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ORIGINAL

Applied research on data analysis in creative multimedia courses in universities

Investigación aplicada sobre análisis de datos en cursos multimedia creativos en universidades

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ABSTRACT

Creative multimedia has become a key component of innovation in today's quickly changing digital world, blending technology and artistry to provide captivating, interactive, visual, and aural experiences. Universities worldwide are offering specialized courses in creative multimedia to equip students with skills for industries like entertainment, advertising, education, and digital communication. This course integrates graphic design, animation, video production, game development, and virtual reality, fostering a holistic knowledge atmosphere. The purpose of the research is to establish the application of data analysis in creative multimedia courses in universities to enhance student achievement evaluation and foster innovative and technical development in university-level graphic design courses focused on packaging design. The Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF) is applied to assess student performance based on various criteria, including creativity, technical proficiency, and the effectiveness of packaging designs. Data collection includes student performance, design samples, teacher ratings, and packaging design. The data was preprocessed using data cleaning and normalization from the acquired data. EAB is used to select the features from data, and ARF is employed to assess student performance and enhance creativity. The recommended EAB-ARF outperforms all other models with the highest accuracy values of 95,8 %, (95,6 %) precision, (99,2 %) recall, and (97,6 %) F1-score. This illustrates how EAB-ARF performs well across all evaluation categories and has a superior ability to forecast student results.

Keywords: Creative Multimedia Courses; Student Performance; Creative Thinking; Skill Development; Packaging Design; Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF).

RESUMEN

La multimedia creativa se ha convertido en un componente clave de la innovación en el cambiante mundo digital de hoy en día, combinando tecnología y arte para ofrecer experiencias cautivantes, interactivas, visuales y auditivas. Las universidades de todo el mundo están ofreciendo cursos especializados en multimedia creativo para equipar a los estudiantes con habilidades para las industrias como el entretenimiento, la publicidad, la educación y la comunicación digital. Este curso integra diseño gráfico, animación, producción de video, desarrollo de juegos y realidad virtual, fomentando una atmósfera holística de conocimiento. El propósito de la investigación es establecer la aplicación del análisis de datos en cursos multimedia creativos en las universidades para mejorar la evaluación del rendimiento de los estudiantes y fomentar el desarrollo innovador y técnico en cursos de diseño gráfico de nivel universitario enfocados en el diseño de envases. El eficiente African Buffalo Tuned Adaptive Random Forest (EAB-ARF) se aplica para evaluar el rendimiento de los estudiantes con base en varios criterios, incluyendo la creatividad, la competencia técnica y la eficacia de los diseños de embalaje. La recolección de datos incluye el desempeño de los estudiantes, las muestras de diseño, las calificaciones de los profesores y el diseño del embalaje. Los datos fueron preprocesados utilizando limpieza y normalización de los datos adquiridos. EAB se utiliza para seleccionar las características de los datos, y ARF se emplea para evaluar el rendimiento de los estudiantes y mejorar la creatividad. El EAB-ARF recomendado supera a todos los otros modelos con los valores más altos de precisión de 95,8 %, (95,6 %) precisión, (99,2 %) recuerdo, y (97,6 %) F1-score. Esto ilustra cómo EAB-ARF se desempeña bien en todas las categorías de evaluación y tiene una capacidad superior para pronosticlos resultados de los estudiantes.

Palabras clave: Cursos Multimedia Creativos; el Rendimiento de los Estudiantes; el Pensamiento Creativo; el Desarrollo de Habilidades; Diseño de Envases; Búfalo Africano Eficiente Sintonía Adaptable Bosque Aleatorio (EAB-ARF).

INTRODUCTION

Teachers at several colleges worldwide are currently very interested in the topic of creativity in the classroom. These teachers aim to create an inventive learning atmosphere where students are more inclined to think creatively, share their opinions, and successfully tackle challenges with original solutions.[1] Alongside the incredible technological development, this interest has been developing, which has made it necessary to reconsider how multimedia could promote creativity in the classroom. Despite the increased focus on creativity, not everyone is proficient in using technology, particularly social media platforms.[2] New and innovative pedagogical approaches have been made possible by emerging digital and multimedia technologies, which have also significantly changed the definition of creativity in the classroom.[3] It has shown that social media along with multimedia tools and applications can stimulate creativity and innovation in educational settings. Its specific goal is to integrate multimedia-based creative educational approaches into digital media, art, and design learning settings.[4] It presents clearly that multimedia-based education has the power to alter important creative thinking exercises and processes related to the fields of digital media, design, and art. This could lead to new definitions of creativity and widen and expand educators' perspectives on creativity in the classroom, particularly when it involves technology, a process known as "digital creativity".[5]

