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ORIGINAL ARTICLE

Judging Primary School Classroom Spaces Via Artificial Neural Networks Model

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ABSTRACT

An experimental study was conducted with 2nd grade students at primary schools in Turkey as part of an attempt to describe the ideal classroom space for primary education students. In the study, photographs of 20 different primary education classrooms were evaluated by 189 students. The students evaluated the images by means of surveys in which they were asked questions on four concepts: belonging, like (partiality), learning and safety. Reliability analyses of numeric data obtained from student surveys were made and they were subjected to various statistical analyses. In the second part of the study, the students' preferences for the classroom spaces were evaluated by means of Artificial Neural Networks (ANN) method, by using numeric data obtained from the student about concepts as well as the classroom space photos. Numeric data were treated and test procedures were performed to ensure that ANN makes decisions in the name of 2nd grade students. This is the first study in which numeric survey results and photographic characteristics have been used together. The ANN results were very similar to the students' evaluation of the ideal classroom space, particularly in terms of belonging and like (partiality) concepts.

Key Words: *Spatial perception, Statistical analysis, Classroom design, Artificial Neural Networks.*

1. INTRODUCTION

Although space is handled differently by different approaches, it can be defined in a broad framework as 'the space separating a human from the environment to a certain extent and allowing him/her to sustain his/her actions'; and as 'the space whose limits can be perceived by the user(s)'. Space underlies the architectural profession. It is the only inevitable quality of an architectural product and the basic condition generating an architectural product. With the space formed by the architect, a limited

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volume, in which a human being could feel himself/herself safe, was created as the first stage of architectural activity. Architectural space is space that is limited in such a way that an observer may perceive it [1]. Clear or unclear limits of the space must be perceivable. Although spatial perception is primarily based in visual perception, other ways of sensing also make varying contributions [2]. A user perceives the space he/she is in as a whole, with limits and stress elements affecting all of his/her senses to differing extents.

Spaces designed for specific purposes meet certain needs of people to conduct their lives without feeling any discomfort in terms of physiological, social and psychological aspects. Considering the direct relationship between the efficiency of work performed in a space and impressions of the space on the users, it is seen that user preferences must be taken into consideration while designing the space. While architectural studies dealt with the structural properties of the space until the 1980s, subsequent studies started to address the psychological impact of space on people. Accordingly, space/perception (environmental psychology-architectural psychology) studies have become very important [3-8].

Various empirical studies were conducted on spatial perception in different disciplines. These studies focused on personal factors (gender, age, familiarity etc.) and physical environmental factors (form, texture etc.) that influence spatial perception. In architectural science, it is quite important to understand the complex relationship (spatial perception) between a person and his/her physical environment, and to use this information to determine design criteria for new spaces.

Reviewing the literature, it is seen that spatial perception studies were generally conducted on adults and just a limited number of studies were conducted on child users. However, it is necessary to conduct studies on spaces frequently used by children (housing space, immediate surroundings of the house, urban playgrounds and school buildings where child gets acquainted with official life for the first time) in developing countries like Turkey, which has large young population, and to analyze the spaces according to the needs of this age-group.

The limited number of studies conducted with child user groups is generally related to housing and school buildings. These studies examined the socio-demographic characteristics of the child; and results were associated with socio-demographic features [9-13]. In addition, there are also studies examining the influence of color, illumination of the space and different seating patterns on the achievement and behavior of the child [14-17]. It was realized that physical properties and arrangements such as color, illumination and seating pattern influence the achievement of students and cause them to display different behaviors. However, there are a limited number of studies that examined the influence of spatial components on the perception and emotional reactions of the child [18-20]. These topics are examined under the titles environmental psychology – architectural psychology. Some studies conducted in educational sciences demonstrate that different space arrangements have impact on student achievement [21-23]. In this context, it is expected that designing and arranging the classroom environments in accordance with student demands will make a positive contribution to learning motivation.

This study, attempted to determine ideal classroom space by evaluating the perceptions and preferences of primary school student users. The assessment used an artificial neural networks (ANN) model that was based on students' perceptions of spatial arrangements and their judgments on photographic images; the study examined the extent to which ANN could make appropriate decisions on behalf of the students.

