

HACIA UN MÉTODO DE PREDICCIÓN DE RESULTADOS DE EVALUACIÓN  
EN UN CONTEXTO DE MICRO APRENDIZAJE

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# Towards a Method to Predict the Evaluation Result in a Microlearning Context

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**Abstract.** This paper presents a method for predicting the evaluation results of learners interacting with a context-aware microlearning system. We use ASUM-DM to guide different data analytics tasks, including applying a genetic algorithm that selects the prediction's highest weight features. Then, we apply machine learning models like Random Forest, Gradient Boosting Tree, Decision Tree, SVM, and Neural Networks to train data and evaluate the context's effects, either success or failure of the learner's evaluation. We are interested in finding the model of significant context-influence to the learner's evaluation results. The Random Forest model provided an accuracy of 94%, which was calculated with the cross-validation technique. Thus, it is possible to conclude that the model can accurately predict the evaluation result and relate it with the learner context. The model result is a useful insight for sending notifications to the learners to improve the learning process. We want to provide recommendations about learner behavior and context and adapt the microlearning content in the future.

## 1. Introduction

In recent years, ubiquitous learning and mobile learning are emerging as models that drive virtual education globally. It is due to the technological evolution of mobile devices and their massive use by academically active populations. Besides, mobile computing provides context variables that help understand exogenous elements that directly influence individuals' learning. Liu et al. [1] mention that the mobile learning context gives students autonomy and the great responsibility to build their learning. Furthermore, through ubiquitous learning, the definition of context is consolidated as it takes advantage of technological means to provide information. According to Engelenburg et al. [2], context-awareness identifies any information relevant to characterize any entity, whether it is a person, place, or object that can be integrated into a given environment. Nguyen and Pam [3] apply Bayesian Networks to the context by enriching

the learners' experiences. Lin et al. [4] present microlearning as an alternative to improve the learning process. Kórosi et al. [5] extract data from an e-learning platform and apply a data mining approach for analyzing students' clickstream data logged. Besides, they propose a machine learning procedure to predict the course completion of students. However, a robust literature review activity did in our research project showed that the learner evaluation in microlearning systems is still a field to explore by applying machine learning or artificial intelligence models. Thus, in this paper, we present a method for predicting the evaluation results of learners' interactions with a context-aware microlearning system. The microlearning system provided us with all data captured from the learners' behavior and context data needed to apply machine learning and artificial intelligence models to predict whether students will get good or bad evaluation results. The method allows us to be aware of the students' context and provide them feedback to improve their learning process. Some of the models used for prediction were Random Forest, Gradient Boosting Tree, Decision Tree, and Support Vector Machine (SVM). In the future, we hope to offer students recommendations through different channels and adapt the contents according to the context to improve the evaluation results.

The paper is organized as follows: Section 2 presents a brief literature review associated with microlearning and context-awareness. Section 3 presents the methodology used in this research. Section 4 presents the performed experimentation and the obtained results. Finally, section 6 presents conclusions and some future works.

## 2. Literature Review

Advancing in ubiquitous and mobile technologies has allowed capturing context information such as location, light intensity, ambient noise, battery level, network speed, and user information such as age, gender, and preferences. Besides, the growing use of mobile devices and networks speed has allowed access to multiple contents from anywhere, at any time. This information has allowed the development of new functionalities, as mentioned by Abowd et al. [6]. In the education field, the context-aware multiple developments seek to enrich virtual education. As the work of Harchay et al. [7], who focused on customizing the evaluation process in a learning environment characterized by context variables, where the type of evaluation assigned to a student depended mainly on the context in which the student was. Chen et al. [8] also present an evaluative method whereby the knowledge-based ontology defines their questions. Thus, they offer content to the users based on their knowledge deficiencies. It has allowed the development of works such as those of [9] and [10], which show effective techniques to evaluate students in virtual educational environments and the challenges they face. These techniques seek to maintain the richness of face-to-face classes and apply them in virtual classes using technological alternatives. According to Gaytan and McEwen [11], it is evident that in mid-2007, one of the main challenges of online courses was to control the exams that students were taking since by its remote nature, it was impossible to have control over the student actions.

