*Fuzzy Logic Toolbox™ User's Guide*, 2011). Mamdanitype and Takagi-Sugenotype FISs are two famous types of fuzzy inference systems. Sugeno-type FIS that uses subtractive clustering in the fuzzy inference engine was employed in this study. For this kind of FIS, the output membership functions are linear or constant. The subtractive clustering is an effective, robust and quick approach to estimate the number of fuzzy clusters and cluster centers (Al-Jarrah and Halawani, 2001).

Adaptive neuro-fuzzy inference system: While neural networks deal with implicit knowledge, fuzzy logic deals with explicit knowledge. ANFIS (Adaptive Neuro-Fuzzy Inference System or Adaptive Network-Based Inference System) is a hybrid systems which combines the benefits of both above-mentioned techniques. In other words, ANFIS is a neural networks based on Sugeno-type fuzzy inference system. An adaptive network is a multilayer feed forward network in which each node performs a particular function on incoming signals as well as a set of parameters pertaining to this node. It's worth noting that while in neural networks the links from each neuron to the next one are weighted connections, the links in an adaptive network only indicate the flow direction of signals between nodes and no weights are associated with the links (Jang, 1993). In an adaptive FIS, the parameters of the membership functions are adjusted using a back propagation feed forward neural network. ANFIS tunes the membership function parameters in a way that the given input-output data would be tracked in the finest possible way. This is because these parameters are chosen so as to tailor the membership functions to the input/output data in order to account for the types of variations in the data values (*Fuzzy Logic Toolbox™ User's Guide*, 2011).

Committee machine: In committee machines, an ensemble of estimators (also called as experts), consisting typically of neural networks or decision trees, is generated by means of a learning process and the prediction of the committee for a new input is generated in form of a combination of the predictions of the individual committee members (Hu and Hwang, 2001). When more than one intelligent agent is available to make a decision, we can form a committee of experts. By combining the different opinions of these experts, the committee approach can sometimes outperform any individual expert. This is because every expert inside the committee machine structure would be good at capturing one particular kind of information from the input data (Heath *et al*., 1996).

Evolutionary computing and genetic algorithms: Evolutionary computing is the computational replication of the Darwinian evolutionary principles through a range of different algorithms like genetic algorithm (GA). The genetic algorithm introduced by (Holland, 1992) is a search and optimization technique that acts based on the principles of natural and genetics selection (Haupt *et al*., 2004). The algorithm begins with a predefined number of individuals called a population. These individuals are the estimates of the answer of the problem. The individuals are produced by genetic combination of a series of numerical arrays called chromosomes. After that, the fitness value of these individuals is computed and the genetic operator, i.e. mutation or crossover, is applied on those with better fitness values to combine them (as parents) and produce new generation (individuals) or children. Then these children are evaluated and the entire cycle repeats till the best possible solution is achieved.

Theory and Methodology: The present study aimed to estimate body fat percentage from other factors of human health using artificial intelligent systems. The employed procedure in this research consisted of three independent steps as explained in the workflow of Figure. These steps included input selection, model establishment and selection of the optimal model, and finally developing the committee machine by using the genetic algorithm optimization technique.

