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A Novel Basketball Result Prediction Model Using a Concurrent Neuro-Fuzzy System

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ABSTRACT

Including uncertainties such as the performance of the teams, player performance indicators, and the quality of the competitors, there are numerous factors affecting the result of a game. Therefore, prediction of the game results is quite a complicated and a conspicuous research problem. Various artificial intelligence models were developed in order to solve this problem. By drawing together the advantageous sides of various artificial methods, this study aims to develop a hybrid intelligent system in order to better predict the result of a basketball game. Firstly, a prediction model was developed via artificial neural network (ANN), which is frequently used in game result predictions. The success of this developed ANN model in predicting the result of the game was 70.8%. In order to increase this success rate, a new concurrent neuro fuzzy system (CNFS) was suggested which was combined with fuzzy logic system that determined whether the team was favorite. The accurate prediction rate increased to 79.2% via this suggested CNFS model. Moreover, the results of the models developed were compared with each other and previous studies predicting the game results. As the conclusion of the comparisons, it was observed that CNFS model had a remarkable talent in predicting the game results.

Introduction

Traditional sports science was contingent upon the experts, coaches, team leaders, and analysts. With the developing information processing technology, important statistical information is produced about each player, team, game, and season of today's sports branches. In recent years, sports science has begun to benefit from the applications of data mining techniques upon this wide statistical data base. Artificial intelligence implementations in sports domain helps the coaches and the managers in result predictions, player performance evaluation, player damage estimation, determining sports talented identification, and evaluating the game strategy (Bartlett 2004; Haghighat, Rastegari, and Nourafza 2013).

With the increasing informatics opportunities of today, following up the results of the games draws attentions of many, and thus, contributes

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particularly to enlarging the sports wagering (Miljković et al. 2010). Many factors such as the motivation of a player or the team, their talents, and current performances influence the result of a sports game (Arabzad et al. 2014). Therefore, considering it as a research question, it is quite difficult to estimate the result of a game.

There are various studies on estimation of basketball game results in the literature. In these studies, generally statistical and machine learning methods are used. In the statistical methods, the prediction of the next game's result is done based on the data of the games from the beginning of the season or in the last n weeks via linear regression methods. As per the machine learning method, the previous statistical data and game results of the teams are evaluated together. An estimation model is established via the machine learning algorithms making deductions. With this model, a choice is made either on host team wins or away team wins for a game with an unknown result (Karaoglu 2016).

The previous studies in literature conducted on prediction of basketball game results are given on Table 1 together with their data sets, methods, software, and prediction accuracy values. In these studies, in order to form a data set, a league or season is determined and statistical data of this league is obtained. A data set is formed, whose input and output features are

Table 1. Studies in the literature on basketball result prediction.

Dataset	Method	Accuracy	Software	Researcher
NBA League, 2007–2008 season	Feed Forward Neural Network (FFNN)	74.33%	MATLAB	(Loeffelholz, Bednar, and Bauer Kenneth 2009)
Two consecutive seasons of the National Basketball Association (NBA) League Basketball	Logistic regression model	72.8%	WEKA	(Zdravevski and Kulakov 2010)
Asociacion de Clubes de Baloncesto (ACB) Basketball League statistics from 2008 to 2009 season	Linear Least Mean Squares (LMS) estimate	66.7%	KEEL	(Trawinsk 2010)
NBA League ,2009–2010 season	Naive Bayes method	67.0%	RapidMiner	(Miljković et al. 2010)
Basketball League of Serbia B, 2005–2006 season until 2009–2010 season	Neural Network	80.9% (*all dataset)	-	(Ivanković et al. 2010)
NBA League, 2005–2006 season until 2010–2011 season	Simple Logistics Classifier	69.67%	Rapidminer, WEKA	(Cao 2012)
NBA League, 2009–2010 season	Adversarial synergy graph model	69.9%	-	(Liemhetcharat and Luo 2015)
NBA League, 2015–2016 season	Support Vector Machine(SVM), Fuzzy-SVM model	88.26%	-	(Kaur and Jain 2017)
NBA League, 2008–2010	Support Vector Machine (SVM) and Decision Tree	85.25%	WEKA	(Pai, ChangLiao, and Lin 2017)
Basketball tournament of the 2004–2016 Olympic Games	Logistic Regression Model	93.2%	The R Project for Statistical Computing	(Leicht, Gómez, and Woods 2017)

