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Araştırma Makalesi/ Research Article

PREDICTION OF COMPUTER GAME ADDICTION IN CHILDREN USING DEVELOPED ARTIFICIAL NEURAL NETWORKS (ANN) AND MULTIPLE LINEAR REGRESSION (MLR) MODELS

GELİŞTİRİLMİŞ YAPAY SİNİR AĞLARI (ANN) VE ÇOKLU DOGRUSAL REGRESYON (MLR) MODELLERİYLE ÇOCUKLARDA BİLGİSAYAR OYUN BAĞIMLILIĞININ TAHMİN EDİLMESİ

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ABSTRACT: Game addiction in children plays a major role in the mental and physical development of the child. Therefore, various scales are used to examine computer game addiction of children and various input parameters (age, gender, daily play time, etc.) are utilized in scales. The purpose of this study is to project a system that estimates whether the child is addicted to the game when looking at the input parameters. Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) techniques were used to design this system. In order to measure the predictive performance of the developed models, the Root Mean Squared Error (RMSE), and Correlation Coefficient (R) criteria were examined respectively and it was observed that the model developed by ANN predicted CGA with high accuracy.

Key Words: Artificial Neural Network, Multiple Linear Regression, Prediction of Computer Game Addiction, Expert System.

ÖZ: Çocuklarda oyun bağımlılığı, çocuğun zihinsel ve fiziksel gelişiminde büyük rol oynar. Bu nedenle çocukların bilgisayar oyun bağımlılığını incelemek için ölçek ve ölçeklerde çeşitli parametreler (yaş, cinsiyet, günlük oyun süresi vb.) kullanılmıştır. Bu çalışmanın amacı, girdi parametrelerine bakıldığında çocuğun oyuna bağımlı olup olmadığını tahmin eden bir uzman sistemi tasarlamaktır. Bu sistemin tasarlanması amacıyla iki model kullanılmıştır. Bu modellerden biri Yapay Sinir Ağları (YSA) diğeri ise Çoklu Doğrusal Regresyon (ÇDR)'dur. Modellerin performansı, Kök Ortalama Kare Hatası (KOKH) ve Korelasyon Katsayısı (R) kriterleri kullanılarak değerlendirilmiştir. Bu kriterler analiz edildiğinde, YSA yüksek tahmin performansı gösterirken, MLR düşük tahmin performansı göstermiştir. Sonuç olarak, YSA ile geliştirilen sisteme farklı girdi değerleri verildiğinde, çocuklardaki oyun bağımlılığı ile ilgili en doğru tahminlerin elde edildiği görülmüştür

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Anahtar Kelimeler: Yapay Sinir Ağları, Çoklu Doğrusal Regresyon, Bilgisayar Oyunu Bağımlılığının Tahmini, Uzman Sistem.