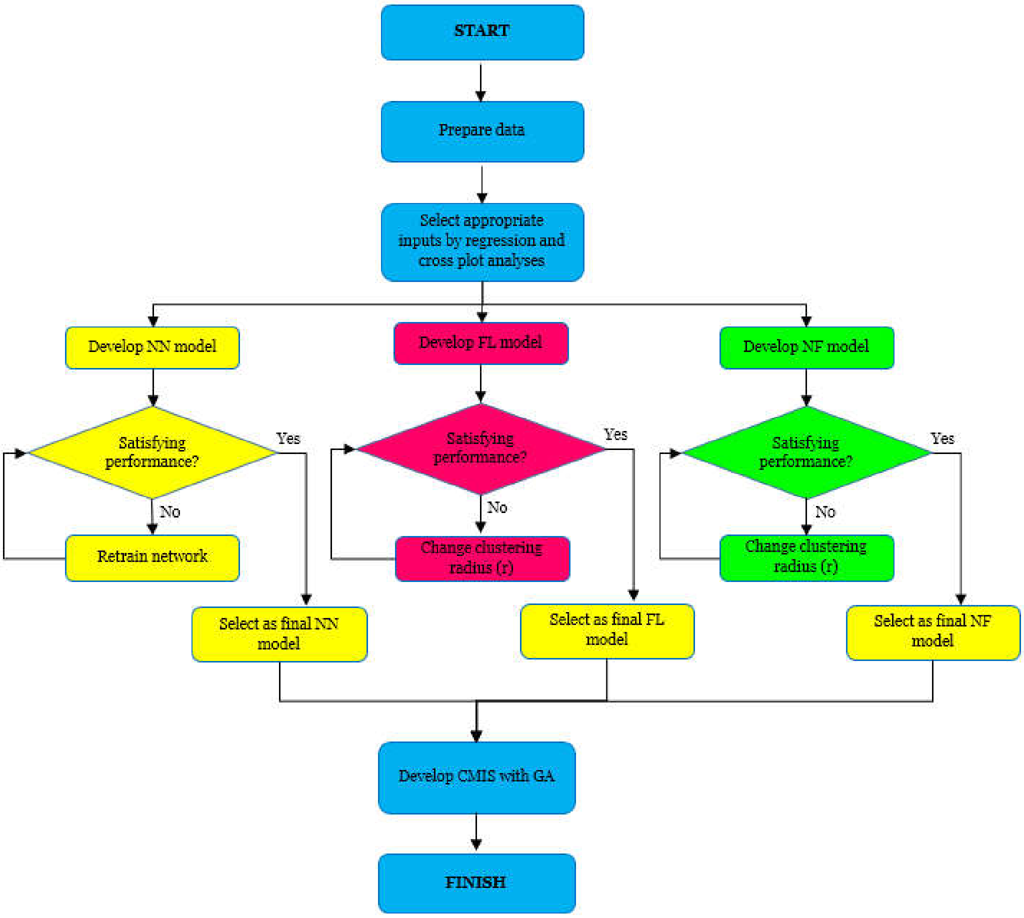
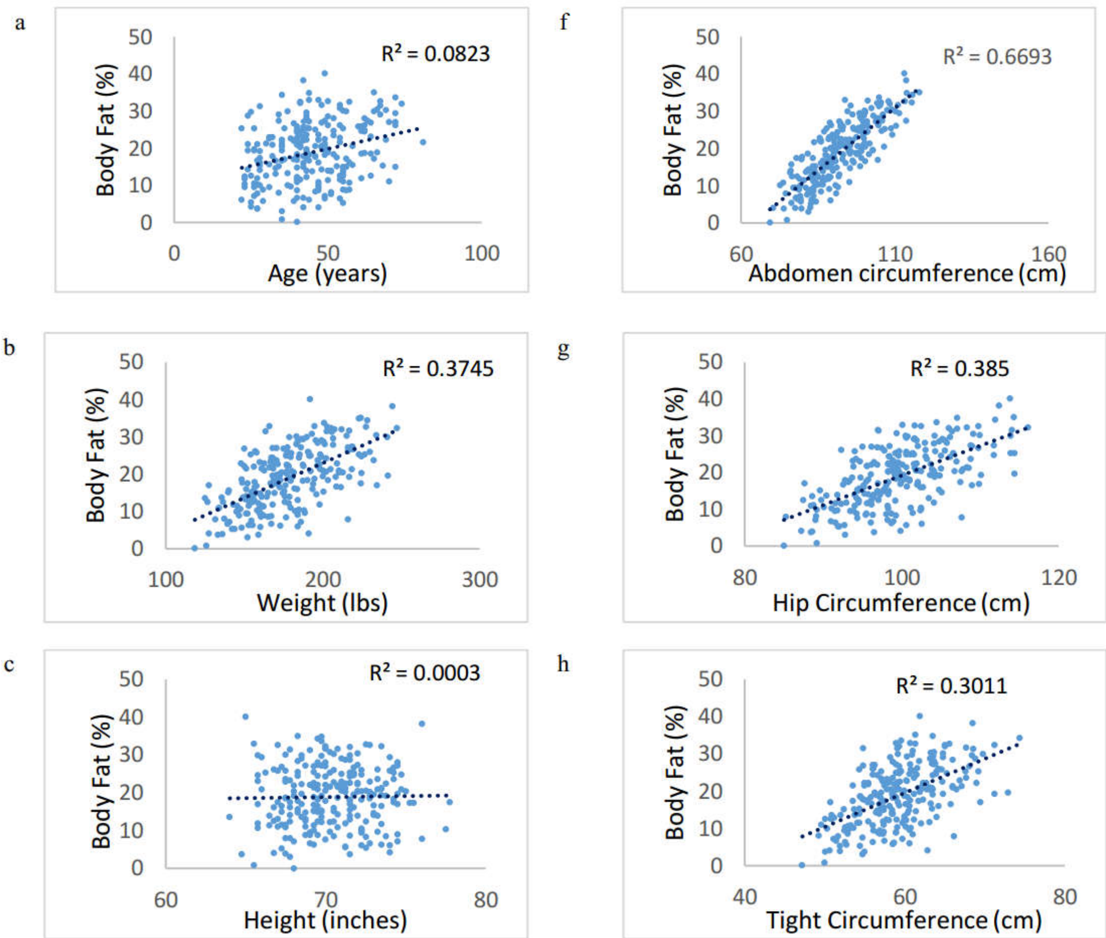