determined, based on this obtained data via prior processing techniques. This dataset is split into two as training dataset and test dataset. The prediction methods formed via various machine learning methods and training data set, are tested by means of test data set, which does not participate in the training. The accuracy rates of the studies on test dataset are given on Table 1. Moreover, more than one different machine learning methods are used in many studies, and the methods of the studies with best accuracy rates are given on Table 1. Additionally, it is observed that the figure of studies on hybrid use of machine learning algorithms for basketball game prediction is increasing. Although these studies are applied in different data sets, and considering that the predictions of future games are based on current data, it is observed that the hybrid machine learning methods have higher accuracy rates. Simply imitating the function of human brain, Artificial Neural Networks (ANN) is an artificial intelligence method, which does the most basic function of brain, learning. ANN has many characteristics such as learning, generalization, and functioning with unlimited variables. ANN can provide linear and nonlinear modeling without needing preliminary information between the input and output variables. Providing advantages owing to these features, ANN method is extensively used in sports domain as is used in other fields (Perl 2001; Tümer and Koçer 2017).

Fuzzy logic is generally used in manifesting uncertain information or a choice structure. The main characteristic of the fuzzy logic and fuzzy sets is their ability in modeling the uncertainty. In conventional set theory, there is an approach, which is simply 'a member either belongs to the set or not'. However, in many real life problems conventional set theory is insufficient. Fuzzy logic simplifies decision making in many fields in modeling uncertain systems without complete and certain information (Ross 2004). Fuzzy logic systems try to imitate the human thinking logic via language simulation.

While fuzzy logic systems try to imitate a human-like logic, ANN attempts to store the human-brain-like learning and information on a complete experimental basis. Both the fuzzy logic and artificial neural networks have abilities particular to each of them (Nauck, Klawonn, and Kruse 1997). For example, while artificial neural network is successful in learning and defining the examples, it is not successful in decision making. Fuzzy logic, on the other hand, produces successful results in decision making, while it cannot create rules by itself. ANN and the fuzzy logic are two methods complementing each other. Therefore, different hybrid methods are developed in order to combine the features of the both (Azar 2010). These hybrid methods are applied successfully in many fields (Boussabaine 2001; Hassan, Schrapf, and Tilp 2017; Kar, Das, and Ghosh 2014).

The objective of this study is to predict the basketball game results with a hybrid intelligent system, which is able to use the advantageous features of ANN method, which can deduce a model based on existing data, and fuzzy

logic, which can model the human thinking logic. There has not been any hybrid study up to now using Fuzzy Logic and ANN methods together in prediction of basketball game results. In this purpose, both an artificial neural network model and a hybrid neuro fuzzy model was established in order to determine the winner team by using the data regarding the general success of the teams, their performances in recent weeks, and the quality of their competitors. With these models, not only the success of the game result predictions but also comparison of the both models were done. In this study the data of 2015/2016 season of Turkish Basketball League, which is accepted as among the best European basketball leagues concerning the teams, players, and competition (Eurohoops 2015). Currently, there is no study examining the prediction of the games in Turkish Basketball League.

The rest of the article is comprised of Material and Method, Prediction Results of the Models, Discussion and Conclusion sections, which include dataset structure, Artificial intelligence method, Fuzzy Logic Model, and Concurrent fuzzy neural model.

Material and Method

Dataset

In this study, the data of 2015/2016 season in Turkish Basketball Super League, which is the 4th toughest basketball league of the Europe according to the ULEB (Wikipedia 2017). The champion is determined after the play-off process following the planned matches in the league, where there are 16 teams. The data used in this study is obtained from the Turkish Basketball Federation official web site (Federation 2017). The raw data set is comprised of 240 games played in 2015–2016 season. In order to form the input features needed in the artificial intelligence models, firstly regulation and prior processing techniques were applied to the raw data as shown on Figure 1. Game result prediction was made via the obtained specialized data set.