Creative multimedia redefines the notion of creativity and explores its role and relationship to technology-centered education. By outlining the diverse and creative uses of multimedia that are currently being employed in the domains of media, design, and art, it explores the connection between technology, creativity, and education and builds the theoretical framework for the research.[6,7] The main purpose of this research is to improve the evaluation of student achievement and to foster the technical and creative skills of students in university creative multimedia courses. The presented research intended to predict student outcomes depending on several factors: originality, technical skills, and interest in the Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF). The purpose of the research is therefore to identify the critical success factors essential to students in creative multimedia areas such as packaging design, animation, and graphic design.

A methodical and objective approach to literature exploration was used in the research [8]. It also discussed the themes found in the literature about the application of AI-based algorithms in digital education. Research conclusions highlight six topics about the application of technology in online learning. Using the Random Forest (RF) method, the research [9] aimed to create a multimedia supplementary teaching effect evaluation model for college physical education. Analyzing the effects of network-assisted teaching platforms and optimizing teaching quality evaluation indices were its goals. The goal of the concept was to improve physical education course management, effectiveness, and quality of instruction. The Pedagogical Content Knowledge (PCK) ability of art teachers in the field of visual art education, using PCK as a standard, was investigated in [10]. A gray clustering-based performance analysis model and an Analytical Hierarchy Process (AHP) were developed to improve AI's efficacy in art education. A novel classification method of the Artificial Intelligence-based Creative Thinking Skills Analysis Model (AI-CTSAM) for examining population heterogeneity using a small number of multivariate variables is model-based cluster analysis. Through visual art education, students can describe, analyze, interpret, and assess artwork. To detect digital distraction, measure the level of noble knowledge assignation, and forecast learning performance, this research [11] used a cutting-edge approach that integrated learning analytics. Research [12] was to build and analyze a unique hybrid customized suggestion for ML public data sets based on transudative SVM. The students' habits have made the learning experience possible. This research developed some of the novel approaches that were tested to enhance a hybrid recommender's performance. Determining that specific Key Performance Indicators (KPIs) derived from student interactions with Blackboard assisted in predicting students' learning outcomes was the goal of this research.[13]

Four Deep Learning (DL) models were analyzed as part of a mixed-methods analysis design to forecast student performance. Information was gathered from seven general preparatory course reports. The usefulness of using neurocognitive data to predict students' answers on a science subject examination was investigated in

[14]. The replication of deoxyribonucleic acids was explained in the lecture video and virtual reality lesson. Based on the resource-based theory and associated studies, the research [15] presented forth a model and hypothesis. Research also suggested ways to reserve and deploy AI resources to enhance instructors' and students' digital literacy, employ AI to drive teaching and learning, and boost students' learning performance and creativity. Higher education was one of the many industries where chatbot use was quickly developing. The impact of a chatbot, a virtual teaching assistant that gives pupils automatic responses to their questions, was examined in [16]. Focus groups and an academic achievement test were used to collect data, enabling a more thorough examination of the student's interactions with the chatbot. The main purpose of this research is to improve the evaluation of student achievement and to foster the technical and creative skills of students in university creative multimedia courses. The presented research intended to predict student outcomes depending on several factors: originality, technical skills, and interest in the Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF). The purpose of the research is therefore to identify the critical success factors essential to students in creative multimedia areas such as packaging design, animation, and graphic design.

The following is the order of the research: methods are developed in section 2, findings are presented in section 3, and the discussions and conclusion is illustrated in section 4 and 5.

METHOD

Research approach used to assess the performance of students in multimedia courses involves the collection of considerably large and comprehensive Student Performance in Multimedia Courses Data (SPMCD). Feature selection and performance prediction are achieved from the EAB-ARF after pre-processing the dataset through Min-Max normalization. The flowchart of the methodology has been described in figure 1.