Chu et al. [12] propose using two-level tests with multiple-choice questions to provide personalized learning guidance in a natural science course. Their proposal indicates that each user uses the location for the detection of conducive learning environments. Maqsood et al. [13] propose a system for learning English, which allows the user to manually enter context variables such as location, concentration-time, and duration of learning time. From this information, the system identifies the complexity of the exercises and sentences shown to the student. El Janati et al. [14] introduce an e-learning system that captures information from the user's context, such as resources, social relationships, time, activity, location, physical conditions, and information from his environment computer. The system aims to present different contents adaptively from the context in which the user accesses. Adnan et al. [15] propose a machine learning system based on context-aware and adaptive mobile learning supported in the cloud, where the context variables are captured by sensors included in the mobile devices. The generation of different

learning paths provides an adaptation to solve real programming problems.

As evidenced in previous works, there are multiple proposals and applications using context-aware in education. A large number of proposals focus on the adaptation and personalization of student learning. Other proposals focus on the evaluation process, which we consider a fundamental factor in learning processes. Unlike the proposals at the evaluative level presented by [7] and [8], this paper seeks to use context-aware to identify the context variables that can negatively affect an evaluation outcome and propose alternatives to control these harmful effects.

Microlearning is a way of achieving informal learning in a new learning environment [16]. According to Hug et al. [17], microlearning processes smaller learning units and focuses on relatively short-time learning activities associated with a single specific learning objective. The microlearning concept also refers to a short time to access the contents, which means that learning contents can be easily accessed, stored, produced, and circulated through the portable learning devices [18]. Microlearning combines micro-content delivery with a sequence of micro-interactions that enable users to learn without information overload [19], allowing them to learn better when engaged in short, focused sessions than hour-long sessions. Mobile devices provide a powerful platform for learning content anytime and anywhere, so they are ideal for microlearning activities. Lin et al. [20] define a typical microlearning system as a structure compounded by a learning resource repository, a recommendation module, and a set of prediction and analysis modules. They work together to provide a complete personalized online learning service in the learning system. Among the most frequently made predictions are the user's future interaction, knowledge level, and the final grade. Edge et al. [21] highlight the relevance of learning in context. They presented a mobile application that supports such microlearning by leveraging a location-based service to provide contextually relevant content about Mandarin Chinese learning automatically. The method proposed in [22] exploited the microlearning concept and provided the learners with the opportunity to quickly retest new items. Beaudin et al. [23] explore ubiquitous computing for context-sensitive microlearning of foreign language vocabulary.

Prior studies investigated the relationship between users' behavior and their quiz scores and concentrated on predicting the Correct on First Attempt (CFA) of a learner in answering a question. For instance, Yang et al. [24] use time series neural networks for predicting the evolution of a student's grade in Massive Open Online Courses (MOOCs). The prediction algorithm uses clickstream data and quiz responses to forecast students' course performance. It tracks and predicts their grades after each answer to each quiz. Their work mainly concerns relating users' video watching behavior to their quiz performance, independent of each quiz cover's specific course topics. Kórosi et al. [5] predict course completion of students, and its work focuses on clickstream data from a course recorded by an e-learning platform. Besides, it describes a statistical methodology for predicting a binary outcome. The highest weighted features were input test grades, followed by the average time, mouse speed, and mouse distance spent in the whole course.

### 3. Methodology

In this paper, we use the ASUM-DM comprehensive proposal by Angée et al. [25]. Three main stages compose this methodology:

- (i) Analysis-Design-Configure & Build. It is an iterative set of actions where research's goals, expectations, and requirements are understood. Besides, business understanding identifies data objectives and analytics requirements. The data understanding activity allows initial data collection, as well as identification of data quality issues. The data preparation activity provides data cleaning actions and covers all activities to construct the final dataset from the initial raw data. Then, modeling activity allows us to build models using data mining tools. The evaluation activity determines if the results meet the project objectives and identify issues that require an early arrangement.

- (ii) Deploy. It provides the solution to the users and prepares for its continuing operation.
- (iii) Operate and optimize. It provides tasks of maintenance and checkpoints to facilitate the successful use of the solution.

The proposal presented in this article only covers the whole stage (i), while stage (ii) is presented as future work allowing us to put the resulting models into practice.

## 4. Analysis-Design-Configure & Build

### 4.1. Business Understanding

We created a progressive web application (called *Omnilearning.Education*) that deploys a microlearning related to “Software Development Patterns” to achieve the paper’s aim. The microlearning content is written in the Spanish language and is open to people of different ages and academic preferences. Every learner interaction is designed pedagogically and supports the understanding of business to the decision-making.