1. INTRODUCTION

The developments in the information and communication technologies in the age we are living make themselves felt in every area of life. Especially computer and internet technologies have become indispensable for people in different areas from education to business life. In addition to facilitating life in many ways, these technologies can also cause negative conditions like addiction. Addiction is the fact that a person continues to useany harmful stimulus against herwill despite its all harms, cannot give up, and tends to reuse even if the person abandons this stimulus by experiencing the symptoms of the deprivation. (Akçakaya, 2013). Addiction, is explained as “being addictive, dependence” by Turkish Language Association (TDK, 2016), has been diversified together with the developing and changing world conditions. In recent years, many changes have been observed in the habits of people in many ways such as eating, spending money, shopping, using mobile phones and computers. The use of the internet in every area and addressing people of all ages has led to an increase in the quality of the web and people have begun to believe that there will be no life without internet and computer. Together with an unlimited, unsupervised and non-restricted computer and internet usage, accessing all kinds of information and ındividuals has become very easy, and the people have gradually broken from social life. Social networks are used for various purposes such as communicating, acquiring a social environment and playing games by entering into all areas of life. People have begun to take the internet as a centre of their lives making it as a purpose rather than a tool and started to be an addiction (Yalçın, 2006; Karaman and Kurtoğlu, 2009; Çakır, Horzum and Ayas, 2013; Fidan, Pekşen Akça and Akgül, 2016). Thus, many different kinds of addictions such as technology addiction, internet addiction, computer game addiction, social media addiction, phone addiction have entered into our lives. Computer game addiction among these different types of addictions has been the one affecting the children and adolescents most. The concept of game which is a natural tool that allows children to develop social and mental skills by affecting their social relationships confronts us today as a digital game by changing its shape (Şahin and Tuğrul, 2012). In the past, games were played interactively in places that are not closed mostly, such as playgrounds and streets. Today, however, they have begun to play with people in closed and virtual environments together with technology, computers and the internet (Horzum, Ayas and Balta, 2008). Digital games are the games played through hardware (computer, mobile phone, game console, tablet, etc.) (Kaya, 2013). Digital games are categorized as action, adventure, combat, puzzle, role-playing, simulation, sports and strategy games (Rapeepisarn, Wong, Fung and Khine, 2008). Computer games are very effective for children to acquire computer literacy, provide hand-eye coordination, develop spatial skills such as imagining, explaining the causes of shapes, and visualising objects related to chemistry and physics, and providing integration of the shapes in space (Cesarone, 1994; cited by Horzum, 2011). These digital games cause children and adolescents to have computer game addiction over time., Considered as innocent and harmless at first, computer game addiction has become a condition that requires intervention or even treatment. This is because the individuals who are addicted to computer games affect the lives of both themselves and their families negatively. Computer game addiction is a part of behavioural addictions like internet addiction and pathological gambling (Horzum, Ayas and Balta, 2008). Since particularly children and adolescents spend hours in front of the game, this affects their academic performance, lessons, social lives, physical health and mental health considerably. It also affects children's mental abilitiessuch as attention and concentration. The causes of computer game addiction are evaluated in three categories as social, physical and psychological. When it is assessed from the social aspect, children and adolescents are now able to easily access computer and internet in internet cafes, at home, at school, in short, wherever they want. With this easy-to-access technology, children can play digital games comfortably whenever and whenever they want. When it is physically evaluated, playing computer games is a pleasant activity. Symbolic awards such as points, bitcoin, gold, weapons, characters in games based on punishment and reward system are attractive. In the brain of the individuals who win these awards, constantly dopamine hormone which causes people to enjoy is released. When it is assessed psychologically, addiction is a person’s effort to fill his/her spiritual gap. In virtual games, people who have self-confidence problems, have difficulty in expressing themselves and establishing social relations and who see themselves worthless find an environment disconnected from the reality but in which they can feel safe and happy for filling their spiritual gaps. These three reasons come together and cause computer games addiction (Akçakaya, 2013).

1.1. Purpose of the Research

The main goal of this study is to design a system of experts that predicts whether a child is addicted to the game. In order to prevent computer game addiction, which affects children and adolescents today, it is necessary to first examine the variables that push children into this addiction. For this purpose, in this study, input parameters affecting the computer game dependency levels of Primary School students will be examined and an expert system will be designed to predict whether the child is dependent on the game when looking at input parameters. As described above, it is evaluated that this study is significant in terms of eliminating deficiencies in field writing.

2. MATERIAL AND METHODS

2.1. Flowchart of Developed Model

The aim of this study is to develop a model to predict whether children are addicted to computer games. As shown in Fig. 1 the Model was developed in 4 stages, respectively. (1) Data collection (2) Pre-processing of data (3) Separation of training and test data, training of models developed with ANN and MLR with training data, examination of test data and performance (4) Statistical analysis of results and the highest accuracy model determination. In the first stage, primary school students who are studying in Kayseri in 2015-2016 academic year were administeredthe Computer Game Addiction Scale developed by Horzum, Ayas and Balta (2008) In the second stage, the most appropriate attributes were determined. Since many techniques performed better with normalized data, normalization was applied and the data was spread over the 0-1 range. In the third stage, model architectures created by ANN and MLR techniques were designed. In the fourth stage, the developed models were applied to the test data and the highest accuracy model was determined.

2.2. Study Group and Selected Variables

The population of the study in the survey model consisted of 4th and 5th-grade primary students studying in Kayseri in 2015-2016 academic year. Survey models, In general, survey arrangements made by the whole population or on a group, case, or sample taken from the population to have a general judgment about a population of many elements (Karasar, 1995).

There were a total of 306 students including 152 girls and 154 boys in the sample group. 241 of the students were 4th graders and 65 were 5th graders. While 240 students had a personal computer or tablet, 66 did not. 179 students had internet connection in their houses. 66 students had no internet connection at their homes. When durations of the computer games within a day were examined, it was seen that 236 students played games for 0-1 hour, 50 students played games for 2 - 3 hours, 14 students played games for 4 hours, and 6 students played games for 5 hours and more. When the time spent by the students on the computer per day was examined, 157 students spent 0 - 1 hour, 56 students spent 2-3 hours, 37 students spent 4 - 5 hours, and 27 students spent 5 hours and more on the computer. While 61 students' mothers were employed, 241 students' mothers were unemployed. While 293 students' fathers were employed, 13 fathers were unemployed. When mothers' occupation was examined, 243 students' mothers were a housewife, 4 students' mothers were workers, 4 were accountants, 5 were cleaning staff, 17 were teachers, 4 were secretaries, and 29 students' mothers worked in other jobs. When the students' father's occupations were examined, 18 were self-employed, 4 were electrician, 14 were drivers, 29 were workers, 10 were police, 4 were cooks, 19 were builders, 25 were tradesman, 15 were civil servant, 4 were cleaning staff, 11 were furniture seller, 22 were teachers, 5 were farmers, 8 were factory owners, 10 were industrialists and other jobs. In the study, ten attributes were selected as independent variables. These:

1) Gender of the child (G)
2) The child's grade (CG)
3) Status of the child to have a personal computer and tablet (C/T)
4) Status of having internet connection at home (SHICH)
5) Duration of playing game on the computer per day (DPG)
6) The time spent in a day on a computer (TS)
7) Mothers' employment status (MES)
8) Fathers' employment status (FES)
9) Mothers' occupation (MO)
10) Fathers' occupation (FO)

Personal information of the students participating in the study is presented in Table 1.

Table 1: Personal Information of the Students

Variables		**Number of students**
Gender	Female	152
	Male	154
Grade	4	241
	5	65
Owning PC/Tablet	Yes	240
	No	66
Having internet connection at home	Yes	179
	No	127
Duration of playing game on the computer per day	0-1 hour	236
	2-3 hours	50
	4-5 hours	14
	Over 5 hours	6
The daily time spent on the computer	0-1 hour	157
	2-3 hours	56
	4-5 hours	37
	Over 5 hours	27
Mother's employment status	Employed	61
	Unemployed	241
Father's employment status	Employed	293
	Unemployed	13

Mother's Occupation	Housewife	243
	Worker	4
	Accountant	4
	Cleaning staff	5
	Teacher	17
	Medical secretary	4
	Other	29
Father's Occupation	Self-employment Electrician Driver Worker Police Cook Constructor Tradesman Civil servant Cleaning staff Furniture seller Teacher Farmer Factory owner Industrialist Other	18 4 14 29 10 4 19 25 15 4 11 22 5 8 10 108
TOTAL		306

In this study, it was aimed to investigate the variables leading the children to computer addiction. These variables are gender, grade, status of the child to have a personal computer or a tablet, having internet connection at home, daily time spent while playing computer games play duration on the computer of each child, time spent by the child on the computer per day, mothers' employment status, fathers' employment status, mother's occupation, and father's occupation. These independent variables were thought to affect the situation of children to play the game on the computer. For example, in the variable of gender, the interests and needs of girls and boys are different from each other. Boys are more interested in technology than girls. Children are more likely to prefer playing games as a result of the period they are in (Horzum, 2011; Chumbley and Griffiths, 2006).