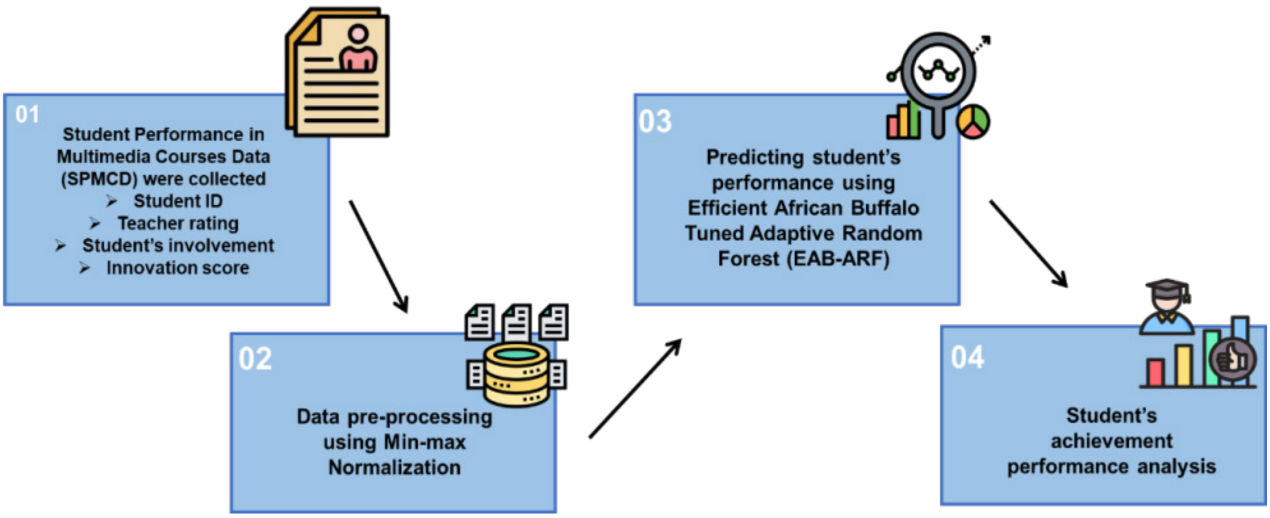

Figure 1. Method flow

Data collection

Research focuses on the packaging design, the research question seeks to determine how data analysis could assist in the assessment of students and foster technical and creative development of university creative multimedia classes. In addition to teacher and project data, Student Performance in Multimedia Courses Data (SPMCD) was collected in Kaggle [https://www.kaggle.com/datasets/ziya07/student-performance-in-multimedia-courses/data]. Stress levels, engagement levels, and scores given to collaboration were collected using surveys and activity tracking. Student's attendance and assignment scores were obtained from the students' records while inventiveness and self-learning hours were estimated from teachers and self-reports. Such a broad base of data allows for the evaluation of the variables that determine the learners' performance and identify the zones of improvement.

Data pre-processing using Min-max normalization

To avoid the dominance of any variable in the analysis or modeling process, the SPMCD dataset uses the Min-Max normalization technique in the pre-processing step to normalize all the feature values into the same range. Min-max normalization rescales the data since each feature is quantified to a percentage ranging from 0 to 1 based on the lowest and highest values. In the process of normalizing all features to be within the same scale, the normalization involves subtracting each feature's minimum value from the data points followed by dividing values by the range of that feature. Equation (1) is utilized to establish the lowest and maximum value that presented in the SPMCD dataset, which comprises the following performance metrics: creative score, technical skill, packaging design score, teacher's score, interaction level, collaboration score, and others.

$$x' = \frac{x - min}{max - min} \qquad (1)$$

Where x' stands for the standardized score, x is the initial value, min is the feature's lowest level, and max is its highest value. As such, by making none of the variables disproportionately influential, this normalization method enhances comparison and modeling.

To predict student's performance using Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF)

By enhancing the model parameters and feature selection, the EAB-ARF aspires to enhance student performance prediction after data preprocessing. To avoid the inclusion of light variables such as count, time duration, and frequency of posts, EABO is first used to select the most relevant features from the data. Therefore, the preferable aim of the EAB-ARF method is to provide a stable model that effectively evaluates or promotes students' performance and creativity in creative multimedia subjects.