2.MATERIAL AND METHOD

2.1.Artificial Neural Network (ANN)

Although ANN was inspired by biological neural networks, it has a simpler structure. The main properties of these systems are that they have a distributed memory, which is completely parallel, adaptable and capable of learning. Constant changes in technology produce new techniques for solving problems. Statistical methods, for example regression analysis, have been used to solve many problems for a long time. However, statistical methods are unsuitable when the number of parameters directly impacting the problem is very large, and when there is a complex or mostly unidentifiable relationship between these parameters and the result. Research on methods to address such problems has shown that techniques such as genetic algorithms, neural networks and artificial intelligence produce more robust results. In particular, the extension of computer technology and the production of high-speed computers make it possible to use more complex methods. Neural networks, genetic algorithms and artificial intelligence have emerged as an alternative to classical statistical methods.

ANN uses properties similar to some organizational principles of the human brain [24]. ANN represents the new generation of information processing systems. It can examine examples of events, make generalizations about the related event, collect information and make decisions about new examples that it has never seen by using the information it has learnt. Generally, ANN is successful in operations such as model selection and classification, function prediction, finding the best value and data classification [25-26]. ANN has been used in solution of many complex problems, particularly in the field of engineering, but has found a limited number of applications in architectural science [27].

In this study, the main problem is that using ANN can be an alternative way to determine the best interior classroom image, or not? From this motivation, a three-layered feed-forward neural network was used and trained with the error back propagation method. The structure of feed-forward multilayer network is given in Figure 1. As it seen from Figure 1, general structure of the neural network consists of an input layer, one or more hidden layer(s) and an output layer. Layers are fully interconnected, as shown by lines. The input data are presented to the ANN at the input layer, which are processed in a forward direction through the hidden layer(s), and the output from the ANN is computed at the output layer. This is known as "feed-forward mechanism". In a feed-forwarded operation, the flow of information is from left to right. In scientific problems the number of input and output parameters is generally determined by design requirements. However, the choice of the number of hidden layer neurons (HN) is left to the user. There is no general rule for selecting the number of neurons in a hidden layer. The purpose of all learning algorithms is to determine the connection weightings that will best represent the relationship between input and output data.

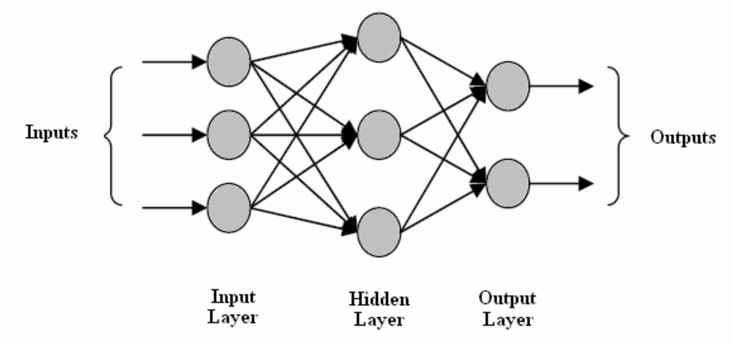

Figure 1. The architecture of multi-layer ANN.

2.1.1. The multi-layered perception neural network (NN) structure and training

A multi-layered feed-forward NN is used and trained with the error back propagation for the prediction of the best classroom space (Figure 1). The cost function utilized in back-propagation algorithm is

$$\varepsilon(n) = \frac{1}{2}\sum_{k=1}^{N_0} e_k^2(n) \qquad [1]$$

where $\varepsilon(n)$ represents the instantaneous cost function at iteration n, $e_k(n)$ is the error from the output node k at iteration n and N_0 represents the number of output nodes [28]. The error is defined for each output node as,

$$e_k(n) = d_k(n) - y_k(n) \qquad [2]$$

where $d_k(n)$ is the desired response of the output node k at iteration n and $y_k(n)$ is the output

of the output node k at iteration n [25, 28] gives a summary of the back-propagation algorithms as follows.

A. Initialization

Set all the weights and thresholds of the ANN to randomly selected small numbers. Assuming that no prior information is available, pick the synaptic weights and thresholds from a uniform distribution whose mean is zero and whose variance is chosen to make the standard deviation of the induced local fields of the neurons lie at the transition between the linear and saturated parts of the sigmoid activation function.

B. Presentations of Training Examples

Present the network with an epoch of training examples.