Figure 1. The employed workflow for the present research study



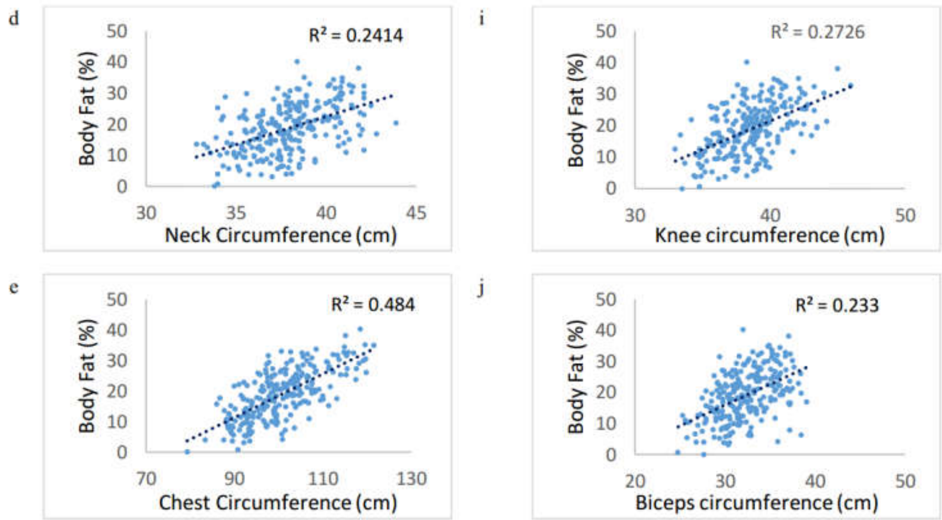


Figure 2. Cross plots showing correlation coefficients between input parameters and body fat

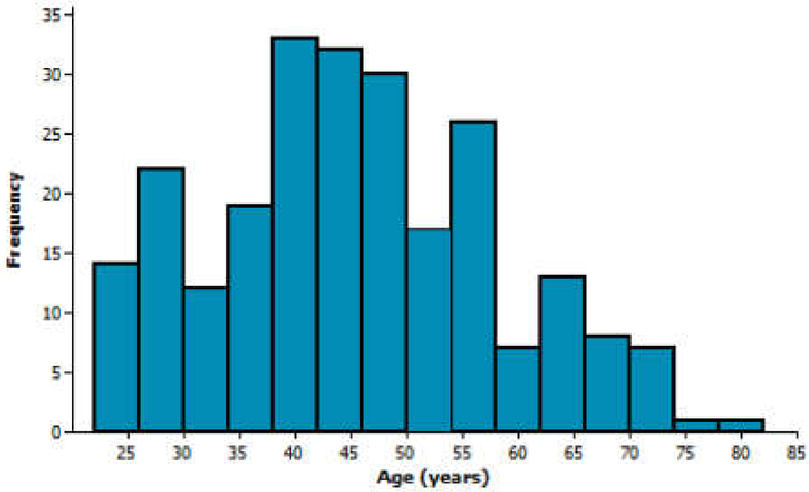


Figure 3. Age distribution frequency of the participants

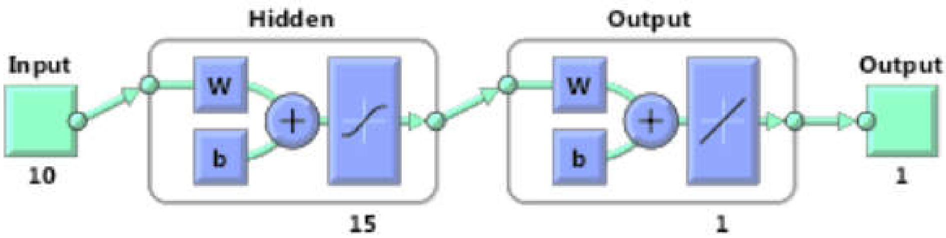


Figure 4. Internal structure of the developed three-layer back propagation neural networks

