Prediction of student satisfaction on mobile-learning by using fast learning network

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Article Info

ABSTRACT

The rapid advancement of mobile technologies over the past decade has had a significant impact on the appearance of M-learning applications. The research proposes the fast learning network model to investigate and identify the factors that affect student satisfaction in M-learning for the University of Tikrit students. The research model is conducted utilizing a questionnaire of 300 participating students based on variables. This research showed that the proposed model's perfor mance was superior to artificial neural network, k-nearest neighbors, and multilayer perceptron algorithms. The accuracy and specificity of predicting the student satisfaction coefficients in M-learning were 91.6% and 92.85%, respectively. The proposed findings demonstrate that diversity in the evaluation, teacher attitude and response, and quality of technology are key operators of student satisfaction.

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1. INTRODUCTION

The rapid development of information technology and communication (ICT) is the "information age" that has addressed most challenges and transformations in work and social life, such as remittances, telemedicine environments, and education, a major issue in the twenty-first century. Hence, ICT is an integral aspect of today's world [1], [2]. Education is one of the most important components of a good life, both for individuals and society. Thus, there is no social, political, or economic progress without education [3].

E-learning has been applied in many advanced countries in the field of technology. In contrast, some have recently used it as a result of the critical circumstance due to the spread of the COVID-19 disease, as educational institutions face many challenges to maintain education and its quality [4], [5]. Electronic learning is a wider method of education that expands learning and teaching opportunities outside the traditional classroom setting in various fields [6]. E-learning is "the learning propped by digital electronic means and media," gaining broad acceptance [7]. Mobile learning (M-learning) refers to the process of mediated learning via mobile technologies such as laptops, smartphones (i.e., cellphone), and tablets [8], [9]. Also, M-learning is derived from e-learning (a learning method that profits from the support and improvement provided by a computer, as well as a variety of communication technologies) [10], which in turn is derived from distance learning, i.e., D-learning [11], [12]. These portable devices' increased flexibility and capabilities have created significant interest in education. For example, in promoting cooperation and social interaction, collecting and sharing data, and communication among peers [8], [13]. With the support of

mobile technologies to e-learning within the concept of distance learning (d-learning), the idea of M-learning has made great progress in the education sector [14].

Many aspects can influence the M-learning experience, including the quality of support for systems and networks, quality of material content such as texts (i.e., e-books and slides), audios, videos, pictures, combined forms, learning time, learning location, evaluations, and capabilities of the mobile device [15]. Therefore, institutions and instructors must consider these aspects to provide optimal and successful learning for their students. Thus it is important to study the aspects that affect student satisfaction in M-learning. Satisfaction (SA) is defined as "the affective attitude towards a particular computer application by an end-user who interacts with the application directly" [16]-[18], which is one of the ingredients for the successful implementation and effective achievement of M-learning. Generally, satisfaction is a factor employed to evaluate the quality of a product or service (learning), as well as to predict customer comfort (student) or other behavioral outcomes [19], [20].

Machine learning approaches have been employed to increase the effectiveness of education platforms [21], [22], where approaches are increasingly being used for predictive purposes under the umbrella of artificial intelligence (AI) [23], [24]. Machine learning has the advantage of constructing models using both categorical and numerical predictions by evaluating linear and nonlinear relationships between variables [25]. Recently, most researchers have used machine learning techniques, as it is highly efficient in prediction models in distance learning [26]. In Jebaseeli and Kirubakaran [27], the authors proposed a neural network-based algorithm is designed to improve the feed-forward network algorithm (IOPNW FFNN) by adding weights from the input layer to the output layer for the M-learning classification. In this work, opinion words are categorized based on their frequency of appearance in all the texts under study. In Aloqaily *et al.* [28] presented a work that used multi-analytics: neural network (NN) and multiple linear regression models for experimental exploration and predicts factors that influence students' behavioral intention for accepting M-learning. Guo *et al.* [29] used an unsupervised sparse auto-encoder approach to create a classification model from learners' unlabeled data. The classification model was trained on a big dataset to wisely pretraining hidden layers of features. The authors have been utilizing machine learning algorithms to examine their model TAM with ECM to address limitations such as the actual use of learning systems from social impact and confirmation of expectations and satisfaction [16]. The proposed M-learning model analyzed the effect of independent feature weights on dependent features. It used the deep learning (DL) technique to accurately divide the target individuals (i.e., learners) into five different groups. In contrast, the random forest (RF) method was used to determine the importance of each feature in making the adaptive mobile learning model [15]. In Akour *et al.* [30] used the CNN deep learning algorithm to predict students' achievements, which could increase education progress. This study relied on many variables, including (1) demographic such as nationality and gender, (2) academic such as educational stage, department, and grade level (3) behavioral such as student satisfaction.