Adaptive Random Forest (ARF)

Following data preprocessing of the SPMCD dataset of students, the ARF technique is employed to assess as well as predict student performance using the normalized characteristics. According to these characteristic correlations, the ARF ML model continuously updates the DTs to improve the performance depending on the input it receives. In this research, ARF helps to evaluate several factors, which are technical skill, creativity, and student engagement, and confirms that all these factors impact the total scores of students. First, it creates an initial forest Θ_0 with an initial feature vector F_0 (.) and a A0 number of trees. Less categorization error by tree τ is indicated by a higher value ofγ. The top v_0number of features are marked as important following feature ranking using equation (2) (It takes $v_0=\surd(\#F_0\ (.))$. If such a feature does not exist, the feature with the smallest global weight in Γ_0' (.) is contained in R0. Features of R_0 are eliminated from Γ_0'.

$$x(i) = \frac{\sum_{\forall\tau} \quad x^{\tau}(i)\gamma^{\tau}}{\sum_{\forall\tau} \quad x^{\tau}(i)\gamma^{\tau}} \qquad (2)$$

F_1 (.)=F_0 (.)-R_0 is the feature vector with the decreased feature set. Next, equation (3) is used to determine Δv and Δu.

$$\Delta v = \neq \Gamma_{m+1} - \neq \Gamma_m, \Delta v = \neq \Gamma'_{m+1} - \neq \Gamma'_m \qquad (3)$$

Equation (4) is used to determine how many trees (ΔA) should be added to the forest-based on these variables. After that, a forest Θ_0 is created from scratch using feature vectors F_1 (.) and A_o+ ΔA.

$$|u\Delta A| < |kr_v\Delta v + kr_v\Delta v| \Rightarrow |\Delta A| < \left|\frac{kr_v\Delta v + kr_v\Delta v}{u}\right| \qquad (4)$$

It first ranks the features at any pass m (after the expansion of the forest Θ_m with A_m trees and the reduced feature set F_m). Next, the set of characteristics that need to be decreased R_m and the set of new, significant features A_m has been determined. It updates the feature bags using equation (5) after obtaining the feature vector with decreased features F_{m+1} (.)=F_m (.)-R_m.

$$\Gamma_{m+1} = \Gamma_m + A_m, \Gamma'_{m+1} = \Gamma'_m - R_m - A_m \qquad (5)$$

Modified feature bags are represented by the symbols Γ_{m+1} and Γ_{m+1}'. Let A_m be the collection of recently discovered significant characteristics. Lastly, it uses A_n + Δ several trees and feature vectors F_{m+1} (.) to create a forest Θ_m+1. After employing the SPMCD data based on the ARF, various procedure information about the prediction of each student's performance, the degree of their involvement, technical skill, and creativity level obtained. This data helped to unveil the main factors that determine the student outcomes in the process.

Efficient African Buffalo Optimization (EABO)

In addition to ARF, after applying EABO, the model accuracy in the SPMCD data is then optimized by moderating the feature selection and the parameter setting. EABO is a bio-inspired optimization method that identifies the optimal characteristics for ARF combined with the finest model parameters using a simulation of the African buffalo tribe's behavior. Following the selection of Cluster Heads (CHs) and cluster organization, the EABO algorithm is used to choose routes. EABO is a novel metaheuristic strategy that mimics and takes advantage of the herd management structure and effective communication found in migratory lifestyles. They use the vocalizations "maaa" and "waaa" for exploration and exploitation throughout the movement. While the "maaa" sound calls the buffalo to remain and exploit the current place because it has enough pasture and is secure, the "waaa" sound is used to explore alternative positions because the current position could not have enough pasture. This sound, which is mathematically represented in equation (6), could assist in facilitating their quest for food.

$$n_{l+1} = n_l + lp1(bg_{max} - x_l) + lp2(bg_{max.l} - x_l) \qquad (6)$$

In this context, n_l symbolizes a "maaa" sound with a specific reference to a buffalo l (l= 1,2,… ,m), $bg_{max.l}$ indicates the buffalo's optimal location within the herd, $bg_{max.l}$ shows the optimal position that a buffalo l,lp1,andlp2 refer to learning parameters ∈ [0,1]. Equation (7), which n_{l+1} represents the buffalo's relocation from its current position n_l to a new position that reflects the wide memory capabilities in migrating lifestyle, is used.

$$x_{l+1} = \frac{(x_l + n_l)}{\lambda} \qquad (7)$$

Equations (8, 9) define the EABO approach by inserting random buffalo l -th such that the optimum solution is determined by changing the buffalo's movement. The fitness value obtained in each iteration is assigned to bg_{max}, while the best for everyone was assigned to $bg_{max.l}$. Assume an M -dimension vector W:

$$W = (w_1, w_2, \dots, w_M) \qquad (8)$$

w_j is in the interval [w_{jmin}, w_{jmax}]. The opposite point of w_j, denoted by $\underline{w}_j$, is as follows:

$$\underline{w}_j = \left(w_{jmax} + w_{jmin}\right) - w_j, j = 1,2,3, \dots M \qquad (9)$$