### 4.2. Data Understanding

The data collected are records of four weeks, from a total of 62 registered students, of whom 43 interacted at least with one content, and 31 made at least one evaluation. In the understanding data task, selected variables related to student information: age; content information: the topic of knowledge, content type (video, pdf, image, or audio), content category: (example, definition, motivational, or code), and rating; context information: ambient noise, accelerometer, device type, device battery, location, and internet network speed; user content behavior information such as time on content, journey, day of the week, entry hour, and focus on the content; and *evaluation\_grade*. Another set of variables was not considered because they did not respond or help the prediction’s objective. Thus, we obtained an initial dataset of 17 variables, which were considered as the most appropriate, in a first instance, for analyzing changes in a learner’s context concerning their evaluation outcome; besides, 906 records regarding entries to contents.

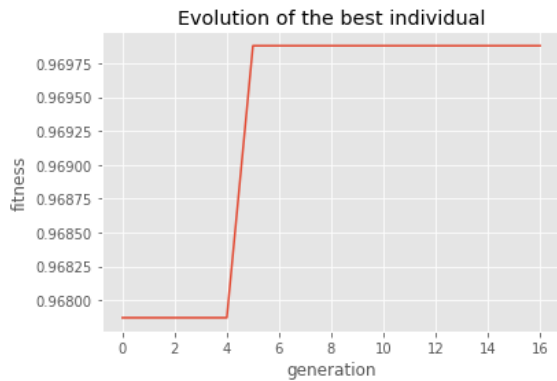
### 4.3. Data Preparation

We apply a filter to obtain only the learners who entered the contents and made evaluations. Those are 551 entries to contents with their corresponding context interactions stored every 10 seconds to obtain a final dataset with 9619 records. At that moment, we have 16 predictors and *evaluation\_grade* as depending variable with values between 0 and 5. We transform it into two classes: **0** (i.e., *evaluation\_grade* < 3) that represents a bad result in the learner’s evaluation, and **1** (i.e., *evaluation\_grade* ≥ 3) that represents a good result in the learner’s evaluation. Thus, 232 entries are related to class **0**, and 319 entries are related to class **1**. It shows that there is a balanced dataset since the number of records from both groups is similar.

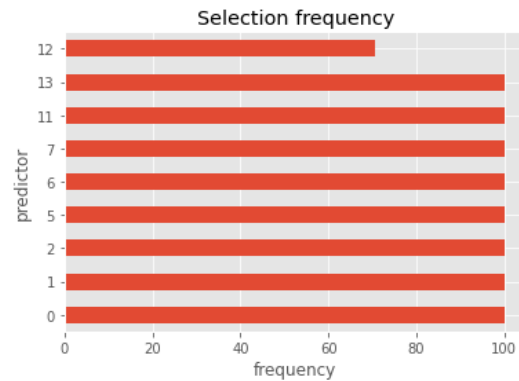
Although the raw dataset has a hierarchical structure of three dimensions, i.e., information about learner’s behavior in the content, content information, and context information, we need to reduce them to two dimensions due to the classification models used. To achieve that, we use different estimators like mean, median, and mode. Besides, we calculate percentiles or quartiles. Thus, we guaranteed good properties such as unbiased, efficiency, convergence, and robustness for each selected variable. Once the reduction is made, we apply Robust Principal Component Analysis (RPCA) [26], [27], which uses the eigenvalues, eigenvectors, and covariance matrix of the data to calculate the principal components of the representation of all the dataset variables. Thus, we can work well with outliers because RPCA is based on the matrix decomposition  $M = L_0 + S_0$  where  $M$  corresponds to the dataset,  $L_0$  to low-rank decomposition (low matrix of the data), and  $S_0$  to the scattered matrix [28]. In this research, we use the scattered matrix to identify the outliers by values that are far from 0. We complement it with the Z-score numerical measurement to identify the outliers where  $Z > 3$ . It means that learners obtained successful

results in the evaluation; after all, they did not need to see the contents because they had previous knowledge or good luck. On the other side, learners who obtained unfavorable results could be because the contents were not attractive.

