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Prediction Model for Adaptive Self-Regulated Mobile Learning Using Multinomial Logistic Regression

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ABSTRACT

Learning is a continuously evolving area of research, especially in the integration of technology into learning. However, the process of making learning interesting, productive and innovative cannot be over-emphasized. Artificial Intelligence is a tool that has impacted several areas of human endeavours and education is not left out. This study focused on the use of artificial intelligence in the adaptivity of mobile learning based on self-regulation. Mobile learning is usually autonomous and the ability of learners to self-regulate helps in maximizing the learning outcome. The model was developed on experimental and survey data using the multinomial logistic regression. The study adopted a mixed method approach and findings indicate that the developed model has an accuracy, precision, recall and F1-scores of 99%., 98.9%, 98.7% and 98.7% respectively. The confusion matrix of the model shows a very high level of accuracy in the classification of the mobile learners into class 0 (low self-regulated), class 1 (moderate self-regulated) and class 2 (high self-regulated) mobile learners. The model was evaluated by comparing it with other standard machine learning models; Decision Tree, Random Forest, SVM, Gradient Boost and Naïve Bayes. The model outperformed them all with a higher accuracy of 99%. The study concludes that the high accuracy of the model makes it suitable for the prediction of self-regulation in mobile learning. The study recommends that the model be deployed in real life predictions and as a basis for content recommendations.

Keywords: Prediction, Adaptive, Mobile Learning, Self-regulated,

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1. INTRODUCTION

Learning is an important part of human existence which has evolved over several centuries. It is an act or process that is defined in several contexts based on the people, environment, methodologies and general objective of the learning. However, no matter the objective or methodologies, the ultimate goal is the achievement of behavioural change. Learning can be formal, informal or non-formal, it can take place in organized settings, homes, workshops or even religious organisations (Mahato et al., 2023). The rapid development in the development and penetration of technology in the developed and developing countries of the world has affected every human endeavour and education is not left out.

Hence the concept of technology emhanced learning (TEL) should be given serious attention. The case of online learning during the COVID-19 pandemic has also opened the eyes of the world towards the immense potentials of technology enhanced learning (Gashoot et al., 2023). In their study, Fatima et al. (2019) reported that the rise in mobile learning is going in tandem with the increase in online shopping, online gaming, social media usage, online marketing, increase in internet penetration and online collaborations. Mobile learning is a paradigm that captures the concept of technology enhanced learning. This is so because it is clearly the use of mobile technology, through mobile devices, telecommunication networks and software to deliver educational content. Mobile learning is defined by the paradigm of anywhere, anytime learning, that is flexible and increases access to learning (Yıldız et al., 2020). Adaptive learning is a learning paradigm where learners receive learning contents or instruction that are tailored directly towards addressing the learning needs or styles of the learners.

Adaptive learning systems diagnose the individual learning needs and personalize their learning in order to ensure that they maximise their learning outcomes (Banerjee et al., 2021). Furthermore, Ennouamani et al. (2020) submitted that context-awareness is an important part of mobile learning hence, the development of smart, personalized learning solutions helps in the improvement of learning achievements. One of the key aspects of context awareness in learning is self-regulation in learning.

Self-regulation in learning is simply the ability of the learners to learn on their own with little or no supervision from instructors. Self-regulated learners are able to initiate, sustain and evaluate their learning activities. Mobile learners are most of the time on their own away from instructors and other learners. Hence, adaptive mobile learners require a good level of self-regulation in order to maximise their learning outcomes (Daniela, 2015). Additionally, there are several types of self-regulation learning contexts or behaviours that are studied in learners. These includes, the cognitive, metacognitive, self-efficacy, collaboration, motivation and self-regulation learning strategy.