Artificial Neural Network Model (ANN)

An ANN model is comprised of an input layer, one or more hidden layers, and an output layer. Input layer neuron number is generally equalized to the number of the input of the problem, and output layer neuron number is equalized to desired output number in ANN (Fausett and Fausett 1994). The number of the hidden layers and the number of the neurons in these hidden layers is determined via trial and error method. The neurons in the input layer send the inputs without making any changes to the next layer. The input data is multiplied by the weight values of the links in the hidden layer and the output layer, and transmitted to the transfer function (Fausett and Fausett

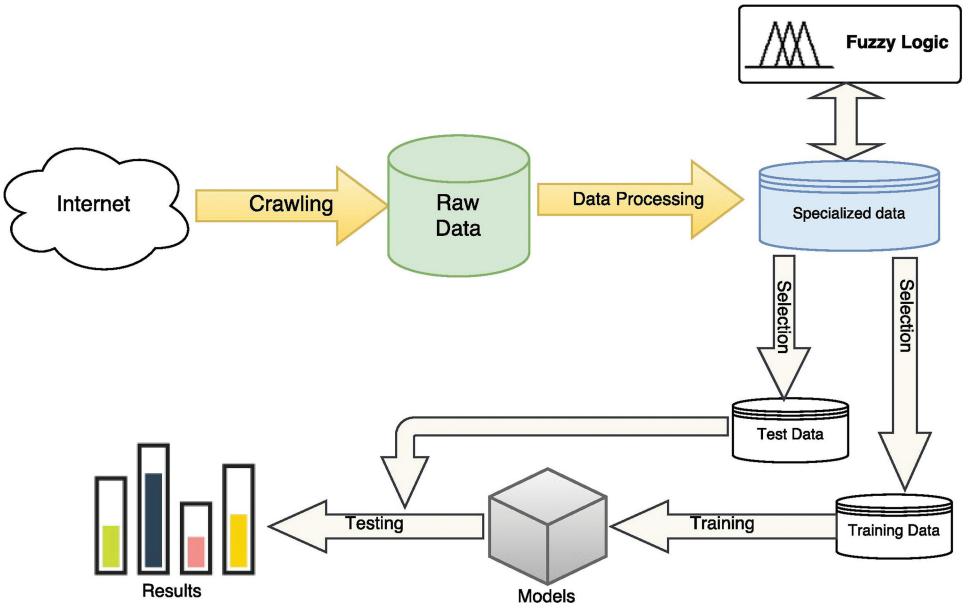

Figure 1. The stages of data mining in records of basketball games.

1994; Haykin 2011; Sabancı and Koklu 2015). The ANN model used in this study is as shown on Figure 2.

One of the most important elements of artificial neural network is the links that provide transfer of data among the neurons (Yasar et al. 2015). Transferring data from a neuron to another, a link has a weight coefficient. $G(x)$ on Figure 3 is an addition function, which calculates the net input into a neuron. The input variables are multiplied by weight coefficients, thus the inputs are formed for $G(x)$ addition function (Fausett and Fausett 1994; Gurney 2003). A neuron structure is given on Figure 3.

The mathematical explanation of an artificial neuron is given in Equations (1) and (2) as $x_1, x_2, x_3 \ldots ..x_n$ being the neuron input values, $w_1, w_2, w_3 \ldots ..w_n$ being weight values of each inputs, b being bias, and y being the output value (Gurney 2003; Tasdemir et al. 2011).

$$net = G(x) = \sum_{i=1}^{n} w_{ij}x_j + b \tag{1}$$

$$y = F(net) = F\left(\sum_{i=1}^{n} w_{ij}x_j + \mathrm{b}\right) \tag{2}$$

The change of the weight values provides the learning process of the ANN. Being an activation function, F is the function that produces output via processing the input (Gurney 2003).

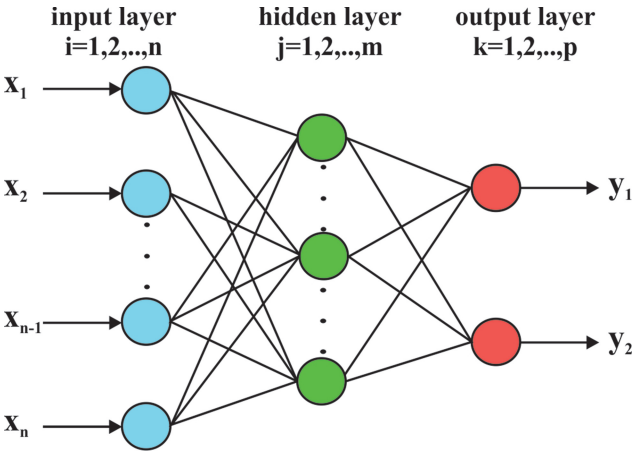

Figure 2. An ANN architecture.