Afterward, we want to find the highest features that will be part of the training and evaluation datasets. To achieve this, we use a genetic algorithm implemented based on the proposals of [29] and [30]. This algorithm improves prediction by evolutionarily identifying characteristics. It does this with each classification model to maximize a metric and detect that model's best predictors. The classification models used are Random Forest, SVM, Logistic Regression, Naive Bayes, Neuronal Network, Decision Tree, and Gradient Boosting Tree. The validation metrics are F1, precision, and ROC, among others. This algorithm works iteratively in the following way: in each iteration, possible solutions are generated, that is, a group of characteristics of the original dataset; the algorithm iterates until it detects that the validation metric reaches a limit, i.e., the best result or does not change, or until it reaches a limit of iterations or generations. Figure 1 shows how the genetic algorithm converges from a given model until finding the metric's maximization through the algorithm pass's generations (iterations).



**Figure 1.** Fitness evolution



**Figure 2.** Best predictors frequency

For example, during the training activity, the Gradient Boosting Tree provided an accuracy of 85%, and the genetic algorithm outcomes six variables: age, topic of knowledge, content type, ambient noise, day of the week, device type. For Random Forest, the genetic algorithm outcomes nine variables: age, topic of knowledge, content type, day of the week, entry hour, device type, device battery, journey, and ambient noise. With these features, we proceeded to re-training the models, increasing their accuracy; for instance, the Gradient Boosting Tree increased its accuracy to 91%; similar behavior occurred in the other models. Thus, the predictors are 0:'age', 1:'topic\_of\_knowledge', 2:'content\_type', 5:'day\_of\_the\_week', 6:'entry\_hour', 7:'device\_battery', 11:'device\_type', 12:'journey', and 13:'ambient\_noise'. Figure 2 shows the individuals who appeared more frequently in the best predictors used to test models.

#### 4.4. Modeling

To achieve our goal of identifying whether a student will get a good or bad result in their evaluation from the information of the context, the contents, and their behavior and interaction with the contents, we use the Random Forest, SVM, Logistic Regression, Naive Bayes, Neuronal Network, Decision Tree, and Gradient Boosting Tree classification models for prediction. We use the 551 pre-processed records for these models' training, which represent the inputs to contents. These records were divided into two sets, one representing the training dataset with 70% of the records (369 records), and the other representing the test dataset with 30% of the records (182 records). The validation of the models' performance is usually done only with the test dataset,

but as in our case, we have few records, we use the complete dataset to validate the models. The validation was done in 2 stages, the first using cross-validation with the training dataset, and the second applying the ROC AUC metric to the test dataset.

When using cross-validation, the training dataset is randomly separated into  $k$  subsets of approximately the same size, in our case  $k = 10$  (when testing with different  $k$ -values and getting similar results, we decided to use the default  $k$ -value that cross-validation handles).  $k - 1$  subsets are used to train the model, and one is used as a test. This process is repeated  $k$  times using a different test subset in each iteration. Finally, the result is the average of the results of each iteration [31].

The equation  $\hat{\mathcal{E}}_{CV} = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(y_i, \hat{f}_{-k}(x_i))$  represents the cross-validation, where  $f_{-k}$  corresponds to the models trained with the  $k - 1$  subsets.  $\hat{f}_{-k}(x_i)$  represents the prediction obtained by the given model  $x_i$  corresponding to the training data. In our case,  $x_i$  predicts one of the 2 classes (*evaluation\_grade*: 0 or 1) from the context information, contents, and the interaction with contents.  $y_i$  represents the real value to be predicted; in our case, it is the real class.  $\mathcal{L}$  is the validation metric, which has as input the predicted values and the real values to measure the models' performance. We use Accuracy, F1 score, Recall, Precision, and Jaccard metrics. The result of cross-validation is  $\hat{\mathcal{E}}_{CV}$ , which corresponds to the average of the results delivered by the metrics used. Table 1 presents the results of all the models used with different metrics. Random Forest was the model with the best results in all cases.