C. Forward Computation

Training example is indicated with (denoted by) [$x(n)$, $d(n)$] , $x[n]$: input vector, $d[n]$: desired response vector. The internal activity level $v_j^{(l)}(n)$ for neuron j in layer l is given by

$$v_j^{(l)}(n) = \sum_{i=0}^{p} w_{ji}^{(l)}(n) y_i^{(l-1)}(n) \qquad [3]$$

where $y_i^{(l-1)}(n)$ is the signal from neuron i in the previous layer $l-1$ at iteration n and $w_{ji}^{(l)}(n)$ is the weight of neuron j in layer l that is connected to neuron i in layer $l-1$ at iteration n.

Logarithmic sigmoid function is used for threshold function. The output of neuron j in layer l is given as

$$y_j^{(l)}(n) = \frac{1}{1+\exp(-v_j^{(l)}(n))} \qquad [4]$$

For the output of neuron j in layer l, the error can be found as

$$e_j(n) = d_j(n) - o_j(n) \qquad [5]$$

where $d_j(n)$ is the j^{th} element of the desired response vector $d(n)$.

D. Backward Computation

Compute the local gradients (δ) of the NN by progressing backward layer by layer. For neuron *j* in the output layer *L*, the local gradient is given by

$$\delta_j^{(L)}(n) = e_j^{(L)}(n) o_j(n)[1 - o_j(n)] \quad [6]$$

For neuron *j* in a hidden layer *l*, the local gradient is given by

$$\delta_j^{(l)}(n) = y_j^{(l)}(n)\left[1 - y_j^{(l)}(n)\right]\sum_k \delta_k^{(l+1)}(n) w_{kj}^{(l+1)}(n) \quad [7]$$

The weight of the NN in layer can be adjusted according to the generalized delta rule

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left[w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)\right] + \eta\delta_j^{(l)}(n) y_i^{(l-1)}(n) \quad [8]$$

where η is the learning rate parameter and α is the momentum constant [25,28].

The training phase of ANN is performed by using an error back-propagation algorithm. The simplest implementation of back-propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly the negative of the gradient. The back-propagation computation is derived using the chain rule of calculus. Various back propagation training algorithms proposed by researchers have been used in the application so far. In this study Levenberg-Marquart (LM) Back Propagation training algorithms that uses standard numerical optimization techniques has been used.

Data scaling is another important step for network training. It is recommended to normalize the input and output data before presenting them to the network [29]. A simple linear normalization function within the values of 0 to 1 is given by Equation 9,

$$s_x = \frac{(z - z_{\min})}{(z_{\max} - z_{\min})} \quad [9]$$

In the Equation 9, s_x is the normalized value of the variable z, z_{min} and z_{max} are the variable minimum and maximum values, respectively.

2.1.2.Calculation of numerical errors

Training and test errors should be conducted according to Eq. (10).

$$\text{Training and Test Error } (\%) = \left(\frac{\sum_{i=1}^{k} |t(i) - a(i)|}{m * n} \right) * 100 \quad [10]$$

where *t(i)* is desired outputs, *a(i)* is outputs of neural network, *k* is the number of samples in training or test data, *m* is the number of segments in training or test data and *n* is the number of outputs of neural network for training or test procedures [30]. A simple explanation based on ANN processing may be explained as follows.

2.1.3. How does ANN operate

1. The input data and the corresponding output data (the targets of ANN) are defined. In this study, the digitized interior classroom photographs were used as the input data, and the numerical evaluations of the students for each classroom by considering four different concepts were taken as the output (target) data.
2. The input and output data are normalized between 0 and 1 (this operation is given in Equation 9) in accordance with the defined range (Equation 4) of the function (defined as activation function) used for the determination of the outputs of the hidden and output layers.
3. ANN is a forecasting system that produces outputs in appropriate to the given inputs. For this purpose, the outputs that should be determined in accordance with the input data are taught to the network (training process of the network), and after this process the system is tested using the new data not used during the training process of ANN (testing process of the network). Therefore, there are defined connections between the input and output data (a network structure is formed). The intermediate layer (hidden layer) providing the connection is formed from the nodal points whose number is not known initially. The ANN layers formed by the input data, intermediate and output layers took the general structure shown in Figure 1 as a result of the connections provided between the layers using certain weight values. Although the aforementioned weights are initially assigned to the system randomly, they are assigned under certain principles in order to speed up the convergence.
4. Immediately after these processes, the training process begins and is performed using a certain part of the data set. Initially, randomly selected weights reach to the expected values by aid of the feed forward back propagation algorithm (Equations 6-8). The acceptable level of the training error is determined according to the error calculation principles given in Equation 10.
5. After training ANN in the frame of these rules, the test procedure was executed using the rest part of the data set. Since the weights were obtained as a result of the training period, higher accuracy ratios were determined in comparison to the training set (by using Equation 10). The steps of the general flowchart of ANN are given in the Figure 2.