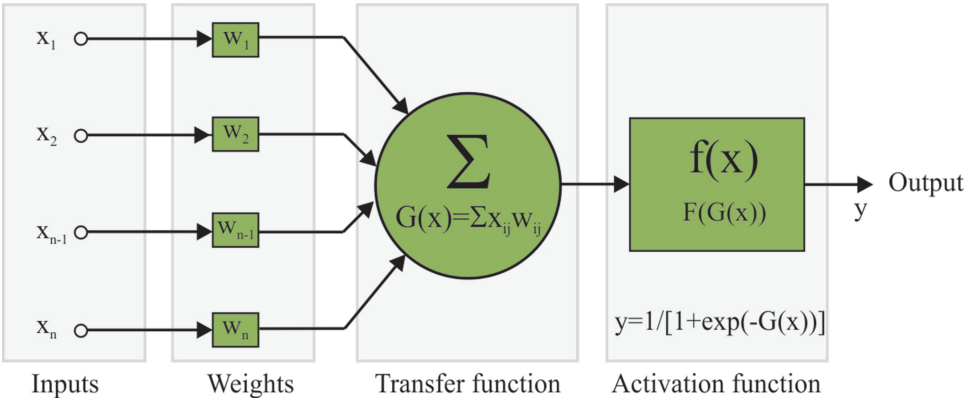

Figure 3. A basic artificial neuron.

Six different criteria are determined in order to predict the game results via ANN. These criteria are the teams, their performances in recent weeks, their position in the league, the quality of their competitors in recent games, and game results. The prediction parameters based on these criteria are given on Table 2.

In order to regularize the distribution of the values in the data set, the inputs and outputs of the data set are normalized in between 0 and 1 via Equation (3).

$$x_n = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3}$$

x_n = Normalized x_i (real value) value
x_{min} = Min value of the data to be normalized
x_{max} = Max value of the data to be normalized

Table 2. Prediction parameters used in predicting basketball results.

Parameter type	Criterion	Prediction parameters	Ranges	Symbols
Input	Teams	Code of the home team	1–16	I_1
		Code of the away team	1–16	I_2
	Team performances in recent weeks	The average points of the home team in the last four games.	1–2	I_3
		The average points of the away team in the last four games	1–2	I_4
	Positions in the league	The average points of the home team in the league.	1–2	I_5
		The average points of the away team in the league.	1–2	I_6
	Quality of the competitors	The average points of the competitors of home team in the last four games.	1–2	I_7
		The average points of the competitors of away team in the last four games.	1–2	I_8
	Week	Week of the league	1–30	I_9
Output	Result	Game result	0,1	O_1

The data set, which is formed according to the input and output parameters on Table 2, is composed of 240 games. The data set is split into two groups as training and test data set. Twenty-four games played in the last three weeks are the test set, while the rest games are chosen as training set.

The steps of forming the ANN architecture, whose network structure is given on Figure 2, is as follows.

(1) Input layer, corresponds to the input vector, which includes input variables. The 9 parameters defined in the data set are chosen as the input parameters of the ANN. They are denoted as I1-I9.
(2) Hidden layer, it is important to determine the number of the neurons in the hidden layer of the ANN structure. In other words, the number of the neurons in the secret layer defines the generalization ability of the network. With the trial and error method, the number of the neurons in the hidden layer is determined as 14.
(3) Output layer corresponds to the game result. It equals to 0 if the home team wins, and 1 if the away team wins. This output parameter is defined as O1.

The features of the ANN structure used in this study are given on Table 3.

Fuzzy Inference System

Fuzzy logic is a fuzzy set-based mathematics discipline, which grounds on our own thinking ability (Mohd Adnan et al. 2015). Contrary to the Boolean Algebra which allows only for 0 and 1 values, fuzzy sets can have any

Table 3. ANN Parameters.

Hidden layer number	1
Activation function, hidden layer	Tansig
Activation function, output layer	Softmax
Learning rate	0.01
Minimum performance gradient	1e-5
Performance goal	1e-3
Maximum number of epochs to train	5000

membership value in between 0 and 1 (Nguyen and Walker 2005). Fuzzy rules are used instead of Boolean logic in order to take result with fuzzy inference system.