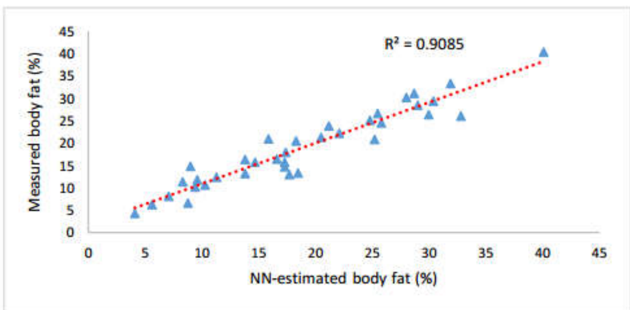


Figure 5. Correlation of the NN-estimated and measured body fat values

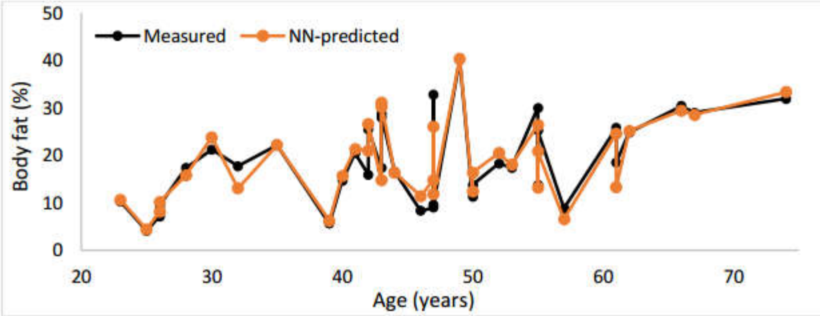


Figure 6. Graphical description of neural network's performances in predicting body fat values

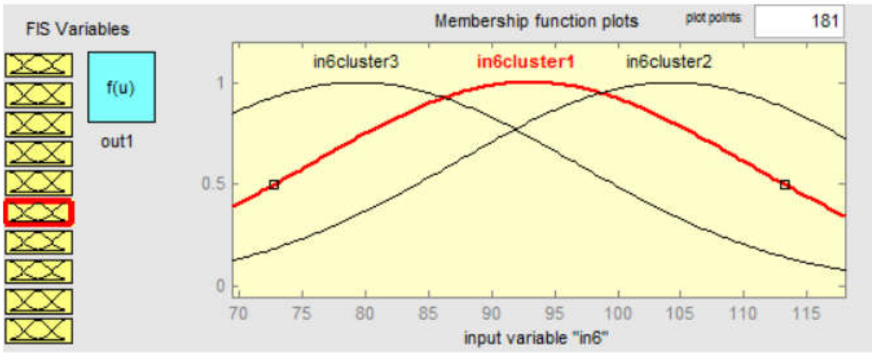


Figure 7. The Gaussian membership function of FIS for input variable "Hip Circumference"

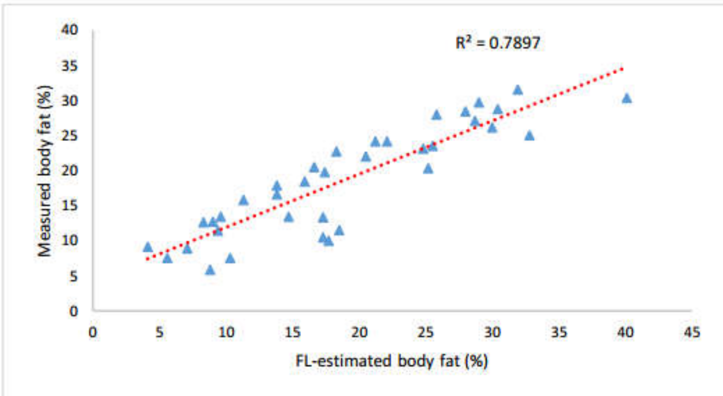


Figure 8. Correlation of the FL-estimated and measured values of the body fat percentage