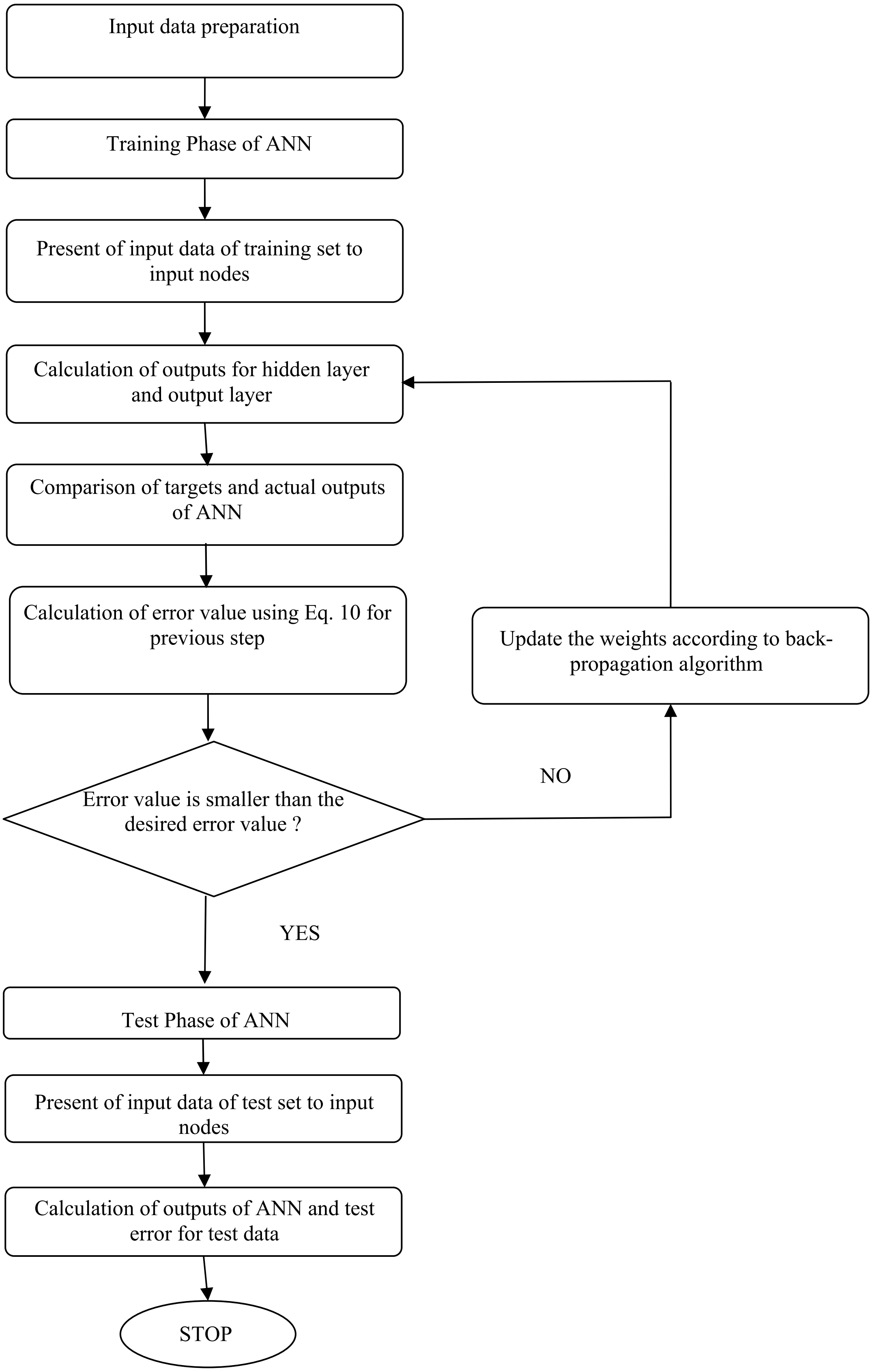

Figure 2. General Flowchart of ANN Process.