**Table 1.** Result of prediction models using different metrics (%)

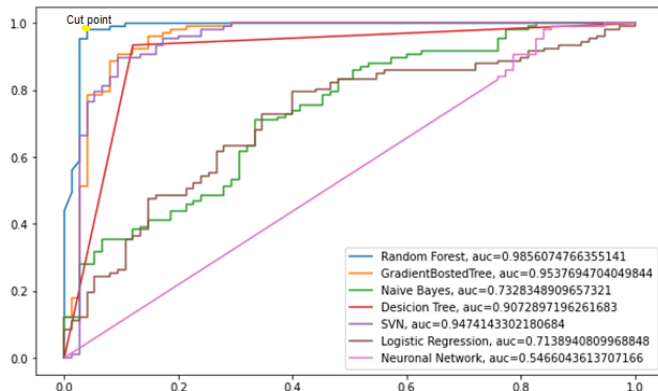
	Random Forest	Gradient Boosting Tree	Decision Tree	SVM	Logistic Regression	Naive Bayes	Neuronal Network
Accuracy	94,4	91,2	89,2	86,5	58,7	56,6	69,5
F1	95,2	92,4	91,5	89,0	68,5	58,6	78,4
Recall	97,3	92,9	91,2	94,4	77,9	53,3	95,3
Precision	93,3	92,0	91,2	84,4	62,0	66,6	67,0
Jaccard	91,0	86,5	83,4	80,3	52,2	41,6	64,7

#### 4.5. Evaluation

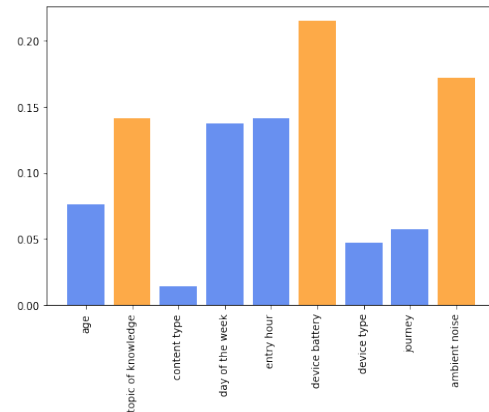
It was possible to identify the gain at using the genetic algorithm to select initial features. When training the models with the 16 initial features, the best models were Random Forest and Gradient Boosting Tree, with an accuracy of 91% and 89%, respectively. The models were then trained with the 9 features selected by the genetic algorithm, whereby again, the best models were Random Forest and Gradient Boosting Tree, but this time with an accuracy of 94.4% and 91%, respectively. The above-mentioned makes it clear that selecting features allowed us to improve the performance of the models used; besides, we reach a model that can be considered successful. With the validation carried out with cross-validation, satisfactory results were obtained with Random Forest with more than 90% in all the metrics used for cross-validation and 98.5% in the ROC AUC metric. These results indicate that it is possible to predict whether a student will obtain a good or bad result in his or her evaluation, based on information about the context, the content, and the behavior and interaction with the content.

After applying cross-validation, we performed the models' training validated in a second instance using the test dataset. In this case, we used the ROC curve to validate the models, which can be seen in Figure 3; it is evident that the Random Forest presents the best results since it has the largest area under the curve, a ROC AUC metric value of 98.5% and a cut-off point between true and false positives that is easy to identify.

According to Table 1, tree-based models performed better than others, especially Random Forest, with more than 90% results in all metrics. It shows that it is a very stable model and has a high precision for making a prediction, unlike the Logistic Regression, the Naive Bayes,



**Figure 3.** ROC curve by model



**Figure 4.** Weight of the variables

and the Neuronal Network, which have results close to 50% indicate high randomness at the time of prediction.

Random Forest allows us to identify the estimators to make the prediction. In this way, from the understanding of the data and the estimators' analysis, it is possible to establish the factors that influence whether a student obtains a good or bad result in the evaluation. Thus, we can recommend that the students understand why they could obtain a bad result in the evaluation and which factors (behavior or context) affect the earning process. Indicating how the result of a future evaluation could be improved, either through their behavior and intervention with the contents or recommending an adequate study context, can improve the student learning process. Besides, the Random Forest model gives us the variables with the highest weight, which are the variables that have the most significant influence at the time of making the prediction. Figure 4 shows these variables, whereby it is evident that the device's battery, the ambient noise, and the topic of knowledge are the variables with the highest weight when predicting the evaluation result. It means that these variables positively influence a student's result; therefore, these variables should be considered when making a recommendation to a student since they can directly influence the students negatively or positively.