As seen on Figure 4, a fuzzy inference system has certain input and output values. The membership degrees and values of these certain input values are determined via fuzzification (Nguyen and Walker 2005; Tavana et al. 2013). The input–output relations concerning the inference system, are defined as IF-THEN rules in fuzzy rules basis, where linguistic variables are also used. Each rule in this structure provides an inference corresponding to a certain part of prediction system. In the inference mechanism unit, fuzzy results are obtained via evaluating the membership degrees according to linguistic rules. In the defuzzification unit, the total of the fuzzy statements coming from the rule-based inference mechanism are turned into numerical statements applicable to the system (Nguyen and Walker 2005; Ross 2004; Vračar, Štrumbelj, and Kononenko 2016).

In this study, it was aimed to determine the favorite team of the game via fuzzy inference system. Since parameters such as the ranking of the team in the league, number of wins in the last four games, and the difference between total scores gained and total scores lost in the last four games are decisive in determining the favorite of the game, these parameters are used as the input variables in our fuzzy inference system. In the fuzzy inference system, the performance of the team is determined as the output parameter. Thus, a fuzzy inference mechanism is designed with three inputs and one output. While choosing these parameters, the expert opinions were considered in determining the favorite teams. The new fuzzy inference system structure is comprised

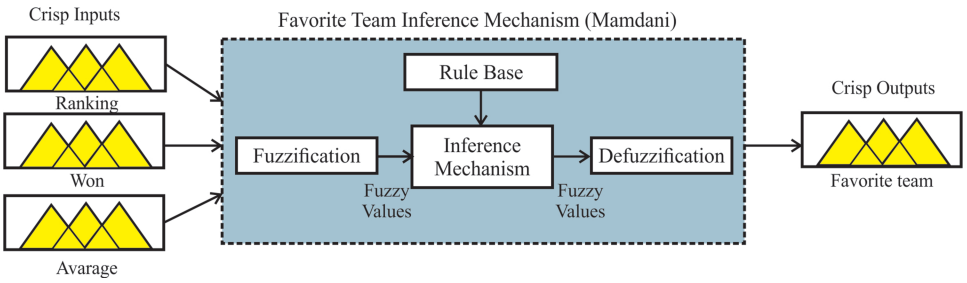

Figure 4. The structure of the Fuzzy Inference system.

of components such as fuzzification, rule base, fuzzy inference engine, and fuzzification as seen on Figure 4.

Input and output crisp numerical data have been fuzzified with human expert and converted into linguistic variables such as very negative (VN), negative (N), zero negative (ZN), zero (Z), zero positive (ZP), positive (P), and very positive (VP) as shown in Table 4.

As is seen on Table 4, rule base is composed of 100 fuzzy rules. When the 48th rule on the Table 2 is examined as an example, it is observed that this is a team ranked in the middle of the league ranking, doesn't have a conspicuous average in the last games, and mostly lost the last games, thus it's determined negative for this team to be the favorite.

The linguistic definition of the team's position in the league (let x) is created with triangular membership functions as VP, P, Z, N, and VN. Here, y being a member of the fuzzy set, $\mu_{\text{ranking}}(x)$ determines its membership degree. The membership degrees of the fuzzy sets are given in Equations (4)–(8). Similar fuzzy sets and linguistic variables were generated for the other parameters.

$$\mu_{VP}(x) = \left\{ \begin{array}{cc} \frac{5-x}{5} & 0 \leq x \leq 5 \\ 0 & otherwise \end{array} \right\} \tag{4}$$

$$\mu_{P}(x) = \left\{ \begin{array}{cc} 0 & x \leq 0 \\ \frac{x}{4.75} & 0 \leq x \leq 4.75 \\ \frac{8.5-x}{3.75} & 4.75 \leq x \leq 8.5 \\ 0 & x \geq 8.5 \end{array} \right\} \tag{5}$$

$$\mu_{Z}(x) = \left\{ \begin{array}{cc} 0 & x \leq 4.75 \\ \frac{x-4.75}{3.75} & 4.75 \leq x \leq 8.5 \\ \frac{12.25-x}{3.75} & 8.5 \leq x \leq 12.25 \\ 0 & x \geq 12.25 \end{array} \right\} \tag{6}$$

Table 4. Example of fuzzy rules.

