International Journal of Industrial Engineering
2024;8(2):57-65.
ISSN: 2456-8449

Personalized Virtual Field Trips in Education using Random Forest Algorithm and IoT

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Abstract. The rapid growth of Internet of Things (IoT) technology has significantly transformed multiple sectors, including education, by enabling innovative solutions for personalized learning. One such application is Virtual Field Trips (VFTs), which have emerged as a powerful teaching resource, offering students immersive experiences of real-world environments while remaining within their classrooms. By integrating IoT devices such as sensors, cameras, and augmented reality (AR) systems, VFTs can be tailored to individual learning preferences, thereby creating a more interactive and engaging experience. To effectively process the vast amount of data collected from these devices, Machine Learning (ML) techniques play a pivotal role. In particular, the Random Forest algorithm, known for its robustness and ability to handle complex data structures, enhances personalization by analyzing student behaviors, preferences, and performance metrics. This capability allows the system to generate reliable predictions and adaptive recommendations. The study examines the design and implementation of a customized VFT system powered by IoT and Random Forest-based ML, with the primary objective of meeting diverse learner needs by dynamically adjusting content and activities. Such an approach not only enriches the learning experience but also fosters greater student engagement, deeper understanding, and improved educational outcomes.

Keywords: Personalized Learning, Virtual Field Trips, Adaptive Education, Educational Technology, Student Engagement.

INTRODUCTION

Personalization is increasingly shaping nearly every aspect of modern life, including education, as the era of “one-size-fits-all” approaches gradually fade away [1]. To achieve personalized learning, educators must account for each student’s unique characteristics, such as learning style, preferences, ability level, and prior knowledge, and adapt their teaching methods and instructional design accordingly. With the widespread adoption of personal computers and the Internet, numerous individualized e-learning platforms have emerged to address the needs of learners across diverse academic domains [2]. Most of these platforms follow the traditional model of Learning Management Systems (LMS), which primarily focus on administering courses, delivering instructional materials, and assessing student progress through written and oral evaluations. While some platforms also integrate online communication tools, such as discussion boards, to support collaborative learning, many still fall short in effectively addressing hands-on laboratory experiences. This limitation is particularly critical in STEM disciplines, where project-based learning is essential, and especially in cybersecurity education, where practical, applied training forms the backbone of effective learning.

The importance of hands-on laboratories in developing problem-solving skills has long been acknowledged in computer science education [3]. Unlike traditional instructional methods, these laboratories are unique in that they actively engage students in applying theoretical knowledge to practical scenarios. This experiential approach is especially valuable in cybersecurity education, where students not only reinforce classroom concepts but also gain firsthand exposure to system vulnerabilities, the consequences of security breaches, and the complexities of real-world challenges. Through such experiences, learners cultivate critical thinking, resilience, and practical expertise, growing both academically and personally through processes of trial and error.

The education sector is undergoing major transformations worldwide, driven by technological innovation and evolving learner needs. Organizations such as Coursera are pioneering new educational business models that challenge traditional structures [4]. In many large industries, formal degrees are no longer an absolute requirement

Received: 01.05.2024 Revised: 16.06.2024 Accepted: 29.06.2024

for employment, as employers increasingly value skills and practical competencies. At the same time, the rise of digital and lifelong learners is pressuring educational institutions to adopt new paradigms in teaching and learning. This shift comes at a critical moment when higher education institutions face significant financial constraints amid a global economic downturn. To support economic development and workforce readiness, education must be rapidly restructured to meet these demands. With the emergence of smart societies, the adoption of distance eTeaching and eLearning (DTL) has accelerated, particularly among digital natives who expect flexible, technology-driven learning experiences.