Each one the aforementioned covers a particular behaviour, however on further breakdown they may lead to slight overlaps in some areas (Sharma et al., 2024; Zhang et al., 2021). The application of artificial intelligence to education is an increasingly researched area today. Machine learning is the use of artificial intelligence algorithms and models to understand and interpret data in order to make decisions that can mimic human reasoning (Tiwari, 2023). This research study aims to develop a model that to predict the self-regulation of mobile learners using Multinomial Logistic Regression. The accurate prediction of the self-regulation status of mobile learners allows the learners to know and adjust their learning with mobile devices

2. RELATED STUDIES

Studies have been conducted to show the impact of artificial intelligence (AI) in self-regulated and adaptive mobile learning. These studies aimed to show the interrelationship between artificial intelligence and personalization of mobile learning, vis the improvement of prediction and/or classification of the learners. In their study, Daoudi et al. (2024) reported that machine learning algorithms are increasingly used in the prediction of mobile learners learning and achievements. These algorithms are immensely crucial in the determination of the self-regulation, self-efficacy and cognition of the mobile learners. However, the study did not cover other contexts of the mobile learners such as collaboration, environmental and motivation factors.

Additionally, in their study, Baars et al.. (2022), developed a mobile app-based solution for self-regulation in mobile learning. Their study employed the Decision Tree machine learning algorithm and evaluated the model using the learner's engagement with the mobile app. The study reported that there was a high accuracy of the use of the model in measuring the self-regulation of the mobile learners. However, there was no numerical report of the accuracy and there was no comparison with other evaluated machine learning algorithms. Furthermore,

Rivers et al. (2022) developed a prediction model for self-regulated online learning. The model was designed and implemented using structural equation modeling (SEM). The study found that self-regulation context of metacognition which include skills such as goal setting and planning are important towards predicting the academic performance of the learners. However, the study did not investigate this relationship by using other machine learning algorithms.

In the same vein, Khalil (2022) conducted a study on fostering self-regulated learning using mobile multimodal learning analytic method (MOLAM). The MOLAM model was design using multidisciplinary approach. The study found that MOLAM has the ability to support the self-regulation of learners, teachers and others. It can be used as a framework to implement other machine learning algorithms and for the prediction of the self-regulation learning behaviours especially in the metacognitive domain.

The study did not report the implementation of MOLAM using standard machine learning algorithms. Furthermore, Clark et al. (2021) studied self-regulated learning using self-rating in the health sector. The self-rating was designed and implemented using machine learning algorithms, in order to achieve predictive status. The study reported that the model achieved a good model fit, making it accurate in the prediction of the self-rated health across the different groups. However, this study was conducted only in the health sector and not extended to include the education sector.

3. RESEARCH METHODOLOGY

The methodology for this study includes the collection of data, data cleaning, data transformation, training of the model, evaluation of the model and comparison of the model performance with other standard machine learning models.

1. The data collection for this study was through the use of a Mobile App-based data collection instrument. The instrument consists of experimental and survey parts. for data collection. The experimental part collected real time data for learners' engagement, read_time and score of the learners. The survey part collected data for the various self-regulation learning context. These includes self-efficacy, cognition, metacognition, motivation, self-regulation learning strategies, self-regulation social support and the mobile device usage. The dimension of the collected data was (1023, 46); this implies that there were 1023 respondents with 46 variables. This was later reduced to (1023, 9) after fuzzification.
2. The data cleaning was done manually by handling missing values. The missing values were handled by replacing them with the immediately preceding values. There were no cases of outliers or wrong values because the instrument was designed to handle the input process automatically.
3. The experimental data were integer values while the survey data ordinal data types. The data were transformed by calculating the means for every context and the resultant transformed data were stored as the new input variables. In order to obtain the output variables, the input variables were clustered using the Fuzzy C Means algorithm. This generated the clusters as 0, 1 and 2, representing the low, moderate and high self-regulation classes respectively.
4. Model Training: the transformed and clustered dataset was trained using the developed model by splitting the dataset into 75% for training and the remaining 25% for the testing of the model. The developed model was implemented using the python programming language.
5. Model Evaluation: the model was evaluated using the standard machine learning metrics of Accuracy, Precision, Recall and F1-scores
6. Comparison of the Model: the performance of the developed model was compared with the performance of standard machine learning models; SVM, Random Forest, Decision Trees, Naïve Baiyes and Gradient Boosting. . Each of the standard machine learning models were applied on the same test dataset as the developed model and their results were compared to that of the developed model

4. RESULTS AND DISCUSSION

The model was implemented on the dataset in order to obtain the performance of the model. Table 1 show the results of the performance of the model, showing the accuracy, precision, recall and F1-score of the model.