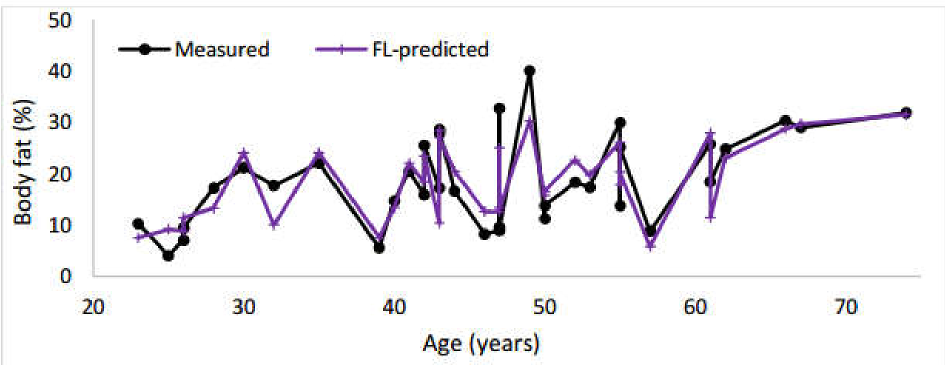


Figure 9. Graphical description of fuzzy logic model's performances in predicting body fat values

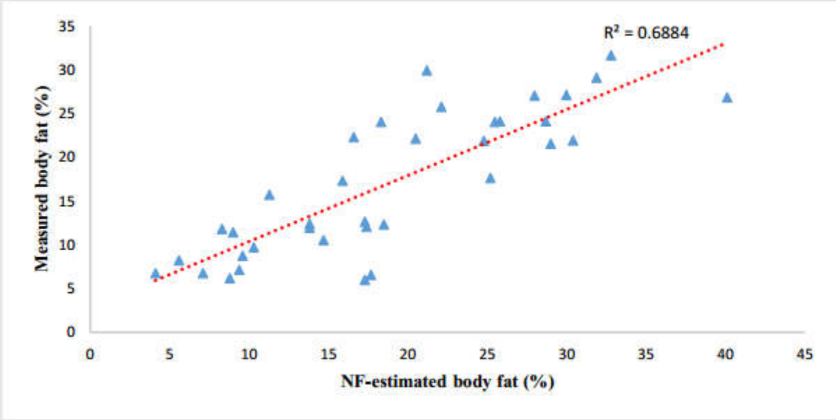


Figure 10. Correlation between the NF-estimated and measured body fat values

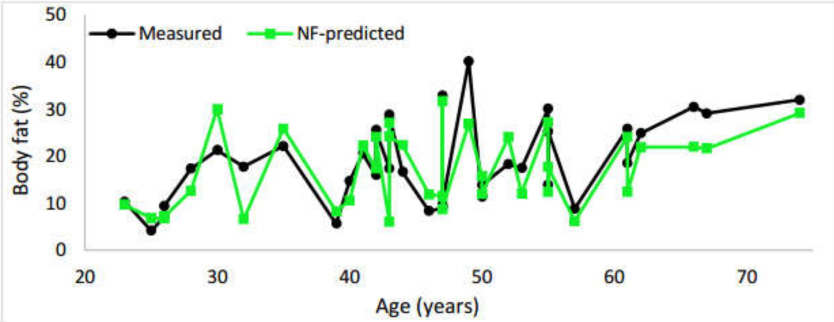


Figure 11. Graphical description of ANFIS model's performances in predicting body fat values