One of the key challenges for the success of the M-learning system is student satisfaction with the aspects affecting the system. Many researchers researched the "satisfaction" factor from previous studies, which is the basis of the learning process. They addressed the considerable impact of mobile technologies on the student in M-learning systems, i.e., the importance of effective implementation and achieving the goals. This research focuses on a special area in predictive ML-based models. This research aims to create a model that can predict student satisfaction from a student's perspective using a fast learning network (FLN). This modern machine learning algorithm is easy, computationally efficient, and has excellent learning performance features [31]. The independent variables of FLN are teacher attitude and response in a virtual classroom, the flexibility of M-learning, virtual engagement, Wi-Fi network quality, diversity in evaluation, and quality of technology (i.e., workshops and explanations). Still, the dependent variable is a satisfaction factor. The remainder of the paper is arranged as follows: Section 2 represents the overview of FLN. The research methodology for predicting student satisfaction using the FLN is discussed in section 3. Section 4 then describes the results and discussion. Next, section 5 depicts the conclusion as well as future work.

2. OVERVIEW OF FAST LEARNING NETWORK (FLN)

The fast learning network (FLN) is a connection in a similar way to a single layer feed-forward neural network (SLFN), which consists of three layers: input, hidden, and output layer [32], [33]. The FLN, as depicted in Figure 1, is described in detail as follows. Assume there are N arbitrarily separate samples (x_j, y_j), where $x_j = \{x_{j1}, x_{j2}, \ldots\ldots, x_{jm}\}^T \in R^m$ is the m-dimensional feature vector of the jth sample, and $y_j = \{y_{j1}, y_{j2}, \ldots\ldots, y_{jk}\}^T \in R^k$ is the k-dimensional output vector. The FLN contains p layer nodes that are hidden. The weight values of the link between the output layer and the input layer are stored in W^{oj}, which is a kxm weight matrix. The pxm input weight matrix is called W^{jm}. The biases of hidden layer

nodes are represented by $b = [b_1, b_2, \ldots \ldots, b_p]$ and W^{oh} are jxp matrix containing the link's weight values between the output layer and the hidden layer. The biases of output layer nodes are: $c = \{c_1, c_2, \ldots \ldots, c_k\}^T$. The following is the procedure for calculating weights or training:
a) Randomly calculate the weight in the input-hidden layer.
b) Using the hidden layer's activation functions and the input data, calculate the hidden output matrix.
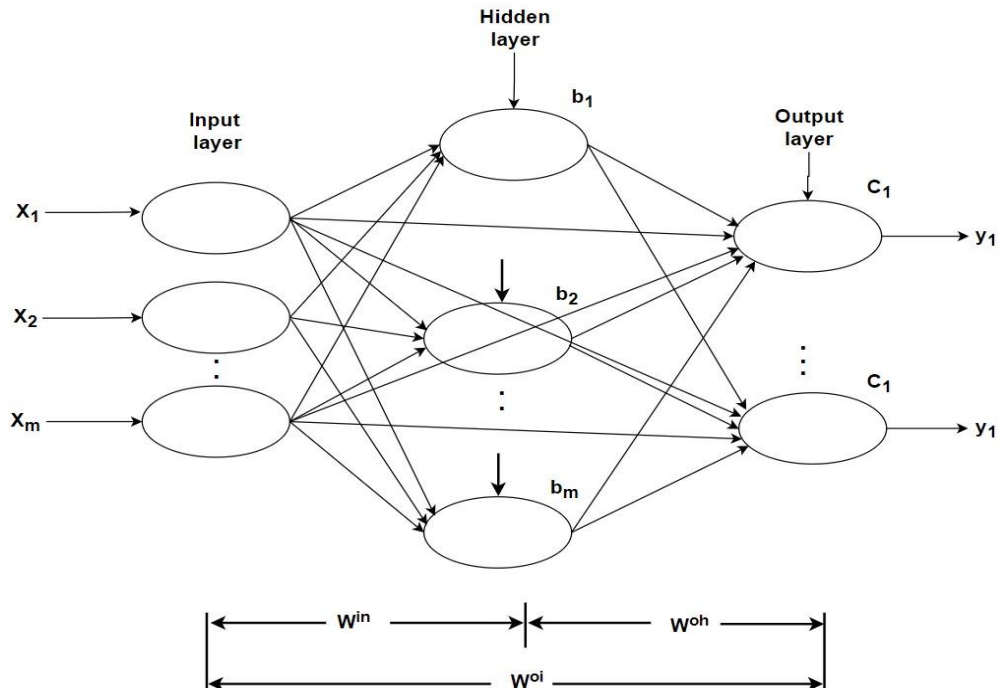c) Using the Moore Penrose model, calculate the parallel weights.