2.2. Case Study

2.2.1. Characteristics of experimental groups and selected classroom settings

Directed at primary school classroom settings, this study was conducted on primary school 2nd grade students (n=189) randomly selected from the regions representing low and high socio-economic groups of Turkey. A questionnaire was given to students to enable them to evaluate the classroom setting using pre-defined concepts as belonging, safety, like (partiality) and learning.

In the scope of the questionnaires, 20 classrooms (with different properties) from public and private primary schools were selected (Table 1). In choosing these 20 classrooms, special attention was paid to select samples (small and large classrooms with different forms and dimensions, equipped with a variety of furniture and with varying design) that would represent primary school classroom settings in Turkey.

To obtain generalizable results for primary classroom settings, the questionnaire was given to students (taught in similar physical environments) attending official primary schools located in different socio-economic regions and planned according to the typical primary school projects that represent the majority of Turkish schools. Students attending the schools of 20 study classrooms were excluded from the experimental group [31].

Table 1. Indoor Classroom Photos.

C-1	**C-2**	**C-3**	**C-4**
			
C-5	**C-6**	**C-7**	**C-8**
			
C-9	**C-10**	**C-11**	**C-12**
			
C-13	**C-14**	**C-15**	**C-16**
			
C-17	**C—18**	**C-19**	**C-20**
			

2.2.2.Questionnaire process

Presenting a pilot study previously carried out with the researcher, the first part of the questionnaire form was given to 2nd grade students before they entered classrooms for evaluating. The second part of the questionnaire included questions on classroom evaluations. Two photos of a classroom setting and four questions related to this classroom were presented in each page of the questionnaire (Table 2). Taking into consideration that the study's target group was composed of young people, scripts were used (in the light of pilot applications) to ensure clear explanation of the concepts in question.

In the questionnaire given to 2nd grade students, the participants were asked to answer the questions by scoring on a Likert-type scale between two opposite answers. Before entering data into analysis program SPSS 15.00 (Statistical Packages for the Social Sciences) scores collected from the scale were redefined in numbers with the help of a transformation scale. Participants were signed each question given on double ended scale. In evaluating process of questionnaire by researchers, double ended scale has been divided five equal parts ranging from 1 to 5 for digitizing the participants' data.

Table 2. Questionnaire: questions.

Concept	Questions
Belonging to space	"Would you immediately sit in this classroom with your friends and teacher and declare it "your own classroom" without making any change to it?"
Safety in space	"If you had to come to school one hour before the lesson and leave it one hour after the lesson for a week, would you enjoy spending these two hours alone in this classroom (perhaps listening to music or studying your lesson)?"
To like the space	"If you were explaining this classroom to a friend, would you define it "as a very beautiful and tasteful classroom"?
Appropriate learning environment	"If your school director asked how you felt about this classroom, would you say "I can easily learn and study in this classroom with my current friends and teacher"?

2.2.3. Reliability analysis

Statistical analyses of the data collected from questionnaries were performed using the SPPS. Before the statistical analysis procedure, data related to concepts in question were subjected to reliability analysis. Questionnaires administered to 2nd grade students were subjected to reliability tests by using Cronbach alpha coefficient known as Alpha method [31] (Table 3).

Table 3. Reliability values of data of the 2nd grade students.

	Concepts	Mean Value	Standard Deviation	Reliability
2nd Grade Students	**Belonging**	3.944	0.466	**0.785**
	Safety	3.468	0.878	0.398
	Like	3.932	0.470	**0.743**
	Learn	3.843	0.526	0.577

As shown in Table 3, the "belonging" (α=0.785) and "like" (α=0.743) scores of the 2nd grade students were above the reliability limit of 0.70. Further analysis of the 2nd grade students completed, on the concepts of "belonging" and "like", as these two elements passed the reliability test.

