E-learning System Development In Existence Of Machine Learning Tools With Prediction Tasks

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Abstract

This paper provides a new machine learning-based technique for evaluating eLearning system usability. To construct prediction models, three machine learning methods (support vector machines, neural networks, and decision trees) are integrated with multiple linear regression to reveal the underlying link between an eLearning system's overall usability and its predictor qualities. A sensitivity analysis is then used to assess the predictors' significance. Using both sensitivity settings and usability scores, a statistic called the severity index is constructed. A Pareto-like technique is used to arrange the severity index values, and the most important usability aspects are chosen. The case study's findings show that implementing the proposed technique enhances eLearning system diagnostics by identifying the most significant usability features. The proposed method might provide crucial information to usability experts on which measures could be improved to improve system usability for a certain group of eLearning system end-users.

Keywords: Moodle, SVM, NN, Linearity, Scores, Survey.

1 INTRODUCTION

Electronic learning (eLearning) is a type of distance education that teaches and learns through the use of electronic communication. eLearning may be as successful as traditional in-class face-to-face teaching and learning if the approaches are acceptable for the educational goals and the student–teacher interaction is well-organized. Both eLearning system users and producers demand high-quality teaching and learning products and services [1]. Consumers of eLearning systems, like users of other web-based systems, want more useful and high-quality solutions. The categories of ergonomics and ease of use, followed by usability, have been investigated as a technique of measuring the quality of computer systems [2]. The term "usability" refers to how simple something is to use [3]. It may also be defined as an app's ability to assist users in completing tasks in a timely, efficient, and pleasant way [4]. Usability is described as "the efficacy, efficiency, and happiness with which individual users may attain goals in specific settings." [5,6], "the ability to be easily and successfully used by people" [6,7], "how easy it is to find, grasp, and utilise information shown on a web-based system" [8,] and "the ultimate quality factor" for software architecture [9. The International Standardization Organization defines usability as "the degree to which a product can be used by specified users in a given context of usage to fulfil stated goals with efficiency, effectiveness, and satisfaction" [30]. (ISO). Usability testing has become one of the most important strategic components to consider in software development in the field of human–computer interaction [10], and usability and quality are seen to be connected in some way [11].

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2 METHODOLOGY

The fundamental flaw with the aforementioned technologies is that they only use checklist-style usability testing, which relies heavily on the judgments of usability specialists or test participants. They don't provide you an analytical framework or data to help you figure out how escalating usability problems will affect future development and repair. To analyse their evaluation findings for each checklist item, they simply average the ratings supplied by a representative sample pool of intended end-users or domain experts. They frequently fail to consider if addressing a single usability issue will have a major impact on end-user views of usability. To put it another way, they highlight the eLearning system's usability issues by saying that the lower the average survey-based assessment score, the more significant the checklist item is and should be addressed first. In this checklist item, they overlook the impact of a single unit change on the entire usability assessment. If one of the usability checklist criteria has a low score, the eLearning system's overall usability may or may not be harmed (from end-users or usability experts). 64 A. is devoted to the most pressing usability issues that necessitate the most time and effort. Both of these factors should be taken into account throughout the usability testing process, since they will have a big impact in the end. As a result, in this study, we devised a hybrid measure, the severity index, that considers both data and can be derived using Eq (1)

$$SI = scores \times AES^{-1} \tag{1}$$

Where SI is sensitivity index and AES is average evaluation scores.

When evaluating usability, the sensitivity score is used to establish how significant a checklist item is. On the other side, the average of checklist evaluation scores looks straightforward, but the argument for using the reciprocal is as follows. The lower the average evaluation rating of a checklist item, the more important it is. On the other side, the sensitivity score is a statistic for measuring the relevance of a checklist item. To make them comparable, we recommend taking the inverse of the former and combining them into one statistic, the sensitivity index. Figure 1 depicts the entire procedure. Collecting sample data from typical end-users is the first stage in the proposed approach for performing usability testing. The data is acquired using the UseLearn checklist, which was designed by merging checklists with literature questions. Throughout the paper, we refer to the first, second, and third questions related to the UseLearn checklist's error prevention factor as EP1, EP2, and EP3, respectively, as input variables for predicting the overall usability of the eLearning system, and we prefer to refer to the first, second, and third questions related to the UseLearn checklist's error prevention factor as EP1, EP2, and EP3, respectively.

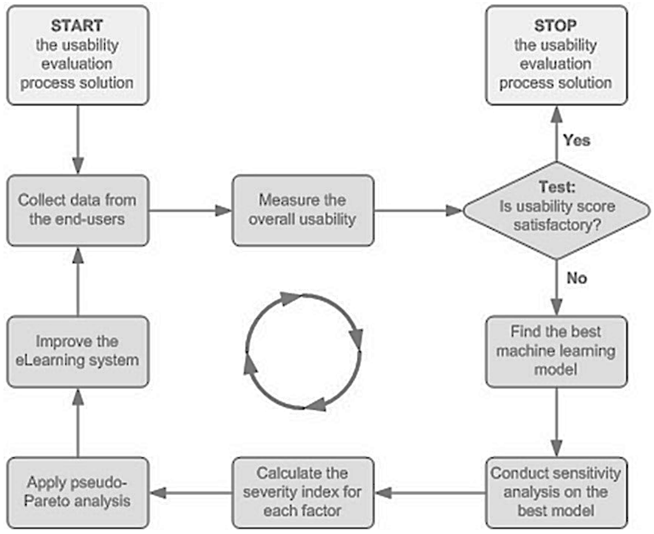

Figure 1: Proposed usability of eLearning evaluation methodology.