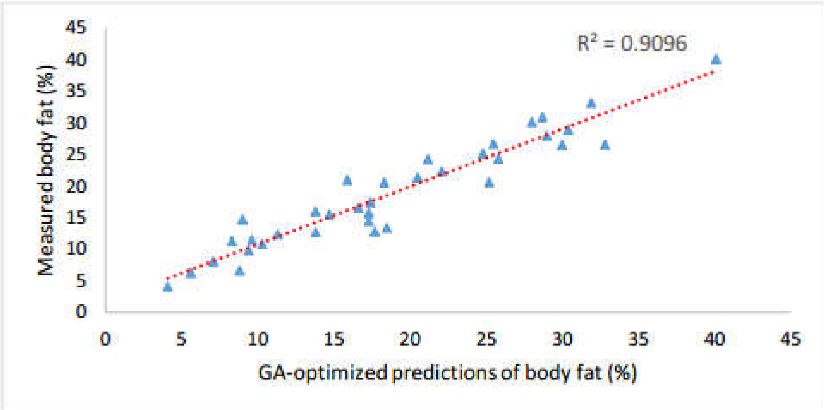


Figure 12. correlation between the NF-estimated and measured body fat values

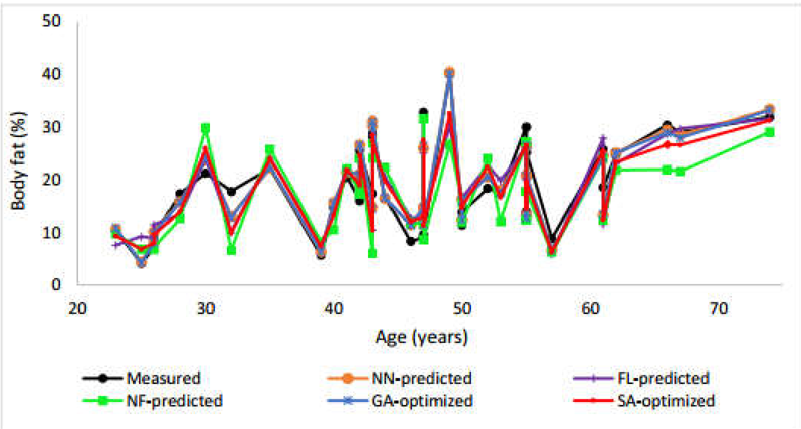


Figure 13.Graphical comparisons of different models' performances in predicting body fat values

Table 1: Performance of different neural network models in estimating body fat from inputs values

Training Algorithm	Correlation Coefficient (R^2)	Performance (RMSE)
LM	0.9085	2.6612
RP	08535	3.3136
SCG	0.8782	3.1783
OSS	0.8917	2.9301

Table 2. Performance of different fuzzy logic models in estimating body fat from inputs values

Clustering Radius (r)	Performance (RMSE)	Correlation Coefficient (R^2)
0.1	6.9220	0.4374
0.2	6.1674	0.5240
0.3	6.8456	0.4884
0.4	20.170	0.2626
0.5	11.246	0.1580
0.6	6.7001	0.4855
0.7	5.1725	0.6732
0.8	4.2271	0.7735
0.9	**4.0501**	**0.7897**
1	4.1235	0.7827

Selecting suitable input characteristics: As mentioned above, the first step was selecting the suitable input data. These input parameters were selected from among 13 different attributes based on cross plot and regression analyses. According to our analyses, 10 parameters namely, Age (years), Weight (lbs), Height (inches), Neck circumference (cm), Chest circumference (cm), Abdomen circumference (cm), Hip circumference (cm), Thigh circumference (cm), Knee circumference (cm), and Biceps circumference (cm) showed stronger linear relationships with body fat percentage values and were selected as the final input data of the intelligent models. The linear relationships between these input data and target values are illustrated in Figure 2.

The stronger this relationship is, the more accurate predictions would be achieved. It should be mentioned that regarding intelligent estimators, establishing a robust model capable of making correct predictions requires inputting noise-free data. This is based on account of the fact that even a single noisy input argument disturbs the initial fuzzy rules or the entire weight matrix of the neural networks. At this step, after processing data and removing outliers, 243 data were remained which were used for training, validating and testing the performance of the intelligent models. Figure 3 shows the distribution frequency of the participants' age. 250 measurement, representing differing characteristics of the same number of participants in the test process, originally existed. After processing data and removing outliers, 243 data were remained which were used for training, validating and testing the performance of the intelligent models.

Establishing intelligent models

Neural network models: The second step of the research was developing the desired intelligent models which included neural networks, fuzzy logic models and ANFIS models. With regard to the neural networks, the models were trained using four different training algorithms namely, Leven berg-Marquardt (Dong *et al*., 2018; Golsanami *et al*., 2019; Sun *et al*., 2016; Yan *et al*., 2017), Resilient Back-Propagation (Riedmiller and Braun, 1993), Scaled Conjugate Gradient (Møller, 1993) and One Step Secant (Battiti, 1992).

The reason for selecting a number of algorithms instead of a single algorithms was to guarantee obtaining the best potential models rather than trying the usually used LM algorithm. The neural networks used in this study consisted of one hidden layer with respectively TANSIG and PURELIN transfer functions in the hidden and output layers. The hidden layer consisted of 15 neurons. About 65% of the total training data pairs (equal to 158 individuals) were used for training the networks and 20% (equal to 48 individuals) were used to validate them. Finally, the remaining 15 % data points (equal to 36 individuals) that were selected randomly from among all individuals were used to test the models and measure their reliability. The results of neural network models for the body fat are presented in the coming sections. Figure 4 shows the topology of the employed neural networks. After all, the best performing NN algorithm and model was chosen as the final NN model for estimating the body fat values. The performance of the neural network models and the correlations between measured and estimated body fat values are presented in Table 1. Figure 5 and Figure 6represent the correlation values between body fat values estimated by neural network models and those measured through practical experience.