2.2.4.ANN application

In this study, student evaluation results were modeled by means of ANN by using numeric images of primary education classroom spaces. Figure 3 presents a general demonstration for statistical data obtained from students according to classroom space images in the first part of the study. As understood from the figure, during the statistical evaluation, the students were asked certain questions for the evaluation of the related interior classroom photographs between 1 and 5. Hence, an evaluation aimed at student perception was made for interior classroom spaces.

In this study, the ANN network structure was formed using the perceptional questionnaire evaluation results as the output layer (targets) and the interior classroom photographs as the input layer of ANN.

The ANN modeling part of the study used images of 20 classrooms that were evaluated by the students. Each image used was 2304 × 3456 pixel (row × column). The use of very large images in ANN increases the processing time required ANN, but also reduces the accuracy of the operation. For that reason, the images were pre-processed and the dimensions of the data were reduced. As seen in Figure 4, images were presented as "the introductory stage of the ANN model" by calculating standard deviation and average pixel values of images in the statistical feature calculation part, which is the first stage of the proposed model. The model was required to predict four different concepts (belonging, safety, like, learning) one by one as output. To this end, a separate ANN model was proposed for each concept. As explained in the "How does ANN operate?" section, the numerical values (input and output values) existing at the initial ANN structure are formed in the matrix form. The input values will not change as long as the used classroom photographs remain same. If the group of people (students) on which the questionnaire was applied is changed (say the same questionnaire is applied on primary school teachers), the output values will naturally change due to the changing answers given to the questionnaire. This condition will affect the prediction power of the ANN processes.

As explained previously, a back propagation algorithm was employed to train the ANN. Nineteen of the twenty images were used in training, and the remaining image was used for testing the trained ANN model. This operation was repeated 20 times and all the images were used in both training and testing. Using this method, known as cross-validation test, a generalization ability test was conducted in an attempt to show the feasibility of applying the ANN model to all the similar data [32].

Learning rate was selected as 1 for all the models in the iterations performed to find the optimum ANN architecture in which the ANN model produced the lowest training and test errors. A series of 5000 iterations were employed for all the models; the optimum number of hidden nodes and, accordingly, the ANN architecture was determined under these fixed values (Table 4). Training and test errors given in Table 4 were found by means of Equation 10. As seen in Table 4, the lowest test error was achieved for the "like" concept, with an accuracy of 97.94 % (100 %- test error %) in predicting student answers related to the "like" concept. An accuracy of 92.28 % was achieved for the "belonging" concept. After separate ANN architectures were found for each concept and rates of correct prediction were calculated, the average value of the four concepts was found and a new model was proposed. Accordingly, the results obtained by the ANN came close to the answers given by students with regard to the four concepts, with an average accuracy of 93.92 % (100 % - test error %).

Coefficient of determination R^2 given in Table 4 is a proportion of variability in a data set that is accounted for by the statistical model [33]. The R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1.0 (100%) indicates that the regression line perfectly fits the data. Values of R^2 for outside the range 0 to 1 can occur where it is used to measure the agreement between observed and modeled values.

Table 4. Optimum Hidden Nodes and Results of ANN.

Used Feature	Number of Hidden Nodes*	Training Error (%)	Test Error (%)	R^2 (%)
Belonging*	**10**	**9.97e-7**	**7.72**	**81.75**
Safety	100	7.83e-7	6.5	33.71
Like*	**8**	**2.85e-6**	**2.06**	**91.39**
Learn	6	0.7	21.01	7.38
Mean value of all features	**4**	**4.28**	**6.68**	**87.67**

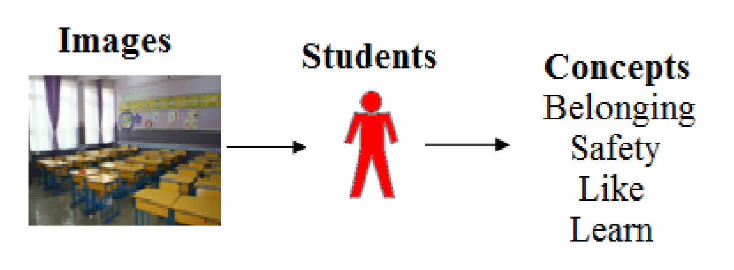

Figure 3. General flowchart of the evaluating process.