## 5. Deploy

We developed a software module in which the models automatically capture information from the database and automatically perform pre-processing, training, and prediction. With the analysis of the results provided by Random Forest, we can identify the variables that influence the student's evaluation result and send feedback to the students through e-mail messages that indicate what is affecting the student and how it could be avoided, notably when the model predicts that the student will get a bad score in the evaluation. An example of a message is the following: "Hi Jose, we noticed that your behavior and your context variables studying might affect your learning process. You seem to have visited the contents with loud ambient noise. It is recommended that you go to a quiet place when visiting our contents to have more concentration". If the students that the model predicts will obtain good results in the evaluation, it is intended to send motivational messages that help maintain the student's interest in microlearning.

## 6. Discussion and conclusions

This article presents a method to predict if the students' evaluation results in a microlearning context will be good or bad. The dataset that used the method was obtained from all the learners'



interactions with the Omnilearning application In the data preparation activity, a genetic algorithm was applied to the dataset that successfully identified the essential characteristics for the prediction model: age, the topic of knowledge, content type, day of the week, entry hour, device battery, device type, journey, and ambient noise. Once the training is done, it is possible to determine that the Random Forest model, with an accuracy of 94%, provides the best results. It shows that the evaluation result can mainly be influenced by the context, whereby the user interacts and his behavior with the contents Specifically, the Random Forest model determines that the topic of knowledge, device battery, and ambient noise have the most weight in the prediction, as shown in Figure 4. It means that these features directly affect the outcome of the student's evaluation.

Random Forest allows us to analyze the estimators. In this way, it is possible to find common behaviors that lead to bad or good results. This estimation and the features knowledge that most influence allows us to give the user feedback to indicate what he should consider improving in the learning experience, either at the level of interaction with the contents or the context in which he visualizes.

In the future, we want to use the result of the prediction to provide automatic feedback to the users who are at risk of getting a bad result in the evaluation. The feedback will contain information about their behavior, context, and recommendations to improve their interactions with context and obtain a better result. Besides, we also expect to have a more robust dataset to apply models such as Long short-term memory (LSTM) to obtain more accurate results. It will guide the way to adapt the microlearning contents according to the context or user interactions.

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## References

- [1] Y. Liu, S. Han, and H. Li, "Understanding the factors driving m-learning adoption: A literature review," *Campus-Wide Information Systems*, vol. 27, no. 4, pp. 210–226, 2010.
- [2] S. Van Engelenburg, M. Janssen, and B. Klievink, "Designing context-aware systems: A method for understanding and analysing context in practice," 11 2018.
- [3] V. A. Nguyen and V. C. Pham, "Bayesian network to manage learner model in context-aware adaptive system in mobile learning," in *International Conference on Technologies for E-Learning and Digital Entertainment*, pp. 63–70, Springer, 2011.
- [4] J. Lin, G. Sun, T. Cui, J. Shen, D. Xu, G. Beydoun, P. Yu, D. Pritchard, L. Li, and S. Chen, "From ideal to reality: segmentation, annotation, and recommendation, the vital trajectory of intelligent micro learning," *World Wide Web*, pp. 1–21, 2019.
- [5] G. Kőrösi, P. Esztelecki, R. Farkas, and K. Tóth, "Clickstream-based outcome prediction in short video moocs," in *2018 International Conference on Computer, Information and Telecommunication Systems (CITS)*, pp. 1–5, IEEE, 2018.
- [6] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, "Towards a better understanding of context and context-awareness," in *International symposium on handheld and ubiquitous computing*, pp. 304–307, Springer, 1999.
- [7] A. Harchay, L. Cheniti-Belcadhi, and R. Braham, "A model driven infrastructure for context-awareness mobile assessment personalization," in *IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications*, pp. 1676–1683, IEEE, 2012.
- [8] B. Chen, C.-Y. Lee, and I.-C. Tsai, "Ontology-based e-learning system for personalized learning," in *International Conference on Education, Research and Innovation*, vol. 18, pp. 38–42, 2011.
- [9] B. Byrd and K. Lott, "Evaluation in online courses," in *Business Education Forum*, vol. 58, pp. 48–50, National Business Education Association, 2003.
- [10] G. Glass and K. Hopkins, "Statistical methods in education and psychology," *PsycCritiques*, vol. 41, no. 12, 1996.