Fuzzy models: For the fuzzy models, 10 Sugeno-type FIS structures with clustering radius(r) of [0.1-1] (with the equal stepsize of 0.1) were developed. For the FIS structures, the membership functions (MFs), their parameters and fuzzy ''if-then'' rules were all determined by the subtractive clustering method which traces the input-target trend of variations in a trustable way. Clustering radius was the major factor controlling the number of clusters, fuzzy rules and accuracy of the fuzzy models. Like the previous case, 206 subjects were used for training purpose and 36 subjects were employed for testing the accuracy of the models. The employed FIS structures consisted of 3 rules acting on a Gaussian type of membership function for each input parameters. Figure 7 shows an example of the membership functions for the sixth input parameter namely Hip circumference. Table 2represents the performance of the fuzzy logic models and the correlations between measured and estimated body fat values. Figure 8andFigure 9show the coincidence between measured and estimated values of the body fat percentage. Finally the best FL model, i.e. the one having the best correllation the smallest error was selected as the final FL model to estimate body fat values from other characteristics.

Neuro-fuzzy models: The developed ANFIS structures were similar to the FL structures with clustering radius changing in the range of [0-1] with the step size of 0.1. However, herein, the parameters of the membership functions were adapted by a back propagation neural network. %50 of the training data, that is information of 103 subjects, were used to train the models and the other %50 was simultaneously used as the checking data to correctly guide the algorithm through modeling process. The appropriate stepsize values and number of training epochs for NF models were obtained using the trial and error approach. The ANFIS models were trained using back propagation neural network and least squares error algorithm. For all NF models, the number of training epochs was set to 10. Among all models, the one with the best performance was selected as the final NF model for predicting body fat values which was achieved for r=0.9. For all NF models the error tolerance was set to 0.1 and MSE (mean squared error) was adopted as the performance criterion. The parameters of the input membership functions of NF models are shown in Table 3.

Table 3. Parameters of the input membership functions for predicting body fat by NF models

Characteristic	No. of MFs	σ	μ
Age (years)	mf1	20.86	40
	mf2	20.86	41
	mf3	20.86	49
Height (inches)	mf1	4.243	69.5
	mf2	4.243	71.5
	mf3	4.243	68
Weight (lbs)	mf1	45.52	173.3
	mf2	45.52	212
	mf3	45.52	140.5
Neck circumference (cm)	mf1	3.924	36.5
	mf2	3.924	41.5
	mf3	3.924	35.8
Chest circumference (cm)	mf1	14.96	99.5
	mf2	14.96	106.6
	mf3	14.96	91.2
Abdomen 2 circumference (cm)	mf1	17.18	93
	mf2	17.18	104.3
	mf3	17.18	79.4
Hip circumference (cm)	mf1	11	99.3
	mf2	11	106
	mf3	11	89
Thigh circumference (cm)	mf1	9.62	60.47
	mf2	9.62	65.07
	mf3	9.62	51.17
Knee circumference (cm)	mf1	4.596	38.2
	mf2	4.596	40.2
	mf3	4.596	35
Biceps (extended) circumference (cm)	mf1	5.056	32
	mf2	5.056	35.8
	mf3	5.056	30.9

Table 4. Performance of different Neuro-fuzzy models in estimating body fat from inputs values

Clustering Radius (r)	Performance (RMSE)	Correlation Coefficient (R^2)
0.1	16.1095	0.0804
0.2	14.1346	0.1753
0.3	27.6893	0.0730
0.4	8.9345	0.5428
0.5	63.3037	0.0184
0.6	11.4381	0.1383
0.7	9.1701	0.3412
0.8	5.3112	0.6919
0.9	5.2815	0.6884
1	5.4075	0.6739

Table 3. Performance of different intelligent models for estimating body fat values

Intelligent System	RMSE	R^2
NN	2.6612	0.9085
FL	4.0501	0.7897
NF	5.2815	0.6884
GA Optimized CMIS	2.6421	0.9096
Simple Averaging CMIS	3.4993	0.8492

Table 4represents the relationship between the developed NF models and actually measured body fat values. Figure 10and Figure 11 depict the precision of the developed ANIFS models.