Assume w_j is a randomly generated solution in M-dimension issue space to use the opposite number idea in the initial population represented in equations (10,11,12). The objective function e is then used to estimate the w_j and $\underline{w}_j$ solution. Therefore, the agent w_j is replaced with $\underline{w}_j$ if $e(\underline{w}_j)$ is greater than e (w_j) (i. e. ,$e(\underline{w}_j)$ <$e(w_j)$); if not, proceed with w_j.

$$e(x) = \left\{j, ForWhich \left|\left(\frac{j}{l} - W_{j_e i}\right)\right| isMinimum, \forall jand\ 1 \le j \le l\right\} \qquad (10)$$

$$e1 = F_{CH} \qquad (11)$$

$$e1 = \frac{1}{\sum_{j=1}^{n} \quad dist(CH_j, NH) + dist(NH, BS)} \qquad (12)$$

The aforementioned sub-objective is regarded as , where each sub-objective's weight is indicated by equation (13).

$$Fitness = \alpha_1(e1) + \alpha_2(e2), where \alpha_1 + \alpha_2 = 1, \alpha_i \in (0,1) \qquad (13)$$

In the EAB-ARF procedure, information shall be gathered about the hyperparameters adopted and the best feature set selected by EABO. This consisted of those aspects that are most relevant to student outcomes such as participation, proficiency, and creativity. For higher feature selection and better model flexibility, Algorithm 1 combines the EAB-ARF and EABO with ARF.

Algorithm 1: Efficient African Buffalo Tuned Adaptive Random Forest (EAB-ARF)

```
Step1: Initializeparametersfortheforest
n_trees = 10
max_depth = 5
min_samples_split = 2
buffalo_tuning_factor = 3
trees = []
Step2: Trainthemodelwithadaptivelytunedtrees
foriinrange(n_trees):
Step2.1: Dynamicallyadjustparametersforeachtree
ifi % 2 == 0:
adjusted_max_depth = max_depth- (i % buffalo_tuning_factor)
```

```
adjusted_min_samples_split = max(min_samples_split- (i % buffalo_tuning_factor),2)
Else:
adjusted_max_depth = max_depth + (i % buffalo_tuning_factor)
adjusted_min_samples_split = max(min_samples_split + (i % buffalo_tuning_factor),2)
Step2.2: TrainaRandomForestTreewiththeadjustedparameters
tree = RandomForestTree(max_depth=adjusted_max_depth,
min_samples_split=adjusted_min_samples_split)
tree.train(X_train,y_train)  # X_train,y_trainaretrainingdataandlabels
trees.append(tree)
Step3: Makepredictionsusingthetrainedforest
predictions = []
fortreeintrees:
tree_predictions = tree.predict(X_test)
predictions.append(tree_predictions)
Step4: Aggregatepredictionsusingmajorityvoting (forclassification)
final_predictions = majority_vote(predictions)
Step5: Outputthefinalpredictions
print(final_predictions)
defmajority_vote(predictions):
final_result = []
foriinrange(len(predictions[0])):
votes = [pred[i] forpredinpredictions]
final_result.append(max(set(votes),key=votes.count))
returnfinal_result
if __name__ == "__main__":
X_train,y_train,X_test = load_data()
model = EAB_ARF(n_trees=10,max_depth=5,min_samples_split=2,buffalo_tuning_factor=3)
model.train(X_train,y_train)
predictions = model.predict(X_test)
print(predictions)
```

RESULTS

The purpose of this research is to improve the assessment of student accomplishment and to foster technical and creative growth in creative multimedia courses at the university level. The research suggested using the EAB-ARF to predict student progress based on several factors, including engagement, technical proficiency, and creativity. Computer memory is 8GM RAM, the CPU is 2,40 GHz, and the experiment is conducted in the Matlab2012b environment.