Table 1: Performance of the Developed Model

Metric	Class 0 (Low self-regulate)	Class 1 (moderate self-regulated)	Class 2 (high self-regulated)	Average	Overall
Accuracy					99%
Precision	99%	100%	97.9%	98.9%	
Recall	97%	100%	99%	98.7%	
F1-Score	100%	98%	98%	98.7%	

From Table 1 the prediction accuracy of the model is 99%. This implies that the model has a very high accuracy level and can be deployed in real life situation to predict the self-regulation status of mobile learners as low, moderate or high self-regulation.

It also implies that the model can be used to aid the self-regulated mobile learning of learners. Additionally, the precision for class 0, class 1 and class 2 are 99%, 100% and 97.9% respectively. This implies that the model has a high precision in the classification of mobile learners into the three classes. Therefore, the model has high effectiveness in the prediction of true positives of the various classes.

Moreso, the recall performance of the model is 97%. 100% and 99% for class 0, class 1 and class 2 respectively. This implies that the model has a high sensitivity and hence predicts the right classes with a high level of correctness. Furthermore, the F1-Score of the model is 100%, 98% and 98% for class 0, class 1 and class 2 respectively. This performance implies that the model has a high specificity in the correct prediction of the negatives. Therefore the model has a high level of predictiveness and can be deployed to predict the self-regulation of mobile learners.

Table 2: Confusion Matrix of the Developed Model

Actual Class	Predicted Class			
	Class 0	Class 1	Class 2	Total Instances
Class 0	67	0	2	69
Class 1	0	95	0	95
Class 2	1	0	91	92
Total	68	95	93	256

From Table 2 the confusion matrix shows a summary of the classifications across the three clusters of self-regulated adaptive mobile learners. The rows show the number of instance of cases in each cluster, for class 0, there are a total of 69 instances while in class 1 (moderate self0regulation) there are a total of 95 instances. Additionally, in class 2 (high self-regulation) there were a total of 92 instances. For class 0, a total of 67 instances were accurately classified to belong to the low self-regulation class while 2 instances were wrongly classified to belong as members of class 2.

This implies that there was a high level of accuracy in the classification of low self-regulated learners, though there were misclassification. In the same vein, for class 1, there were a total of 95 instances and the entire 95 instances were all correctly classified as members of class 1. Therefore, there was no case of misclassification. Hence all moderate self-regulated learners were correctly classified. Furthermore, for class 2 (high self-regulated) mobile learners, there were 92 instances. In the classification, 91 were correctly classified as class 1, where 1 was mis-classified as class 0. This implies that the model has low number of misclassified cases, hence a high level of accuracy. However, a further test of the model with different test datasets can further shed light on the implication of the misclassifications.

Table 3: Comparison of The Performance of MASRML Model with Other Standard Machine Learning Models

S/N	Model	Accuracy	Precision	Recall	F1 Score
1	Decision Tree	0.921875	0.925178	0.925178	0.925178
2	Random Forest	0.957031	0.958775	0.958775	0.958775
3	Support Vector Machine	0.980469	0.980853	0.980853	0.980853
4	K-Nearest Neighbors	0.960938	0.963142	0.963142	0.963142
5	Gradient Boosting	0.949219	0.951194	0.951194	0.951194
6	Naive Bayes	0.953125	0.955938	0.955938	0.955938
7	Developed Model	0.988281	0.955938	0.955938	0.955938

From Table 3 The Decision Tree model achieved an accuracy of 92.19%, which is notably lower than the Developed Model's 98.83%. Its precision, recall, and F1 score were approximately 92.52%, also less than that of the Developed Model's precision and recall (95.59%). The Developed Model outperforms the Decision Tree in all metrics. The Random Forest model performed better than the Decision Tree, achieving 95.70% accuracy and a similar 95.88% precision, recall, and F1 score. However, it still falls behind the Developed Model's 98.83% accuracy. The Support Vector Machine model achieved an accuracy of 98.05% and a precision, recall, and F1 score of 98.08%. This performance is very close to the Developed Model's metrics. The Developed Model's slightly higher accuracy (98.83%) makes it better than SVM in the accuracy metric.