- [11] J. Gaytan and B. C. McEwen, "Effective online instructional and assessment strategies," *The American Journal of Distance Education*, vol. 21, no. 3, pp. 117–132, 2007.
- [12] H.-C. Chu, G.-J. Hwang, C.-C. Tsai, and J. Tseng, "A two-tier test approach to developing location-aware mobile learning systems for natural science courses," *Computers & Education*, vol. 55, no. 4, pp. 1618–1627, 2010.
- [13] S. Maqsood, A. Shahid, F. Nazar, M. Asif, M. Ahmad, and M. Mazzara, "C-pos: A context-aware adaptive part-of-speech language learning framework," *IEEE Access*, vol. 8, pp. 30720–30733, 2020.
- [14] S. El Janati, A. Maach, and D. El Ghanami, "Context aware in adaptive ubiquitous e-learning system for adaptation presentation content," *Journal of Theoretical and Applied Information Technology*, vol. 97, pp. 4424–4438, 09 2019.
- [15] M. Adnan, A. Habib, J. Ashraf, and S. Mussadiq, "Cloud-supported machine learning system for context-aware adaptive m-learning," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 27, no. 4, pp. 2798–2816, 2019.
- [16] Z. Zhu, H. Zhang, and X. Gu, "Micro learning–practical mode of informal learning," *Beijing: China Educational Technology*, vol. 2, pp. 15–18, 2008.
- [17] T. Hug, M. Lindner, and P. A. Bruck, "Microlearning: Emerging concepts, practices and technologies after e-learning," *Proceedings of Microlearning*, vol. 5, no. 3, 2005.
- [18] X. Li, J. Liu, J. Han, and Q. Zhang, "The architecture design of micro-learning platform based on cloud computing," in *Proceedings of the International Conference on Innovative Computing and Cloud Computing*, pp. 80–83, 2011.
- [19] P. A. Bruck, L. Motiwalla, and F. Foerster, "Mobile learning with micro-content: A framework and evaluation.," *Bled eConference*, vol. 25, pp. 527–543, 2012.
- [20] J. Lin, G. Sun, J. Shen, T. Cui, P. Yu, D. Xu, L. Li, and G. Beydoun, "Towards the readiness of learning analytics data for micro learning," in *International Conference on Services Computing*, pp. 66–76, Springer, 2019.
- [21] D. Edge, E. Searle, K. Chiu, J. Zhao, and J. A. Landay, "Micromandarin: mobile language learning in context.," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 3169–3178, 2011.
- [22] D. Edge, S. Fitchett, M. Whitney, and J. Landay, "Memreflex: adaptive flashcards for mobile microlearning.," in *Proceedings of the 14th international conference on Human-computer interaction with mobile devices and services*, pp. 431–440, 2012.
- [23] J. S. Beaudin, S. S. Intille, E. M. Tapia, R. Rockinson, and M. E. Morris, "Context-sensitive microlearning of foreign language vocabulary on a mobile device.," in *European conference on Ambient intelligence*, pp. 55–72, Springer, 2007.
- [24] T.-Y. Yang, C. G. Brinton, C. Joe-Wong, and M. Chiang, "Behavior-based grade prediction for moocs via time series neural networks," 2017.
- [25] S. Angée, S. I. Lozano-Argel, E. N. Montoya-Munera, J.-D. Ospina-Arango, and M. S. Tabares-Betancur, "Towards an improved asum-dm process methodology for cross-disciplinary multi-organization big data & analytics projects," in *Knowledge Management in Organizations*, pp. 613–624, Springer International Publishing, 2018.
- [26] T. P. Barnett and R. Preisendorfer, "Origins and Levels of Monthly and Seasonal Forecast Skill for United States Surface Air Temperatures Determined by Canonical Correlation Analysis," *Monthly Weather Review*, vol. 115, pp. 1825–1850, 09 1987.
- [27] S. K. Sapra, "Robust vs. classical principalcomponent analysis in the presence of outliers," *Applied Economics Letters*, vol. 17, no. 6, pp. 519–523, 2010.
- [28] Q. Wang, Q. X. Gao, G. Sun, and C. Ding, "Double robust principal component analysis," *Neurocomputing*, vol. 391, pp. 119–128, 2020.
- [29] K. R. Coombes, "Genetic Algorithms for Feature Selection," tech. rep., 2018.
- [30] J. A. Rodrigo, "Selección de predictores mediante algoritmo genético," 2019.
- [31] D. Berrar, "Cross-validation," *Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics*, vol. 1-3, no. April, pp. 542–545, 2018.