Figure 1. Structure of fast learning network [23]

3. METHOD
This section introduces the methodology for predicting students' satisfaction using the FLN. Sub-section 3.1 is allocated the description of the data. Sub-section 3.2 presents the recommended technique and evaluation in sub-section 3.3.

3.1. Dataset characteristic
This research data was collected during the academic year 2020-2021 at Tikrit University/College of Computer Science and Mathematics-Department of Computer Science. The research was based on collecting data using a questionnaire distributed to 300 students at random. The six independent variables used to construct the FLN were identified in this research. Use a five-weight Likert scale, ranging from 1 where strongly disagree to 5 where strongly agree.
a) Teacher attitude and response in the virtual classroom
b) The flexibility of M-learning
c) Virtual engagement
d) Wi-Fi network quality
e) Diversity in evaluation
f) Quality of technology (i.e., workshops as well as explanations)
Student satisfaction is considered a binary dependent variable with values 0 and 1. If the value of the dependent variable equals "1", that indicates satisfaction; otherwise, the dependent variable indicates dissatisfaction.

3.2. FLN design
The algorithm FLN has been selected for the prediction of the satisfaction of students for many reasons: First, fast learning network (FLN) has the benefits of compact network scale, secondly, strong fitting

ability; thirdly, short training and learning time [34]. Figure 2 depicts a network structure used to predict student happiness (unsatisfied = 0; satisfied = 1) using six input variables. The diagram depicts the six input nodes, four hidden nodes, and two output nodes representing satisfaction and dissatisfaction.
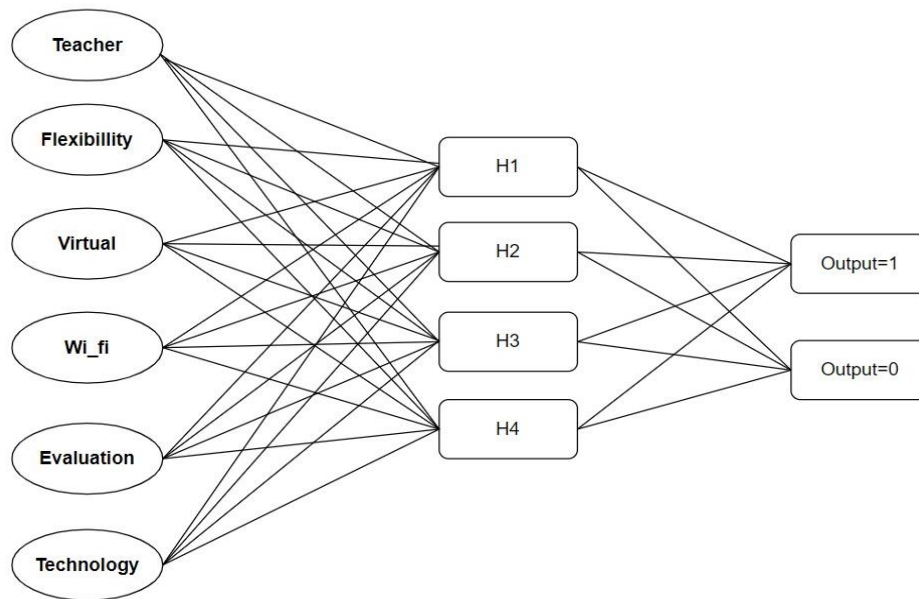