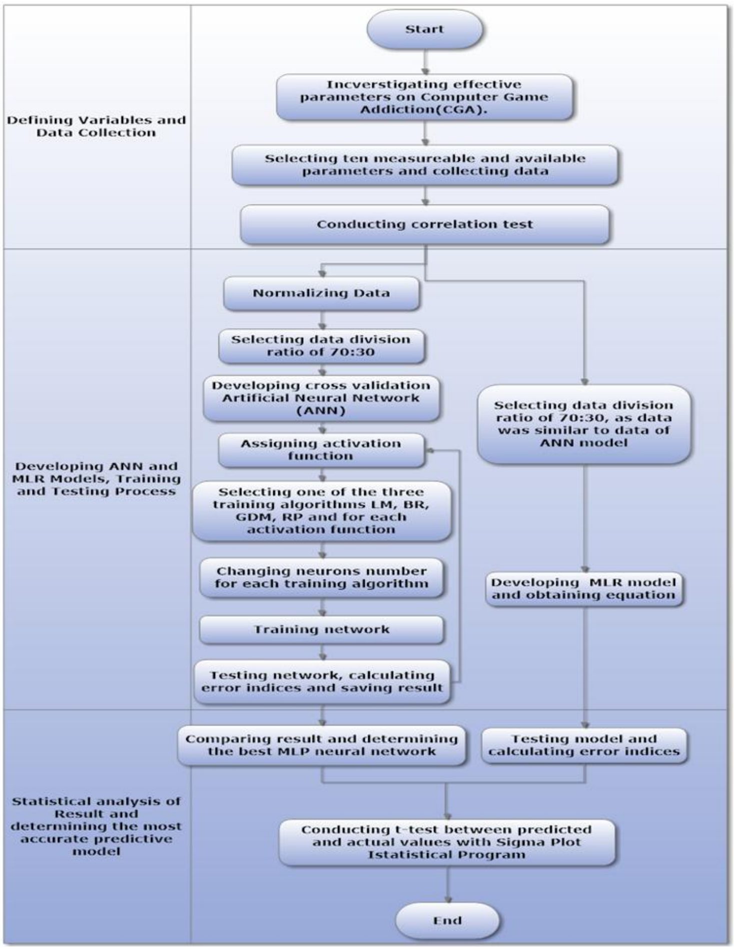

Figure 1. Flow process determined to predict Computer Game Addiction
Source: (Azadi S., Karimi-Jashni A., 2016. Verifying the performance of artificial neural network and multiple linear regression in predicting the mean seasonal municipal solid waste generation rate: A case study of Fars province, Iran. Waste Management 48, 14–23.)

The answer to the question whether this preference differs regarding ages or not was sought. When it was examined regarding the duration of the computer gamesin a day, the time spent on the internet is not enough alone to determine the computer addicts, the purpose of the expenses this time is also significant (Günüç and Kayri, 2010). The negative and active causes of computer use are related to the reasons and purposes of computer usage (Bayraktutan, 2005). It is thought that one of the important concepts believed to be linked to the computer game addiction is the time spent by a child on the computer in a day. Internet addiction is expressed as spending a long time on the internet and not being able to control the internet usage (Günüç and Kayri, 2010; Leung, L. 2004). In other words, it can be asserted that the biggest symptom and factor in expressing and describing internet usage as addiction is the excessive time spent by the individual on the internet. In particular, computers make daily life easier and are used as an important means of providing continuity and maintaining order at home, industry, banking, entertainment and education. Because of all these facilities provided by computers, it is seen that in recent years they have intensively entered and adopted into every aspect of social life. Almost everything in daily life depends on technological tools, which has reduced the relations among people. Instead, human-machine relations have increased. Today, individuals are surrounded with technological communication (Bayraktutan, 2005; Erkan, 1997). Employment status of the parents and their profession are thought to affect the child's computer game addiction status. The family is the most fundamental element that teaches children responsibilities and duties which make children to gain various behaviours and habits. It causes an individual to gain some forms of behaviours, values, customs and habits. In this regard, the age between 0-12 is the most critical period of human life. In this critical period, the child is affected mostly by his/her family (Bayraktutan, 2005; Doğan, 2000; Nurin, 1994).

Ten relevant variables as input and 306 research data set are used for this study. The descriptive statistics of the data are indicated in Table 2 - 3 and shows Correlation between ten independent attributes and CGA.

Table 2: Descriptive Statistics of All Research Data.

Varıables	Mean	SD	Minimum	Maximum
G	1,529	0,5	1	2
CG	3,618	1,517	1	9
C/T	1,291	0,455	1	2
SHICH	1,389	0,488	1	2
DPG	2,195	1,466	1	5
TS	1,591	1,199	1	5
MES	1,801	0,4	1	2
FES	1,042	0,202	1	2
MO	7,405	14,903	1	81
FO	30,458	22,753	2	84
CGA	1,526	0,842	1	3

Table 3: Calculated Correlation Coefficients Between CGA and ten İndependent Variables.

	G	**CG**	**C/T**	**SHICH**	**DPG**
	0,0239	0,0358	-0,309	-0,267	0,623
CGA	**TS**	**MES**	**FES**	**MO**	**FO**
	0,301	-0,0225	0,0518	0,00608	-0,0294

2.3. Model of ANN

A particular structure of ANNs is Feed-Forward Neural Network (FFNN) has a wide range of applications in ANN (Wang et al., 2015; Azadi and Sepaskhah, 2011). Fig. 2 illustrates FFNN with a hidden layered architecture.