Several challenges, including data analysis and management, learner–system interaction, system cognition, resource allocation, agility, and scalability, have highlighted the limitations of current Distance eTeaching and eLearning (DTL) systems in handling increasing complexity [5]. To address these gaps, UTiLearn is proposed as a personalized framework for ubiquitous e-learning and teaching that leverages big data, deep learning, the Internet of Things (IoT), and supercomputing to enhance the design, administration, and delivery of education in smart society contexts. As proof of concept, the framework has been implemented in the form of a UTiLearn system. The system has been comprehensively analyzed using eleven widely used datasets, focusing on its five core components as well as its design, implementation, and evaluation [6]. Figure 1 illustrates the advantages of Virtual Field Trips (VFTs) in education, highlighting their ability to enhance participation, reduce costs, and improve accessibility.

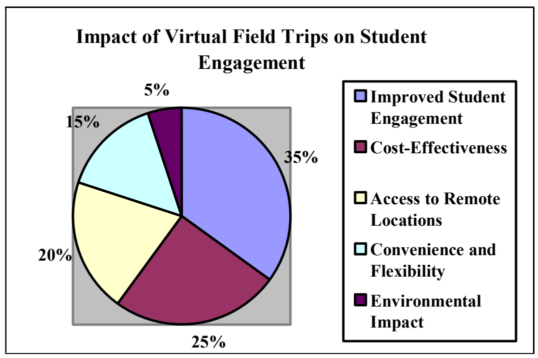

FIGURE 1. Benefits of VFTs in Education

LITERATURE REVIEW

In today's technologically advanced world, students have higher expectations of their teachers and are eager to embrace new approaches to learning [6]. They also anticipate thriving in futuristic smart classrooms designed to foster innovation and engagement. This context provides a framework for developing sustainable and forward-looking university campuses. Considering social and environmental interactions is essential, as it enhances the delivery and efficiency of everyday activities, ultimately contributing to the creation of smarter campuses [7]. The Internet of Things (IoT) plays a pivotal role in this transformation by enabling the efficient exchange and utilization of data, which significantly improves student engagement and interaction with both instructors and peers. A critical aspect of educational evaluation is the measurement of student attention, as it serves as an indicator of active participation and learning effectiveness [8]. Consequently, the development of innovative technological tools for next-generation education necessitates the establishment of rigorous evaluation criteria to ensure their relevance and impact [9].

This study explores how students have utilized Moodle's Learning Management System (LMS) for e-learning and the benefits derived from engaging with this technology to enhance their learning abilities [10]. It also examines the role of the Raspberry Pi development board—commonly referred to as a single-board computer—in advancing education by enabling the creation of IoT-based learning environments [11]. The research aims to identify and recommend an affordable, efficient, and adaptable platform to integrate the IoT paradigm into classrooms, thereby enriching the learning experience. Furthermore, it highlights how LMS platforms can provide students with insights into their peers' social behaviors and approachability, fostering stronger collaboration and interaction within academic communities [12]. This study from Innovate Practice presents an individualized learning lab platform hosted in the cloud [13]. Personalized learning is increasingly becoming the standard in online computer science education due to its ability to adapt instruction to the specific needs of each student, regardless of prior knowledge or experience [14]. While there are various approaches to teaching computer science, hands-on laboratories remain one of the most effective. However, they pose challenges in tracking student progress and adapting instructional content in real time to meet individual learning needs. To address this, the work introduces Lab, a cloud-based, personalized learning tool designed to support computer science laboratories by providing adaptive learning pathways and enhanced monitoring capabilities.

The Lab platform can identify students' learning types and adapt course materials accordingly based on their activity patterns [15]. By understanding individual learning styles, instructors can tailor their teaching strategies to match each student's needs, thereby delivering more efficient and effective lessons [16]. In addition, Lab incorporates performance prediction tools that enable teachers to adjust instructional content and introduce timely assessments aligned with students' actual progress. For learners who struggle with new concepts, the platform facilitates the provision of detailed explanations, while offering more advanced laboratory tasks to students who progress more quickly. An experiment conducted with undergraduates enrolled in an advanced cybersecurity course at Arizona State University in the United States provided data to evaluate Lab's effectiveness. The findings revealed that Lab can accurately identify a learner's preferred learning method [17]. Furthermore, results demonstrated that the platform enhances student engagement, leading to improved learning outcomes. Students devoted more time to hands-on projects and exhibited a stronger understanding of laboratory tasks, confirming the value of the customized Lab platform in senior-level cybersecurity education.