Figure 2. FLN model

The SPSS application was utilized to analyze the data. Training (60%), testing (20%), and validation (20%) subsets were randomly assigned to the data. The training dataset is used to discover the weights and build the model. During training mode, test data is utilized to identify faults and prevent overtraining. The model is validated using the validation data. The sigmoid function was selected to solve the nonlinear problem. This function is usually used in a hidden class because of the simple relationship between the function and its derivatives. The sigmoid function receives the real values as parameters from the input neuron and converts them into real values between [0, 1] as outputs (i.e., the sum of the resulting activations equals 1). It is computationally easy to perform [35], [36].

3.3. Evaluation

Common metrics used for evaluation are sensitivity, specificity, and accuracy, calculated based on the confusion matrix. A Confusion matrix is represented by the columns that indicate the actual class, and the rows refer to the predicted class [5]. Table 1 explains the confusion matrix.

Table 1. Confusion matrix

Confusion matrix		Actual	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN

Where:
- TP is a True Positive which means that many positive samples were appropriately labeled.
- FP denotes False Positive, which refers to negative samples mislabeled as positive.
- TN stands for True Negative, which refers to the number of negative samples that have been appropriately labeled.
- FN refers to False Negative when a positive sample is mislabeled as a negative.

In (1)-(3) represent sensitivity, specificity, and accuracy. The sensitivity measure represents the percentage of satisfied students, while the specificity measure (true negative rate) indicates the percentage of unsatisfied students. Accuracy is the proportion of the total number of correct predictions [37].

$$Sensitivity\ (\%) = \left(\frac{TP}{TP+FN}\right) * 100\% \tag{1}$$

$$Spectivity\ (\%) = \left(\frac{TN}{TN+FP}\right) * 100\% \tag{2}$$

$$Accuracy(\%) = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) * 100\% \tag{3}$$

4. RESULTS AND DISCUSSION

The MATLAB platform was utilized to conduct the experiments. These are involved in predicting student satisfaction in M-learning and can aid universities in increasing satisfaction by analyzing data. The datasets that were utilized to build the FLN model are listed in Table 2. The learning technique was repeated until the test resulted in 20 consecutive steps with no decrease in the error function. The result of the model summary is in Table 3. According to the table, the percentage of correct predictions based on training, testing and validation samples is 95%, 96.7% and 91.6% respectively. While the percentage rate of incorrect prediction in validation data set is 8.4%.

Table 2. Summarize of datasets

Data	Number
Training data	180
Testing data	60
Validation data	60
Total	300

Table 3. Details of the model

Type of prediction	Training	Testing	Validation
Correct	95%	96.7%	91.6%
Incorrect	5.0%	3.3%	8.4%

The predicted student satisfaction M-learning is defined as satisfied when the predicted likelihood is more than 0.5 in each case. The FLN network correctly recognized 171 students out of 180 in the training sample and 58 students out of 60 in the testing sample as shown in Table 4. Overall, 95.5% of the training instances were classified correctly. The sensitivity was 88.88%, the specificity was 92.85%, and the model's accuracy was 91.6% in the validated sample, indicating that the model is extremely accurate. Five students (8.4%) were incorrectly identified as false positives by the FLN network model. For a student who is likely to be dissatisfied, the probability of being satisfied should be as low as possible.