Number of rule		*Ranking*		Won		Average		Favorite
1	If	*VP*	and	*VN*	and	*VN*	then	*P*
2	If	*VP*	and	*VN*	and	*N*	then	*P*
3	If	*VP*	and	*VN*	and	*Z*	then	*P*
4	If	*VP*	and	*VN*	and	*P*	then	*VP*
….								
48	If	*Z*	and	*N*	and	*Z*	then	*N*
49	If	*Z*	and	*N*	and	*P*	then	*N*
50	If	*Z*	and	*N*	and	*VP*	then	*ZN*
51	If	*Z*	and	*P*	and	*VN*	then	*ZN*
….								
97	If	*VN*	and	*VP*	and	*N*	then	*VN*
98	If	*VN*	and	*VP*	and	*Z*	then	*N*
99	If	*VN*	and	*VP*	and	*P*	then	*N*
100	If	*VN*	and	*VP*	and	*VP*	then	*N*

$$\mu_N(x) = \left\{ \begin{array}{cc} 0 & x \leq 8.5 \\ \frac{x-8.5}{3.75} & 8.5 \leq x \leq 12.25 \\ \frac{16-x}{3.75} & 12.25 \leq x \leq 16 \\ 0 & x \geq 16 \end{array} \right\} \tag{7}$$

$$\mu_{VN}(x) = \left\{ \begin{array}{cc} \frac{x-12.25}{3.75} & 12.25 \leq x \leq 16 \\ 0 & otherwise \end{array} \right\} \tag{8}$$

The membership function graphics of the used parameters are shown on Figure 5.

When the input data is entered into the system, one or more rules can be triggered. In this case, the inference mechanism determines the output. In this study, mamdani approach is used as the fuzzy inference mechanism. Mamdani max-min inference is used in order to determine the grade of accuracy for each rule. Grade of accuracy is calculated for each rule, and this grade of accuracy is used in order to estimate whether the team will be the favorite (Castellano, Fanelli, and Mencar 2003).

For defuzzification of the fuzzy output value obtained in this study, "Centroid" method is used (Ying et al. 1999). The formula used in Centroid method is given in Equation 9.

$$x^* = \frac{\int^x \mu_A(x)dx}{\int \mu_A(x)dx} \tag{9}$$

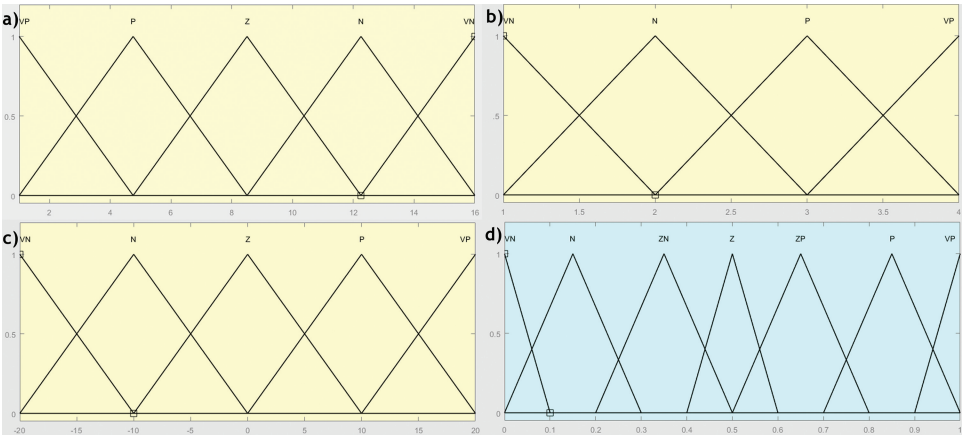

Figure 5. Membership functions of input and output parameters: (a) ranking, (b) won, (c) average and (d) favorite team.

Concurrent Neuro-fuzzy System Model (CNFS)

In recent years, hybrid methods, which can use the advantages of artificial neuron networks (ANN) and fuzzy inference systems (FIS) together, have been successfully used in various disciplines (Sabanci, Toktas, and Kayabasi 2017). In order to compensate the limitations of a single model, ANN and FIS are used together. This combination is called as neuro-fuzzy system. In this study, as a type of concurrent neuro-fuzzy system (CNFS) FIS and ANN are connected respectively (Vieira, Dias, and Mota 2004). The schematic sight of the developed CNFS is given on Figure 6.