Furthermore, the K-Nearest Neighbors model achieved an accuracy of 96.09%, which is 2.7% lower than the Developed Model. Its precision, recall, and F1 score of 96.31% also falls behind the Developed Model's 95.59%. The Developed Model is superior in terms of the accuracy metric.

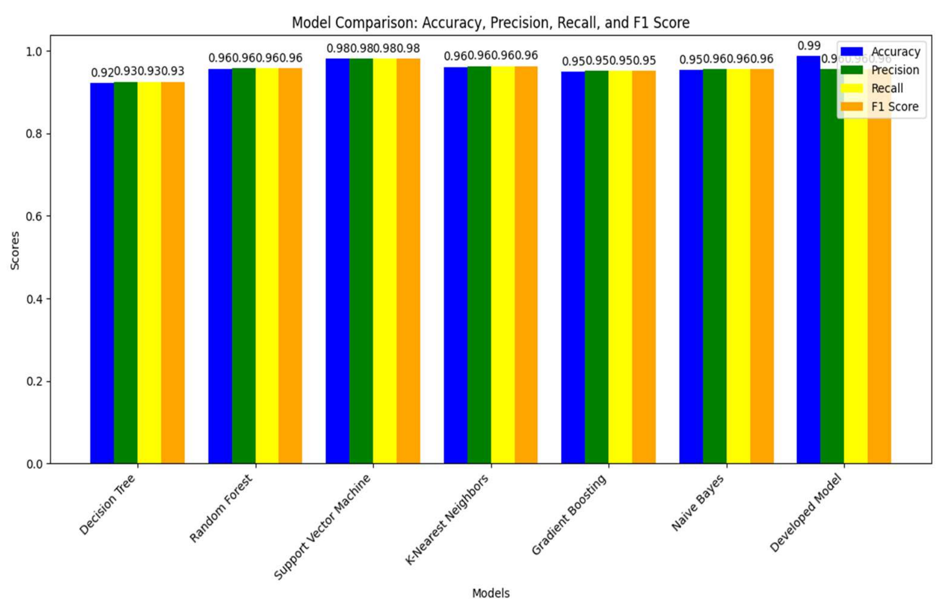

Fig 1: Performance Comparison Of The Developed Model With Standard Machine Leaning Algorithms

The Gradient Boosting model achieved an accuracy of 94.92%, which is approximately 3.9% lower than the Developed Model. Similarly, its precision, recall, and F1 score of 95.12% are lower than those of the Developed Model. This indicates that Gradient Boosting does not match the Developed Model's performance. The Naive Bayes model had an accuracy of 95.31% and precision, recall, and F1 scores of 95.59%. While Naive Bayes matches the Developed Model in precision, recall, and F1 score, it falls behind in accuracy. Figure 1 shows bar chart for the performance comparison. Figure 1 showed the performance comparison of the developed model with standard machine leaning algorithms of Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbour, Gradient Boosting and Naïve Bayes. From figure 1 the developed model outperforms all the other standard machine learning algorithms with a na accuracy of 99%.

5. CONCLUSION

This study developed a prediction model adaptive self-regulated mobile learning using the multinomial logistic regression. Data was collected using an instrument that contained experimental data from the learning engagement and survey data from different educational self-regulation contexts. The data were normalized using the Min-Max formula data and clustering was done using Fuzzy C-Means Algorithm in order to obtain the correct cluster values. This action transformed the datasets from an unsupervised to supervised data form, through the generation of clusters 0, 1 and 2 representing the low, moderate and high self-regulated learner. The results from the implementation of the model showed that the model had high performance metrics. The accuracy of the model was 99%. The model's performance was compared to the performance of other standard machine learning models; SVM, Random Forest, Decision Tree, Naïve Baiyes and the developed model gave better prediction performance. This implies that the developed model has the ability to accurately predict the self-regulation status of a learner and help in the future learning of the mobile learners. A proper classification of the learner can serve as a basis for learning contents recommendation, learners diagnosis and the improvement of personalization of learners in the mobile learning domain.

6. SUGGESTION FOR FURTHER STUDIES

Based on the study, the model can be improved by testing it on diifrerent contexts of educational datasets across different learning group. Developing and ensemble of motion learning algorithms may further open up results that can be compared to the performance of the model. This model can be used to develop recommendation systems based on the self-regulation behaviours of mobile learners.

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