Table 4. The output of prediction using a confusion matrix

Data	Output	Type of predict		Percentage
		Unsatisfied	Satisfied	
Training	Unsatisfied	44	4	91.7%
	Satisfied	5	127	95.5%
	Percentage	27.22%	72.77%	95%
Testing	Unsatisfied	18	1	94.7%
	Satisfied	1	40	97.6%
	Percentage	31.66%	68.33%	96,7%
Validation	Unsatisfied	16	2	88.88%
	Satisfied	3	39	92.85%
	Percentage	33.66%	68.33%	91.6%

Table 5 indicates the relative importance of the research variables and the effect of each independent variable on the FLN model. The normalized importance of diversity in the evaluation ratio is the largest, while the normalized importance of the Wi-Fi network quality is the lowest. Thus, the findings reveal that diversity in assessment, teacher attitude and response, and the quality of technology have a significant impact on student satisfaction.

Table 5. Normalized importance of independent variables

Input (independent) Variables	The importance	The normalized importance
Teacher attitude and response	0.174	91.58%
The flexibility of M-learning	0.131	68.95%
Virtual engagement.	0.125	65.79%
Wi-Fi network quality	0.122	64.21%
Diversity in evaluation	0.190	100%
Quality of technology	0.166	87.37%

The performance evaluation of FLN, artificial neural network (ANN) [28], k-nearest neighbors (KNN), and multilayer perceptron (MLP) [25] algorithms on a dataset based on sensitivity, accuracy, and specificity, as shown in Figure 3. The results showed that the FLN model succeeded in predicting student satisfaction. The comparison shows that our FLN algorithm scored the highest accuracy value among other related works that accomplished 91.6%. The KNN algorithm has the lowest performance for predicting student satisfaction toward 78%, while the sensitivity of MLP is superior to the ANN, FLN, and KNN algorithms. In addition, the FLN specificity is highest than MLP, but the specificity of MLP is outperforming ANN and KNN.
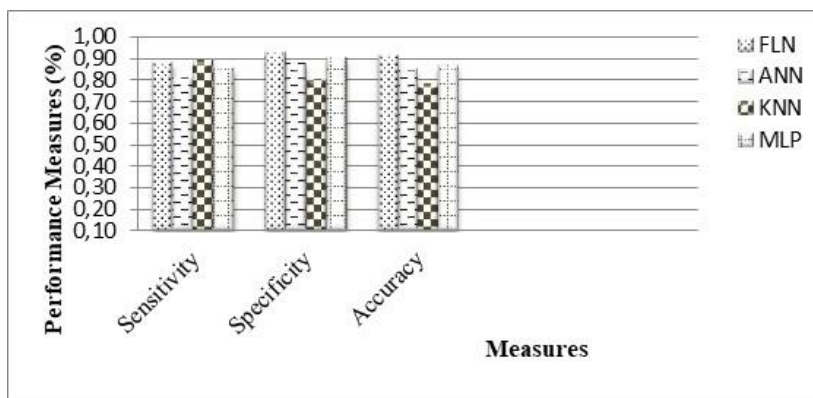

Figure 3. Comparison predictive results for FLN, ANN, KNN, and MLP

5. CONCLUSION AND FUTURE WORK

This research has proposed the FLN algorithm to construct a model to predict that illustrates the correlation between students' satisfaction with M-learning and factors affecting the success of education, where student satisfaction is an important factor for evaluating the educational service. Predicting students' satisfaction depends on several independent variables such as teacher attitude, the quality of the Wi-Fi network, and the variety of assessments. The research data were collected using a questionnaire from 300 participating students from Tikrit University and six attributes. Based on data obtained from students' M-learning, the empirical results showed that diversity in assessment, teacher attitude and response, and quality of technology used are three important factors in determining learner satisfaction. The performance of FLN has better than ANN, KNN, and MLP in terms of accuracy and other criteria. The accuracy value for classifying the students into the expected satisfied and unsatisfied categories was 91.6%. The future work will expand the dataset to strengthen the prediction's generalizability. Also, a deep learning algorithm could be applied to predict teacher satisfaction about M-learning achievements and their impact on student performance.

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