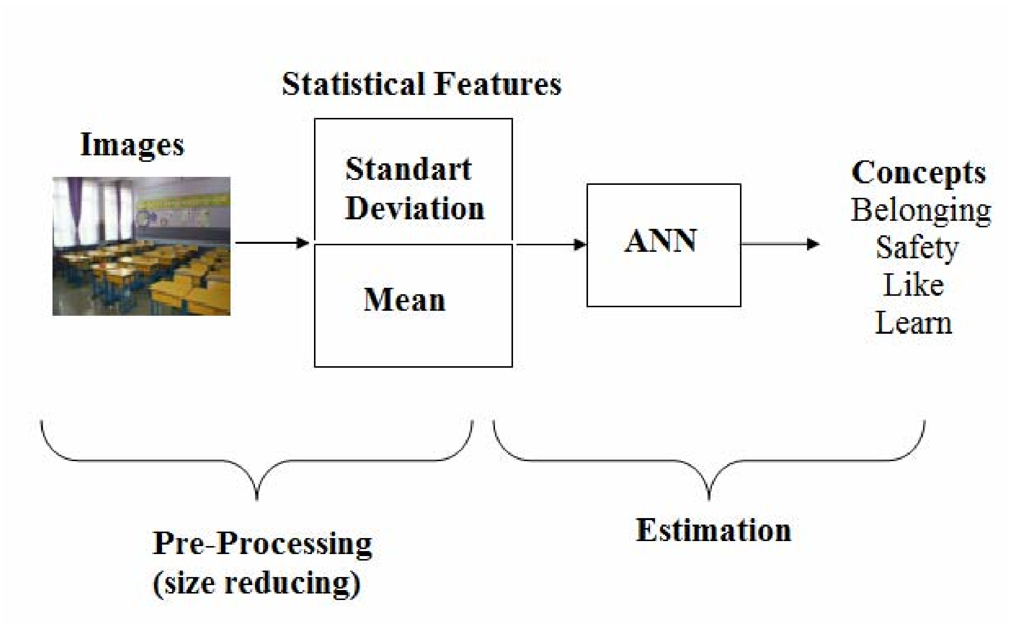

Figure 4. Proposed model with two stage (pre-processing and estimation) for the determining the best classroom.

5. RESULTS AND DISCUSSION

The study findings can be summarized as follows:

- The results of ANN application and of the photo-based survey administered to participant students were recorded to match to a large extent (Figure 5-6). As mentioned above, in the questionnaire given to 2^{nd} grade students, the participants were asked to answer the questions by scoring on a Likert-type scale ranging from 1 to 5. Numerical data given in the axes obtained from students and ANN for each concept. Numeric in lateral and horizontal axes represents average values of 20 different primary education classrooms evaluated by 189 students and ANN for each concept, respectively.
- According to the survey data, the safety and learning concepts did not produce sufficiently robust results in reliability analysis. Similarly, it was seen that ANN performed relatively weakly in making predictions for these two concepts.
- The study tried to access as much different primary education classrooms as possible, from small classroom spaces to large ones, from classrooms with various seating furniture and luxurious decoration to the simplest ones, irrespective of the age group, in order to obtain a classroom space that would set a proper example. Although this study was conducted with quite young users, the satisfactoriness of the results will be an important resource for age group discussion in this kind of study.
- The evaluation by Douglas and Gifford [6] of university classroom spaces by students and professors, used classroom spaces of various sizes, which could set proper examples. In the study of Cohen-Trostle [18], evaluation of primary education students' discrimination of environmental differences was made for physical features determined using photographs of inner spaces and facades representing different educational environments. In this type of study, different spaces from different environments were used, related to the topic being investigated. The present study aimed to determine classroom space characteristics for primary education students, and so various primary education classrooms were selected. Accordingly, in this kind of spatial perception studies, which are conducted mainly on visuals to obtain numeric data, conducted with images via which numeric data are obtained, it is highly possible to make correct comments on the basis of the concepts tested via ANN method.