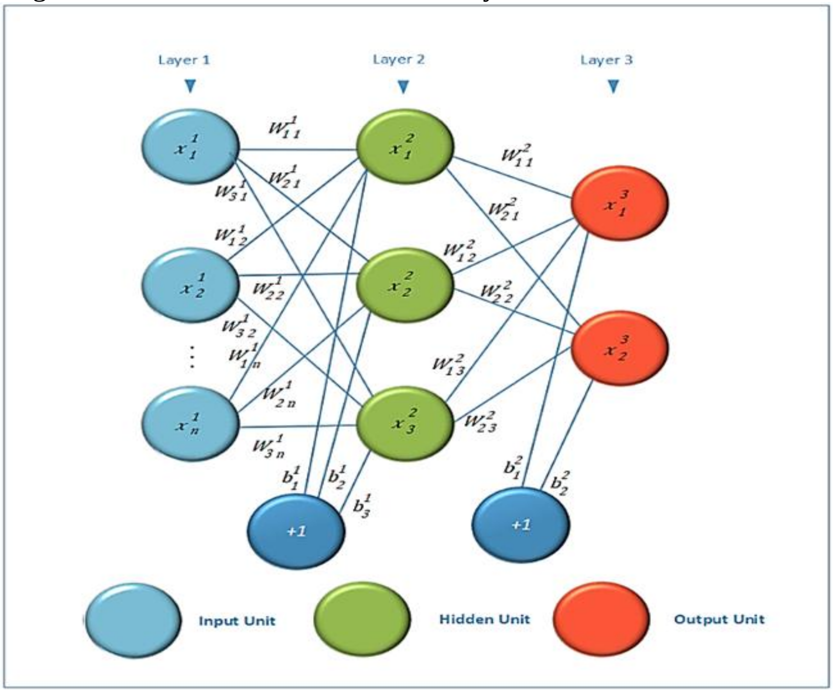

Figure 2. A typical FFNN.

ANN is basically composed of three layers. The input layer is the layer in which the attributes specified as input are accepted to the network(Azadi and Sepaskhah, 2011). The input layer contains as many nodes as the number of input attributes. The hidden layer is the layer in which the data is made meaningful for estimation and the training of the network is performed accordingly. Each node in the input layer connects to the nodes in the hidden layer. In ANN, each connection has a certain weight. The data from each node in the input layer is multiplied by these weights and the net input is obtained by adding the function to the nodes in the hidden layer. The net input obtained from the total function is converted to a nonlinear form with the activation function and output from the hidden layer. In this way, ANN tries to establish a connection between inputs and outputs (Zhang et al., 1998; Wang et al., 2015). Eq. (1) shows output y_j of each knot j (Kocadağlı, 2015).

$$y_j = f\left(\sum_{i=1}^{m} W_{ji} X_i + b_j\right) \tag{1}$$

X_i is the output of the node of the previous layer. W_{ji} is the weight of the connections between the two nodes. is the input value that is considered a node threshold. This operation performed at each node in the hidden layer and then the values obtained from the activation function are multiplied by weights and sent to each node from the output layer. The data processed by a linear activation function in the output layer is presented as output. The number of output layers is related to the research topic. (Zhang et al., 1998; Wang et al., 2015; Beale et al., 2010).

In this study, ten variables G, CG, C / T, SHICH, DPG, TS, MES, FES, MO, FO were defined as input and CGA was defined as the output attribute. The model was developed with 306 datasets and after many preliminary studies, the highest accuracy estimation was obtained with two hidden layers and the number of neurons in these hidden layers.

When the literature is reviewed, many activation functions are used in the studies. However, the basic activation functions are logsig, tansig and purelin functions (Wang et al., 2015; Zhang et al., 1998). In the study, the activation functions were used in the hidden layers and output layers in different variations and the best performance was provided by the tansig function in the hidden layer and purelin and tansig functions in the output layer.

During ANN training, network weights are randomly determined in the range of -1, 1. The optimization algorithms are used as changing the weights to minimize the error value between the estimated values and the actual values. However, no optimization algorithm guarantees the global minimum. This is a major problem for optimization algorithms, but these algorithms can be fitted to the local minimum (Zhang et al., 1998; Kocadag lı l, 2015). ANN uses the backprobpagation method to adjust the weights to find the global minimum (Fukuoka et al., 1998). In the study, the network is trained 500 and 1000 times, but with each new training process, the network starts with new weights and thus shows the best predictive performance without being caught on the local minimum.

In this study, 4 optimization algorithms are used. These algorithms are Resilient back Propagation (RP), Bayesian Regulation (BR), Levenberg-Marquardt (LM) and Gradient Descent with Momentum (GDM). The algorithms used in the study were compared by looking at the estimation errors.

Many algorithms produce more accurate estimates with normalized data. One of the reasons is that the high peak values in the data are compressed to a certain range. For this reason, normalization is carried out before starting the training of the network (Wang et al., 2015). Here, for data normalisation, was used as Eq. 2

$$x_n = 0.8\ x\ \left[\frac{x - x_{min}}{x_{max} - x_{min}}\right] + 0.1 \qquad (2)$$

Here, x represents the actual value, while xn represents the normalized value. xmin and xmax represent the real min and max values for each attribute.

Another major problem of ANN is that the network over-fitting the data. With the over-fitting of the network, estimation error can be increased to a high level with data not seen before. In such a case, the technique of stopping is used during the training of the network (Kocadag ˘ l, 2015, Sama Azadi et al., 2015).