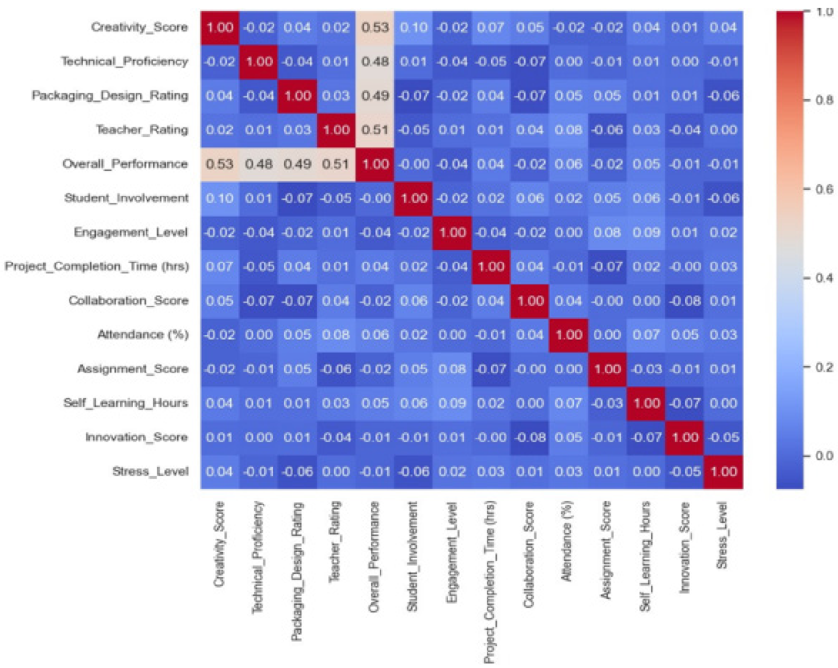

Figure 2. correlation matrix of student performance features

Figure 2 represents the forecast student performance in creative multimedia courses; the correlation matrix shows the relation between several elements, including technical proficiency and originality. Figure 3 represents the feature importance chart directs enhancements in instruction and evaluation by ranking the elements that, according to the EAB-ARF model, have the greatest impact on student achievement.

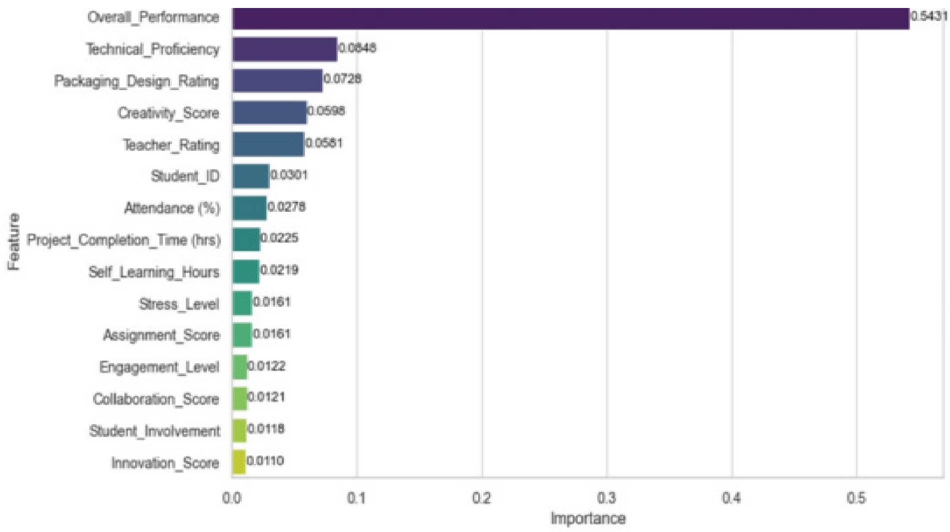

Figure 3. Feature importance

Figure 4 and figure 5 shows the distributions of technical proficiency, creative score, and overall performance show the different levels of student achievement in these important areas as determined by the EAB-ARF model.