CMIS models: The final optimal models of FL, NF and NN for body fat percentage data were combined in a committee machine with intelligent systems through two different approaches. In the first approach, the equal weigh factors were assigned to each CMIS expert. In this method which is also renowned as the simple averaging method, all experts have equal contribution in estimation of the overall output. The final results of this approach were not satisfactory in comparison to the weighted averaging method.

In the second approach, the genetic algorithm optimization technique was employed to obtain a better combination of the individual experts. The optimized weight values led to the acceptable results and the developed CMIS led to a better performance in comparison to the individual experts acting alone. For the genetic algorithm model, the initial population size was set to 50. The next generation was produced with a crossover fraction of 0.8 and elite count of 2.5. The objective function that should have been optimized with GA was defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(w_1 \times FL_i + w_2 \times NF_i + w_3 \times NN_i - T_i)^2$$

This function shows MSE of the CMIS prediction where w_1, $w_2$and $w_3$are the weight factors corresponding to the NN, FL, and NF predictions respectively. $T_i$is the target value (measured body fat percentage) and n is the number of training data which was equal to 36 in this research. A comparison of the performance of the different intelligent models is illustrated in Table 5. Graphical comparisons between the measured and estimated body fat percentage values are also depicted in Figure 12and Figure 13.

DISCUSSION

In the present study, the researchers tried to establish a new method in estimating one of the most important characteristics of human health called "Body Fat Percentage". The introduced method included application of such artificial intelligent algorithms as NNs, FISs, and ANFISs. According to our obtained results, regarding the neural networks, all of the four employed algorithms proved trustworthy as the difference between the predictions coming from each of them was very subtle. This shows the high capability of neural network training algorithms. However, Levenberg-Marquardt algorithm still proved to yield the best results from both aspects of prediction error and correlation of the predicted and measured values. This is another proof of the high efficiency of this algorithm. When coupled with its reasonable memory usage and higher speed, it would be considered as an optimal choice in many different applications. However, OSS algorithm stood in the second rank of performance excellence and acted better than two other algorithms namely, RP and SCG.

The performance of these two algorithms were almost the same. With regard to the fuzzy logic models, the best model was obtained for the clustering radius of 0.9 where the prediction error and correlation of measured and predicted values were much better than those for very small clustering radiuses. In the case of this study, the fuzzy models led to very close results for clustering radiuses of r ≥0.8 where all these three models showed an acceptable performance and fairly good correlation. It is worth mentioning that for r=0.1-0.5, the correlations fell in the same range but the performances were of major differences. With respect to neuro-fuzzy models, like in case of the fuzzy models, the smallest difference between measured and predicted values as well as the best correlation was observed for r=0.9. Again, for r=0.8, 0.9, and 1, the obtained results were almost the same which indicated that for the present subjects, wherever the fuzzy reasoning was involved, the larger clustering radius resulted in better predictions. For r=0.6, and 0.7 an acceptable performance was observed but there didn't exist a good correlation.

Nonetheless, the most excellent performance was accomplished by using the GA-weighted CMIS where the simple averaging CMIS performed even weaker than such individual experts as neural networks. By taking a comprehensive look at all the employed approaches together, it was observed that the neural networks were of far superior predictions compared to FL and NF techniques. This is the reason that in the weighted averaging CMIS, a higher weight was assigned to the NN models by the GA optimization method. In this research study, Root Mean Squared Error (RMSE) was used as the major criterion to investigate and compare performance of different models. Since RMSE measures the average mismatch between each data point and the model, we would explore RMSE values as one of the tools to inspect the quality of the fit where a high RMSE values can indicate serious problems.

Conclusion

This research intended to introduce a time-effective and cost-effective method to estimate body fat values from other ordinary inexpensive measurements with a reasonable degree of accuracy. This work demonstrates that using such routine parameters as age, weight, height, and circumference values of different body organs, can offer prediction of body fat percentage in a convenient way and with an acceptable accuracy. A particular group of input data having both accuracy and adequacy possesses the relevant properties defining the body fat amount. Therefore, the employed intelligent systems were capable of finding logical patterns between routine body characters and definite amounts of the body fat. The established CMIS showed a better prediction capability than every single expert which implies the high trust ability of this approach. However, the high dependency of the intelligent systems on the quality of input data was also highlighted. Considering the time and practical effort required to measure body fat percentage in medical labs, the merit of the mathematical modeling of medical parameters is better understood. This research can be further extended by investigating application of numerical or other mathematical techniques like statistical decision trees.

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