As seen on Figure 6, fuzzy logic and ANN structures are used in a cascade connected structure. In the first place, the favorite of the game was decided over the home team and the away team using fuzzy logic structure, which was developed according to the thinking structure and used in predicting the favorite team. The obtained home and away team values for being the favorite were added as new inputs into ANN structure, which was previously given, to be combined with the modeling ability of the ANN.

Results

By means of holdout method, the obtained data set was split into two sets as training set and test set. The results of the first 21 weeks composed the training set, while that of the last 3 weeks comprised the test set, which included 24 games. Test data set is utilized for measuring the prediction performance of the models created in this study.

Accuracy of a classification can be evaluated by calculating the number of the class examples defined "accurate" (true positives), number of verified nonclass examples (true negatives), and examples inaccurately assigned to class (false positives) or not accepted as class examples (false negatives) (Ting 2017). These four counting compose the confusion matrix presented on the Table 5.

Measures, which are obtained based on the values of the confusion matrix and most frequently used in game result classification, are presented on Table 6.

The values of Accuracy, Sensitivity, and Specificity were determined as 70,8%, 54.5%, and 84.6%, respectively, which were obtained through application of the model, that was procured by the ANN structure with 14 neurons in the hidden layer, to the test data set. The confusion matrix for the ANN model are presented on Table 7.

The values of Accuracy, Sensitivity, and Specifity were determined as 79,2%, 72.7%, and 79.1%, respectively, which were obtained through application of the newly developed CFNS model to the test data set. The confusion matrix for the CFNS model are presented on Table 8.

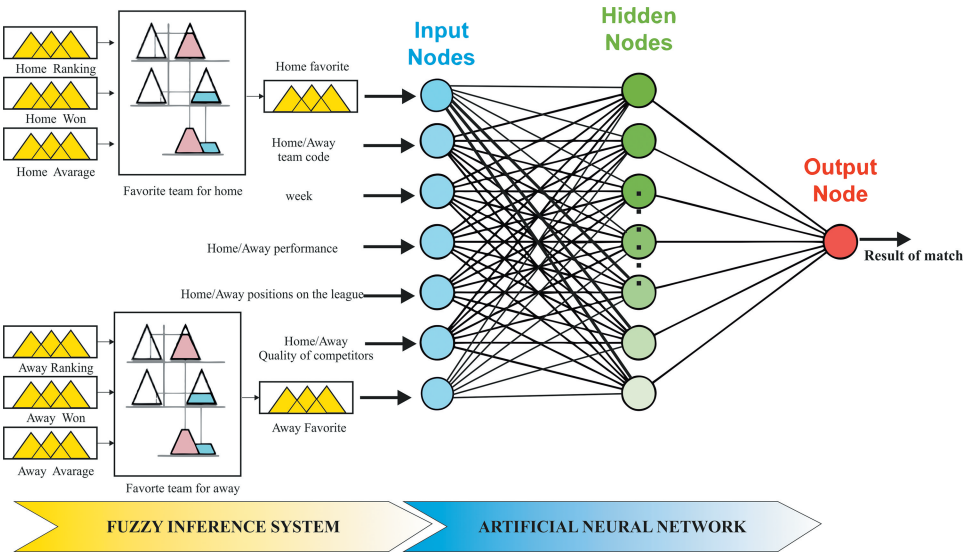

Figure 6. Schematic structure of developed Concurrent Neuro Fuzzy System.

Discussion

In this study, a hybrid artificial intelligence model was developed in order to predict the game results using the data of the Turkey Men's Basketball League season. Until today, no CFNS model has been developed, which combines ANN and Fuzzy logic and which can predict game results using the previous game results data. Criteria that reflected the performances of the teams were determined in order to predict the game results. Nine parameters determined according to these criteria were used in the study. These parameters were obtained from the results on the score history data table of 240 games played in 2015–2016 season. Firstly, an ANN model was developed that could predict which team (the home or the away team) would win the game via these nine parameters. It was observed that this newly developed model predicted the last three game results with 70.8% accuracy. Although the effectiveness of this model in classifying the last winning of the home team was 84.6%, its effectiveness in classifying the last winning of the away team was in a lower rate, 54.5%.