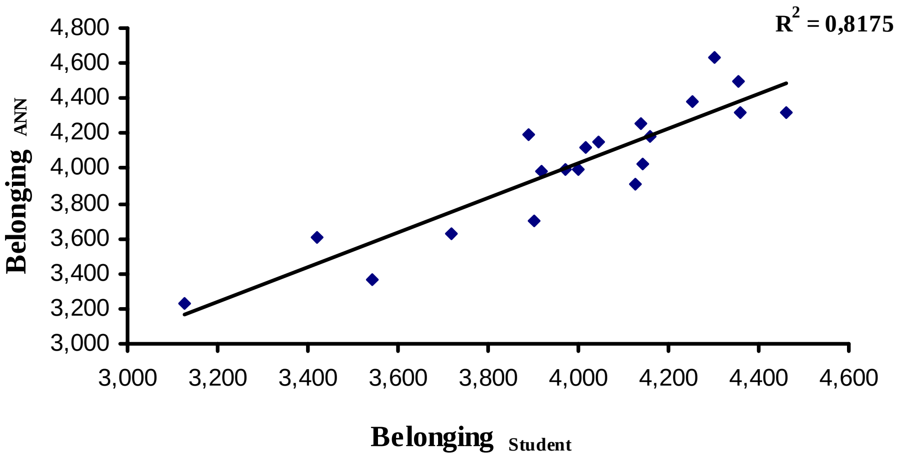

Figure 5. Relationship between belonging-student and belonging-ANN assessment**.**

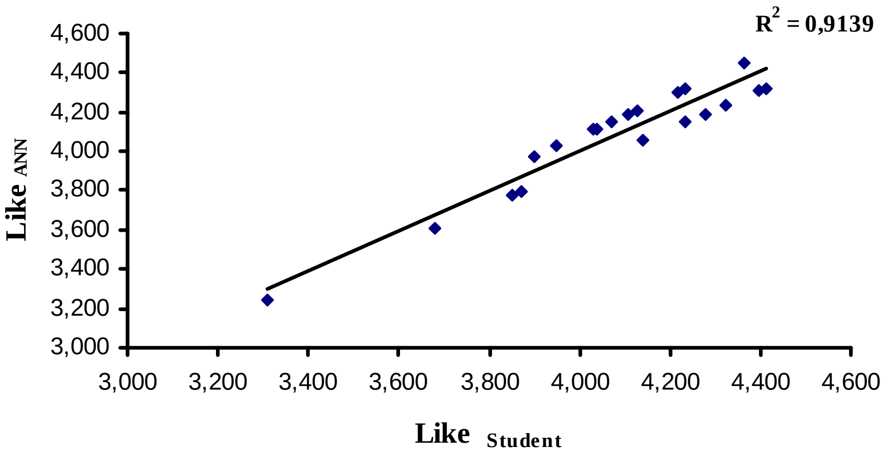

Figure 6. Relationship between like-student and like-ANN assessment**.**

6. CONCLUSION

This is an experimental study conducted with 2nd-grade students at primary schools in Turkey in order to describe ideal classroom space. The student responses and images used in the study were modeled via an ANN. The prediction power of ANN was investigated in determining ideal classroom space. It was seen that the results of the ANN method were very similar to the evaluation responses of the 2nd-grade students (classroom users). The students' perceptions of the classroom space were based on four different concepts (belonging, safety, like, learning). Statistical analyses showed that the success rates of the ANN varied for the same concepts. It was seen that ANN is successful in addressing complex problems such as user – perception evaluation, due to its' dynamic structure. It is important that ANN, which is frequently used in the field of image processing, is applied in a discipline like architecture, which is based on visual elements. Considering that each item of visualized information is digitized and each digitized item can be processed by means of computable intelligence techniques, this study reveals that architectural science can be evaluated by means of artificial intelligence techniques.

Nevertheless, it is obvious that the results obtained can vary according to the subject group and the classes selected. The success of ANN may vary if similar studies are conducted on different age groups, different subjects and spaces. The results of this study should be taken into consideration in order not to limit the number of buildings / spaces to be evaluated in these studies to the lower threshold, to keep the number of architectural components/ spatial features high, and to develop clearer statistical assessment of the effectiveness of architectural components/ spatial features for the examined concepts. Determining user demands in spaces used by young users and designing an ideal classroom space according to these demands is a challenging process. Evaluations of this age group of users by means of ANN method allows accurate comparison between the evaluations of groups regarding the same space and provides architects with information that can be used as inputs for the design process.

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