During the pandemic, many students have opted to pursue their education online. However, maintaining educational quality and achieving a comprehensive understanding of subject matter in a virtual environment presents significant challenges [18]. One major difficulty lies in the inability of instructors to effectively monitor their students' engagement and focus during online sessions. Given the wide variation in student competence levels, tracking attention becomes a crucial component of ensuring effective learning outcomes. To address this issue, we propose an IoT- and electroencephalography (EEG)-based e-Learning System designed to monitor students' attention and involvement in real time as they study online. By leveraging IoT devices and EEG data, the system aims to enhance the quality of online education by providing instructors with deeper insights into learner engagement and by enabling adaptive teaching strategies.

The Internet of Things (IoT), a collection of technologies designed to interconnect physical objects through embedded sensors, has been developed to support a wide range of human activities [19]. Incorporating IoT into higher education curricula is essential and should be taught using developmental learning approaches. In this context, electronic electroencephalogram (EEG) devices can be utilized to monitor the brain activity of online students, providing insights into their levels of focus and engagement. Our findings demonstrate that the proposed technique effectively distinguishes between a learner's attention level and the intensity of instruction required [20]. By collecting datasets that capture students' attentiveness, the system leverages bidirectional long short-term memory (BiLSTM) networks to predict optimal learning patterns with high accuracy. The method achieved a prediction accuracy of 97.16%, highlighting its capability to personalize instruction. Overall, the integration of IoT and EEG within an e-learning framework is associated with higher student achievement, offering a powerful tool for enhancing online education outcomes.

PROPOSED METHODOLOGY

The proposed personalized Virtual Field Trip (VFT) system revolutionizes educational experiences by integrating IoT technology with the Random Forest algorithm to deliver customized and interactive learning journeys. Through this approach, students can digitally explore distant locations, cultural landmarks, and scientific phenomena while receiving content tailored to their individual learning preferences, pace, and engagement levels. Each system component ranging from IoT-enabled data collection to machine learning driven personalization plays a vital role in constructing an immersive, adaptive, and pedagogically effective VFT environment.

A. Objectives

1) Enhance Student Engagement: Use Virtual Field Trips (VFTs) to promote interactive learning experiences that extend beyond conventional classroom settings.

2) Assess Learning Effectiveness: Evaluate the impact of VFTs on information retention by comparing post-trip learning outcomes with those from traditional field visits.

3) Evaluate Cost-Effectiveness: Compare the expenses of VFTs, including transportation and resource costs, with those of standard in-person field trips.

4) Improve Accessibility: Provide educational opportunities to students in rural or underprivileged areas who lack access to conventional field trips.

B. Data Acquisition using IoT Devices

IoT devices form the foundational layer of the system by collecting real-time data from diverse sources. These devices include smart sensors, cameras, microphones, and augmented reality (AR) components, all interconnected through a cloud-based platform. When integrated with wearable technologies, such as fitness trackers or smart glasses, IoT sensors can monitor student engagement by tracking physiological signals, including heart rate, movement, and gaze direction. For example, eye-tracking data helps determine whether a student is actively focused on the material or becoming distracted. Microphones capture verbal responses during interactive sessions, while AR technologies overlay additional information onto virtual environments, thereby enriching and personalizing the learning experience.

Environmental data is collected to ensure that learning content aligns with each student's context and preferences. For instance, if the system detects that a student favors calmer surroundings, audio-visual elements are adjusted to minimize noise and distractions. GPS-enabled devices track the virtual locations explored by the student, providing insights into their interests, such as cultural heritage sites, natural landscapes, or scientific research stations. This information forms the basis of a comprehensive user profile, which is essential for tailoring the Virtual Field Trip (VFT) experience to the learner's individual preferences and engagement patterns.