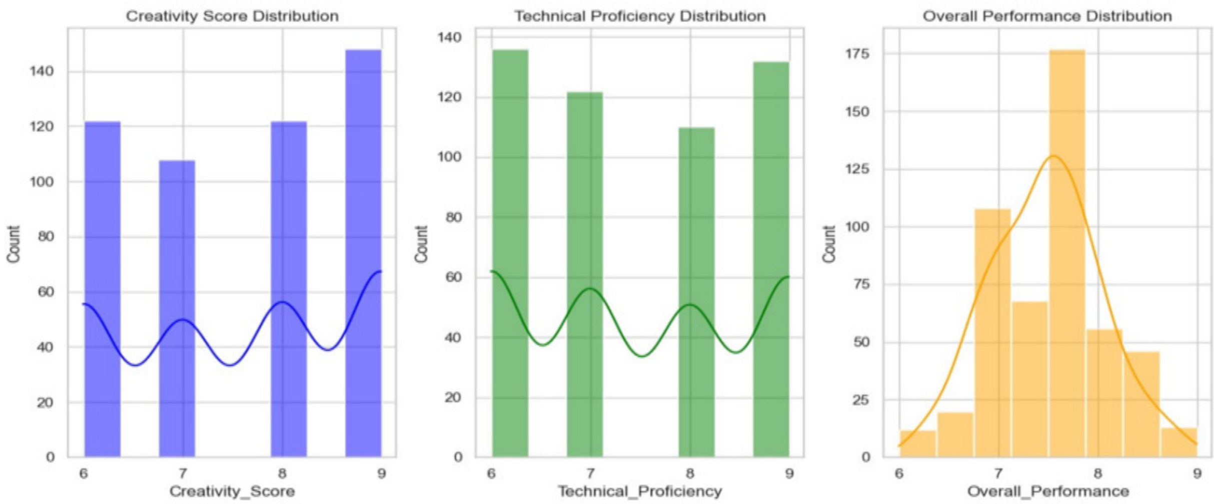

Figure 4. Key performance indicator distribution

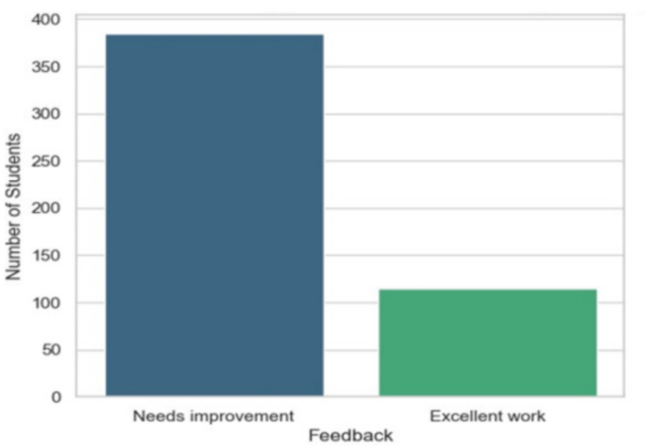

Figure 5. Distribution of feedback

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Comparative analysis

To evaluate the prediction of students' performance, the suggested method, EAB-ARF, was contrasted with various existing approaches, including Linear Regression (LR),[17] RF,[17] Multilayer Perceptron (MLP),[18] Extreme Gradient Boosting (XGBoost),[18] Linear Support Vector Machine (Linear SVM),[19] and Linear Regression (Linear Reg).[19] Accuracy, precision, recall, and F1 score were the performance parameters that were utilized in the computation. A comparison of model accuracies used to forecast student success in creative multimedia courses is shown in figure 6 (a). With an accuracy of 95,8 %, the suggested EAB-ARF model outperforms more conventional models such as RF, and LR. With accuracies of Linear SVM and Linear Reg similarly demonstrate excellent performance, although MLP and XGBoost demonstrate fewer efficacies. The significant outcome demonstrates the EAB-ARF model's improved predictive potential as a result of its adaptive capabilities and feature selection optimization. This illustrates how well it performs to enhance performance evaluation in the teaching of creative multimedia.

The precision of the several ML models is shown in figure 6 (b); the suggested EAB-ARF has the highest precision, at 95,6 %. Both Linear Reg and Linear SVM achieved lesser precision than EAB-ARF. LR performs the poorest, while RF shows a more pronounced difference. EAB-ARF performs outstandingly better than any other approach, proving its greater capacity to find pertinent predictions. In this research, recall is used to determine how effectively the model can capture relevant results about student performance. The proposed EAB-ARF has the highest level of recall presented at 99,2 %. The recall of LR and RF were slightly lower than EAB-ARF (figure 6 (b)). The recall of Linear SVM and Linear Reg is quite less compared with EAB-ARF. As for quantifying model correctness, the F1 score used in this research is to ensure that precision and recall are equal. Once again, the proposed EAB-ARF gets the maximum F1 score of 97,6 %. Conversely, Linear SVM, RF, and LR are defined as shown in figure 6 (b). As it can be seen from the analysis, even though Linear Reg has a slightly higher F1-score, it yet suffers from lower performance compared to EAB-ARF. A summarized performance analysis of the various models used for predicting student performance is presented in table 1.