The output variable (the overall usability of the eLearning system) must have a score of 4 or higher on the checklist item in order for the usability of an eLearning system to be classified as "acceptable." If this is true, the system has been determined to be usable by end users, and no more testing is required. Aside from that, the technique for evaluating is as follows: Because the complicated relationship between the output variable and the input variables is unknown a priori, the next stage is to find the best prediction model that explains this potentially puzzling relationship while taking a range of performance factors into consideration (i.e. error rates and correlation). Using this prediction model, the input variables are subjected to a sensitivity analysis (checklist items). After that, the severity index is applied to the checklist components, allowing them to be ranked in order of severity. This grade might help you prioritise which traits to concentrate on first if you only have a limited amount of time and money. To identify the most effective checklist items and the eLearning system's related usability issues, a pseudo-Pareto chart might be employed. The Pareto principle states that just 20% of the causes are accountable for 80% of the problems. As a result, rather of treating all of the underlying causes at once, it recommends focusing on 20% of them, which might help alleviate 80% of the problems. This method may be used to identify and fix the most essential usability concerns, resulting in an overall improvement in usability. As shown in Figure 1, the usability evaluation technique is a loop that will come to an end once the target degree of usability is attained.

3 PREDICTION PARADIGM

In prediction models, the output variable and the input variables are expected to be linked. Multiple linear regression, decision trees, neural networks, and support vector machines were used to find these relationships. NNs are very complex analytical procedures that rely on a "learning" process to predict future observations (on specified variables) based on previous observations (on the same or other variables). Support Vector Machines (SVMs) are supervised learning systems that use a collection of labelled training data to construct input–output mapping functions. They're a type of generalised linear model that uses the value of a linear combination of features to generate a classification or regression decision. These processes are referred to as "kernel methods" in the industry. A classification function (used to categorise data) or a regression function can be utilised as the mapping function in SVMs (used to estimate the numerical value of the desired output).

3.1 Data Preparation

The UseLearn checklist questions were translated into Turkish to make them more understandable for the test participants. As a consequence, a preliminary exam was done with five students to determine whether there were any translation errors and if any of the questions were baffling due to the poor translation. Based on their comments and thoughts during the pretest, certain questions were amended and reworded to increase clarity. Following these modifications, the real test was utilised to collect data for the cell biology course's usability evaluation of the eLearning system. 52 percent of 11th grade high school students and 48 percent of first-year university biology majors completed the test. Males accounted for 64% of the total participants, while females accounted for 36%. A total of 105 students participated in this study.

4 RESULTS & DISCUSSIONS

In the case of Table 1, the standard usability testing procedure would be to address the usability issues using CM3, CM4, and CM1 in that sequence. If we apply our recommended technique, which considers not only the average value for the checklist items but also the value of completing each improvement on overall usability via the severity index, the order in which these usability concerns are handled will be different. In this work, the performance of the prediction models was assessed using a 10-fold cross-validation technique. 10 folds appears to be the optimal quantity, according to empirical studies (that optimises the time it takes to complete the test while minimising the bias and variance associated with the validation process). The entire dataset is partitioned into ten mutually exclusive subgroups in 10-fold cross-validation (or folds). Each fold is tested once to assess how well the prediction model built from the previous nine folds performs, resulting in ten different performance estimations. The average results of 10-fold cross-validation are shown in Table 2, with NN, SVM, MLR, and DT representing neural networks, support vector machines, multiple linear regression, and decision trees, respectively. All of the prediction models have correlations that are much greater than the rule-of-thumb cut-off value of 0.3. The multi-layer perceptron (MLP) neural network is the most successful prediction model in this case study for comprehending the links between the output variable (overall usability) and the input components. For prediction and classification tasks, the MLP is well-known as a strong and trustworthy function approximator. It is without a doubt the most well-known and studied NN architecture. In our tests, we observed that MLP outperforms other machine learning methods.

Table 1: Results outline.

Algorithm	Mean Square Error (MSE)
Dynamic neural network	0.081
SVM	0.233
MLR	0.2
DT	0.103

5 CONCLUSION

An online cell biology course utilising the eLearning system Moodle® was used to develop and test a machine learning-based technique for usability evaluation of eLearning systems. The proposed technique, according to the results of the studies, makes it simpler to identify usability issues and provide relevant change alternatives. The proposed approach has the advantage of prioritising the most significant checklist items based on their contribution to overall usability using a newly devised metric (the severity index), allowing for the most efficient use of time and effort to enhance usability. Because the outcomes of the case study revealed that this algorithm effectively identifies critical usability issues in order to improve eLearning usability, it may be regarded the most important quantitative instrument among usability evaluation methodologies. This is accomplished by prioritising some, but not all, of the usability considerations.

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