In order to apply the early stop technique, the data is divided into 3 sections. These sections are identified as training, validation and testing. While the training set is used to train the network, the validation set is used to stop training before memorizing the data of the network. In this study, the minimum number of iterations used to train the network was determined as 500 and maximum 1000. When the validation error value is 6 iterations, the training process is stopped. In the study, 306 data sets were divided into 70% (training), 15% (verification) and 15% (test). In order to avoid close relationship and preliminary help in the data, all sections are assigned randomly, not sequentially. Then, the developed network was trained with 4 learning algorithms and the estimation capabilities of these algorithms were measured with test data.

2.4. Model of MLR

MLR is a model that is formed by calculating the relationship between the dependent variable and one or several independent variables. Although MLR is a statistical method, it was introduced into the literature by Francis Falton in the 19th century (Jahandideh et al., 2009, Shu and Lam, 2011.).

In equation 3, n gives the number of observations for MLR.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \mathcal{E} \text{ for i = 1, 2, ... n.} \qquad (3)$$

$y_i = dependent\ variable$

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$y_i = dependent\ variable x_i = independent\ variable$

$\beta_p = \ slope\ coefficients\ for\ independent\ variable$

$\beta_0 = constant\ term$

$\mathcal{E}$ = residuals (error term)

In this study, 10 input attributes (G, CG, C / T, SHICH, DPG, TS, MES, FES, MO, FO) were determined in 306 data sets. Then, 70% (214 data) of the data was used to construct the model, while the remaining 30% (92 data) was used to measure the predictive ability of the model.

2.5. The Method Used To Evaluate The Prediction Performance

There are many different techniques to measure the estimation ability of the developed model. In this study, Root Mean Absolute Error (RMSE) was calculated in order to examine the error difference between the estimated values and the actual values. When the RMSE value approaches zero, the model has a high predictive ability.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_{sim}^{i} - P_{obs}^{i})^2}{n}} \qquad (4)$$

3. RESULTS AND DİSCUSSİON

3.1. Evaluate Correlation Coefficient

In this study, firstly, linear relationship between independent variables and dependent variable is examined. Correlation Coefficients (R) were calculated to measure the linear relationship between the variables. As a result, the effect of independent variables on the dependent variable was investigated. Table-3 shows that the correlation coefficients are positive and negative. The positive values in this table indicate that the increase or decrease in the independent variable affects a change in the same direction in the dependent variable. Negative values indicate that there is an inverse effect between dependent and independent variables, i.e. one increases and the other decreases. When Table 3 is examined, it is seen that the lowest correlation value is between MO and CGA attributes and the highest correlation value is between DPG and CGA.

Linear relations between dependent and independent attributes were examined and then MLR and ANN models were developed and prediction capabilities were compared.

3.2. Investigation of ANN's ability to predict CGA

In order to estimate CGA with the lowest error, four layer network architecture is proposed. In the developed architecture, different neuron numbers are determined for each hidden layer and the network consists of an input layer, an output layer and two hidden layers.

Table 4: Performance of ANN Models in Training and Testing Situations

Training Algorithms	**Layers and Number of Neurons**	**Training Correlation Coefficient (R)**	**Testing Correlation Coefficient (R)**	**RMSE (Root Mean Squared Error)**	**Epoch**	**Activation Function**
Resilient back Propagation (RP) (trainrp)	10-4-40-1	0.75292	0.83656	0.278029	1000	Tansig-Tansig-Purelin
Levenberg–Marquardt (LM) (trainlm)	10-4-40-1	0.70781	0.91372	0.274591	500	Tansig-Tansig-Purelin
Gradient Descent with Momentum (GDM) (trainGDM)	10-2-20-1	0.63373	0.70271	0.288271	1000	Tansig-Tansig-Tansig
Bayesian Regulation (BR) (trainBR)	10-4-16-1	0.85171	0.62329	0.303809	1000	Tansig-Tansig-Tansig

In the developed network architecture, four types of optimization algorithms have been determined to compare two types of activation functions and performance in different layers. The RMSE value was calculated to measure the network's ability to predict. When Table 4 is examined, the architecture with the highest estimation ability is tansig as the activation function, LM as the optimization algorithm and 4 and 40 (10-4-40-1) as the number of neurons in the hidden layers.