Table 1. Overall performance analysis

Models	Accuracy	Precision	Recall	F1-score
LR[17]	93	79	98	90
RF[17]	93	86	96	91
MLP[18]	78	-	-	-
XGBoost 18)	76	-	-	-
Linear SVM [19]	90,9	92,4	94,7	93,5
Linear Reg [19]	90,8	91,8	95	93,3
EAB-ARF [Proposed)	95,8	95,6	99,2	97,6

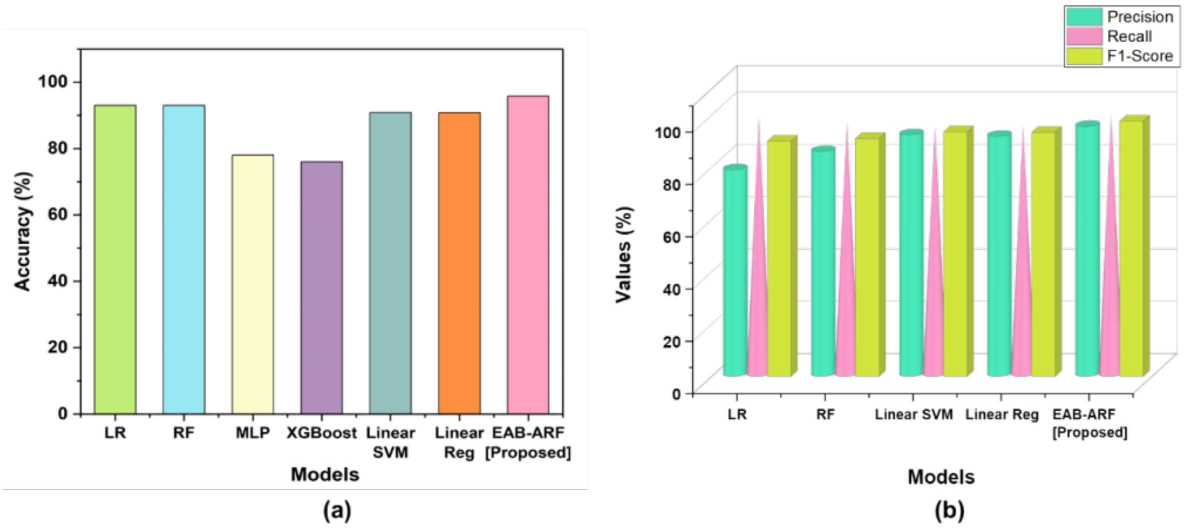

Figure 6. (a) Accuracy (b) Precision, Recall, and F1 score to predict Student Performance

DISCUSSION

Research findings indicated that the EAB-ARF model significantly improves student performance prediction in creative multimedia education. Compared to traditional models, EAB-ARF demonstrated higher accuracy, precision, recall, and F1-score, highlighting its robustness in handling complex relationships among student performance factors. Linear Reg,[17] while widely used, assumes a linear relationship between variables, limiting its effectiveness in capturing non-linear interactions in student performance data. RF,[17] though better at handling complex relationships, can suffer from overfitting and lacks adaptability to evolving student learning patterns. MLP[18] is powerful for deep learning tasks but requires extensive computational resources and large datasets to avoid convergence issues. XGBoost,[18] despite being an effective boosting technique, struggles with high-dimensional data and is sensitive to hyperparameter tuning. Linear SVM,[19] although effective for classification, has difficulty handling noisy data and may perform poorly in highly imbalanced datasets. Linear Reg[19] shares similar limitations with LR, particularly in its inability to model complex student learning behaviors. By integrating feature selection and adaptive learning, EAB-ARF mitigates these limitations, ensuring a more accurate and reliable approach for student performance prediction. These results align with prior research advocating for adaptive models in educational analytics and reinforce the need for dynamic frameworks in assessing creative multimedia education.

CONCLUSIONS

Creative multimedia courses in universities play a crucial role in equipping students with both technical and artistic skills, preparing them for industries such as entertainment, advertising, and digital media. These courses integrate various disciplines like graphic design, animation, and game development, fostering innovation and interdisciplinary learning. This research enhanced the assessment of learning outcomes and supports the development of technical and creative skills in university-level creative multimedia courses. By leveraging an adaptive ML approach, the study introduced a robust model for evaluating student performance, addressing key challenges in traditional assessment methods. The proposed framework effectively captures complex relationships in student learning patterns, reducing overfitting and improving predictive accuracy. While the study demonstrates the potential of intelligent models in educational analytics, its applicability may be influenced by dataset size and quality. As for this research's limitations, future research could focus on working on enhancing the prediction of real-time performance adapted for dynamic learning environments and optimizing the model's capabilities across the various creative multimedia domains to which it could be applied.

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