An inference system was developed that could predict the favorite of the game using fuzzy logic in order to increase the accuracy and enhance the sensitivity of the obtained ANN model. This newly obtained fuzzy inference system produces the favorite of the game based on the performance values of the team. A CNFS model was developed, with the nine input parameters in the ANN structure and favorite positions, which were defined via fuzzy inference system. It was observed that the newly developed CNFS model predicted the game results of the league's last three weeks' games with 79.2% accuracy. The CNFS model, which was developed in a hybrid structure, gave a higher

Table 5. Confusion matrix for binary classification.

Data Class	Classified as pos	Classified as neg
pos	True positive (tp)	False negative(fn)
neg	False positive (fp)	True negative (tn)

Table 6. Measures for classification using the notation of Table 5.

Measure	Formula	Evaluation focus
Accuracy	$\frac{tp+tn}{tp+fp+fn+tn}$	General effectiveness of the classifier
Sensitivity	$\frac{tp}{tp+fn}$	Effectiveness of the classifier in deciding the positive tag
Specificity	$\frac{tn}{fp+tn}$	Effectiveness of the classifier in deciding the negative tag

Table 7. Confusion Matrix obtained for the ANN model.

		Actual results		
		Away win	Home win	Classification overall
Predicting results	Away win	6	2	8
	Home win	5	11	13
Actual overall		11	13	Accuracy: 70.8%

Table 8. Confusion Matrix obtained for the CFNS model.

		Actual Results		
		Away win	Home win	Classification overall
Predicting Results	Away Win	8	2	10
	Home Win	3	11	14
Actual overall		11	13	Accuracy:79.2%

prediction accuracy compared to the ANN model. Moreover, the CNFS model gained a higher performance compared to the ANN model with its 72.7% classification effectiveness of the away team's winning success. The classification effectiveness of the CNFS model in the home team's winning success was the same with that of the ANN model.

There is not a study, yet, conducted with Turkish Basketball League data. Therefore, our study was compared with other basketball prediction studies conducted with different methods in different leagues. For instance, (Loeffelholz, Bednar, and Bauer Kenneth 2009) predicted a basketball game result with a % 74.33 accuracy in their study using four different ANNs. (Zdravevski and Kulakov 2010) achieved an accuracy of %65.7 in their basketball game result prediction work. (Cao 2012) predicted a basketball game result with an accuracy of 66.67% using the ANN model in the study conducted with NBA league data between 2005 and 2010. Compared to other ANN studies, it is seen that the model obtained with ANN has a high degree of accuracy in this study.

Also (Kaur and Jain 2017) proposed the Hybrid Fuzzy-SVM model, which combines the advantages of the fuzzy model and the SVM for a basketball match result prediction. And they stated that they were able to get better game

prediction result with Hybrid model. Similarly, in the study, the CNFS model, which combines the advantages of the Fuzzy Logic model with the ANN model yielded better results with %79.2 accuracy ratio. This developed Hybrid model is more successful than other ANN model studies according to the accuracy of the match prediction result. In addition, when the basketball prediction studies using different methods, given on the Table 1, are examined concerning their accuracy, it is observed that this study, with 79.2% accuracy rate owing to the suggested CNFS model, has the highest accuracy rate among all of the studies, except two, in the literature. This comparison proves that the hybrid artificial intelligence method suggested in this study has a high success in predicting the game results.

Conclusion

Since game result prediction in basketball league depends on many factors, it is a difficult research problem. With this study, it is proved that the ANN model, which is developed depending on the team performance parameters obtained from the score history table of the league, has a remarkable success in predicting the game results. This result coincides with many ANN model results in the literature conducted on game result prediction. In this study, the fuzzy inference system and a fuzzy logic model defining the favorite team is basically a system predetermining the favorite of the game. This FIS was combined with the ANN structure in cascade connection as a CNFS model. Thus, the modeling ability of the ANN was combined with the inference ability of the fuzzy logic. This CNFS model in the suggested hybrid structure is observed to increase the success rate of ANN model. It was also manifested that the parameters for the favorite team obtained according to the team performance values contributed positively to the prediction model. This case is encouraging for different inference parameters, that reflect the performance of teams, to be combined with the models. Moreover, the determination process of the verbal statements used in the FIS and the rule base directly influences the general prediction performance.

This study was conducted based on generally the performance data of the teams. Individual player parameters such as the individual talents of the players, their performances, and motivations were neglected. In the further studies to be conducted in the future, individual player parameters can be added to the structure obtained in this study. Moreover, different optimization techniques can be used in order to determine the parameters of the generated model.

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