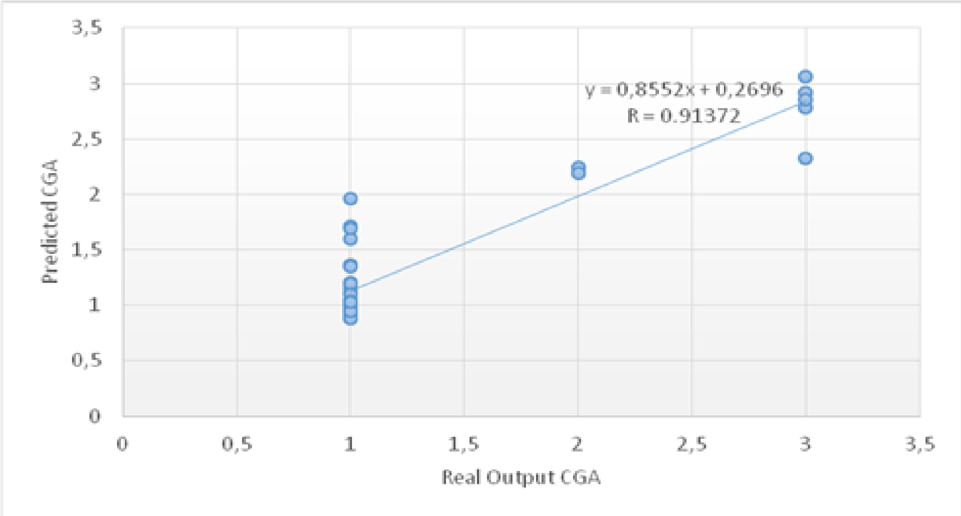

Figure 3. Distribution of the estimated and actual CGA values obtained by ANN model

Table 5: Statistical t-test Showing the Relationship Between Real and Estimated CGA Values for ANN

	N	Missing	Mean	Std Dev	SEM	P Value
Predicted CGA Values	46	0	1,348	0,606	0,0894	0,508
Real CGA Values	46	0	1,261	0,648	0,0955	

One of the most effective tools to show the chorealtive relationship between variables is the distribution graphs (Flott, 2012). If the overall distribution of the data in the graph is in the form of a straight line and the correlation coefficient is close to the upper limits of 1 and -1, there is a close relationship between the values that make up the distribution. As shown in Fig. 3, the correlation between the estimated CGA values obtained with the ANN model and the actual CGA values is quite high. In addition to this distribution, when the Table 5 is examined, the results of the statistical t test between the estimated and actual CGA values are seen. According to these results, P value is greater than 0.05. This shows that there is no significant difference between the actual CGA value and the estimated CGA value.

When the graphical distribution in Fig. 4 is considered, there is a significant relationship between the actual CGA values and the exact CGA values. As a result, graphical and statistical results show us that ANN has high predictive ability.
Looking at the overall, ANN can predict CGA sufficiently, and this field can be considered as an expert system.

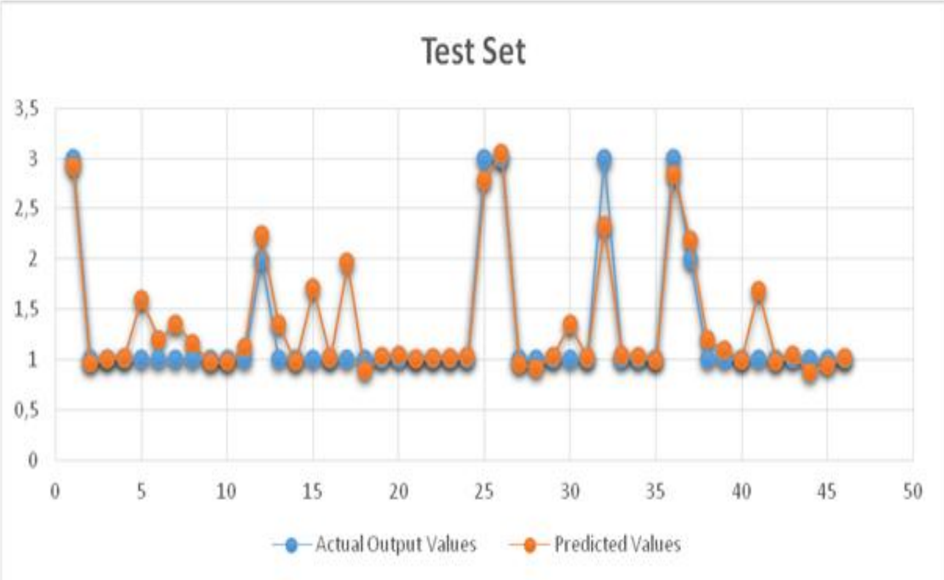

Figure 4. Graphical Representation of the Distribution Between Estimated and Actual CGA Values LM Algorithm in ANN.

3.3. Investigation of MLR's Ability to Predict CGA

As in the process of developing the ANN model, the data was divided into 70% and 30% in order to form an estimation process using the MLR model. Using the data within 70% (dependent and independent variables), the coefficients of the equation constituting the MLR model were calculated as shown in the formula below.

*CGA = 0,267 - (0,00405 * G) - (0,239 * CG) - (0,0994 * C/T) + (0,0342 * SHICH) + (0,758 * DPG) - (0,0842 * TS) - (0,0442 * MES) - (0,0390 * FES) - (0,0113 * MO) - (0,00912 * FO)*

The data within the 30% slice were presented as input to the developed MLR model and estimated output values were obtained. The error (RMSE) and correlation coefficients (R) between estimated and actual values are 0.380202 and 0.4188, respectively.

As shown in Table 6, statistical t-test was applied between estimated CGA values and actual CGA values and P value was higher than 0.05. This shows us that there is no statistically significant difference between the estimated values and the actual values.

Tablo 6: Statistical T-Test Showing the Relationship Between Real and Estimated CGA Values for MLR

	N	Missing	Mean	Std Dev	SEM	P Value
Predicted CGA Values	46	0	1,304	0,695	0,102	0,111
Real CGA Values	46	0	1,518	0,572	0,0843	

Figure 5 shows the relational distribution between the estimated and actual CGA values.

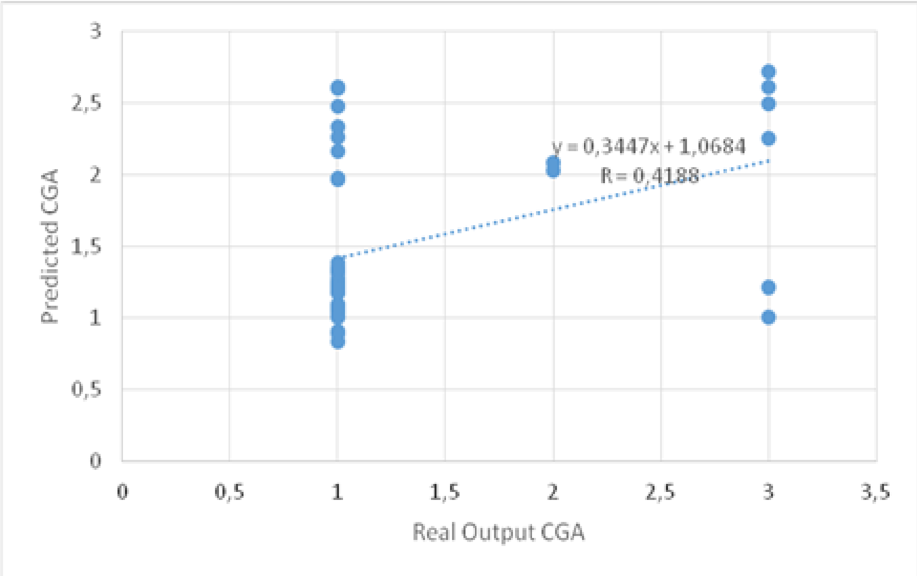

Figure 5. Distribution of the estimated and actual CGA values obtained by MLR model.

Figure 6 shows the comparative graphical distribution between the estimated and actual CGA values. Although there is no significant difference between the estimated and actual values in Table 6, it is seen that the ability of MLR model to estimate CGA is not sufficient when Fig. 5 - 6 is examined.

Figure 6. Graphical representation of the distribution between estimated and actual CGA values for MLR.

3.4. Evaluation of Prediction Capabilities of Models Developed With MLR and ANN

Comparative error and correlation coefficients for ANN and MLR models developed in Table 7 are examined. According to the results, the RMSE values for ANN were 0.274591 and 0.380202 and the correlation coefficients were 0.91372 and 0.4188, respectively. These results show that ANN has better predictive ability than MLR.

Table 7: Comparison of Prediction Capabilities of Developed MLR and ANN Models for CGA

Models	RMSE	R
ANN	0.274591	0.91372
MLR	0.380202	0.4188

4. CONCLUSIONS

Artificial intelligence (AI) studies are being carried forward to the next day. This shows that instead of manual human interventions, artificial intelligence-supported machines that can make decisions like human beings, but produce faster, more efficient and accurate results are increasingly being replaced.

Therefore, the aim of this study is to develop a system that can accurately predict game dependence (CGA) in children when new input value is reached by using statistical - MLR and artificial intelligence - ANN models. These models were compared from many different angles and their predictive capabilities were measured. As a result, it was seen that the model developed with ANN can predict CGA at a higher rate than the model developed with MLR.

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