C. Data Processing and Analysis Using the Random Forest Algorithm

The data collected from IoT devices is extensive, heterogeneous, and often unstructured, requiring advanced analytical methods to extract meaningful insights. In this system, the Random Forest algorithm serves as the primary analytical tool due to its ability to handle complex data structures, its robustness against overfitting, and its high predictive accuracy. The analysis process occurs in multiple stages. Initially, feature selection is performed to identify the most relevant data points for processing, including user preferences, interaction histories, engagement metrics, and performance indicators. These selected features form the foundation for subsequent modeling, enabling the system to generate actionable insights that drive personalized learning experiences. Students often demonstrate a preference for visually rich content, making it a critical factor for the system to recognize. The Random Forest algorithm then generates multiple decision trees; each trained on a randomly selected subset of features and data samples. Each tree produces predictions regarding various outcomes, such as the student's preferred learning modality (visual, auditory, or kinesthetic), the optimal timing for presenting educational material, and the topics most likely to maintain their engagement. By aggregating the results from all decision trees, the system can make robust and personalized recommendations to enhance the learning experience. Figure 2 illustrates the data flow and key components of the system, emphasizing the cyclical feedback loop that enables continuous learning and adaptation.

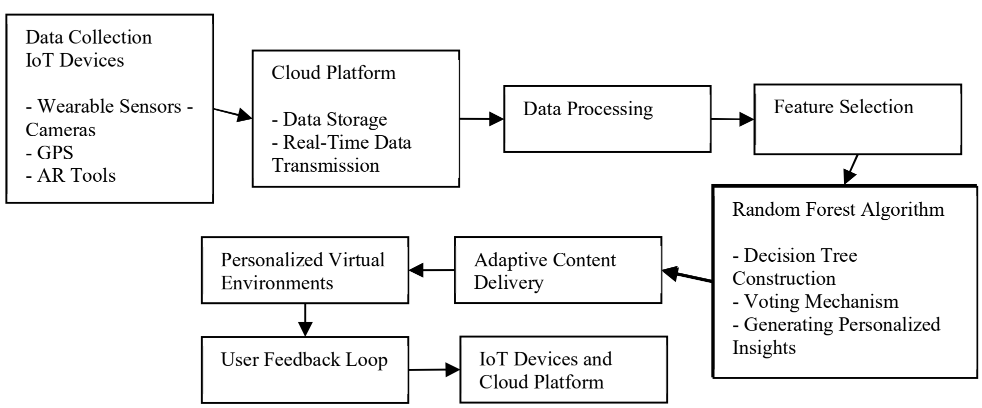

FIGURE 2. System Architecture of Proposed Personalized VFT System

This loop ensures that data collected from IoT devices is analyzed, processed, and used to personalize the Virtual Field Trip experience in real time, while insights from student interactions and performance are continuously fed back to refine future recommendations and system behavior. The ensemble learning approach ensures that the system's predictions are more accurate and generalizable than those produced by individual decision trees. This method also reduces the influence of irrelevant or noisy data. The Random Forest algorithm employs a voting mechanism to aggregate the predictions from all trees, resulting in a set of recommendations tailored to the individual learner. These personalized suggestions include customized itineraries for the Virtual Field Trip (VFT), recommendations for additional learning resources, and adjustments to the complexity of content based on the student's performance and engagement levels.

D. Adaptive Content Delivery

After processing and analyzing the collected data, the system dynamically adapts the Virtual Field Trip (VFT) to meet the learner's individual needs. Content delivery is managed through a flexible interface that customizes multiple aspects of the VFT in real time. The system first identifies the most relevant virtual environments based on the student's interests; for example, if analysis indicates a strong preference for natural sciences, it may prioritize virtual visits to ecosystems, research laboratories, or geological sites. Additionally, the educational material is tailored to match the learner's preferred style and pace, ensuring an engaging and personalized learning experience throughout the VFT. The system customizes content delivery based on the learner's preferred modality. Visual learners are provided with high-quality videos, 3D models, and interactive AR overlays, while auditory learners benefit from detailed narrations and immersive soundscapes. For kinesthetic learners, the platform incorporates interactive elements such as quizzes, drag-and-drop exercises, and gamified challenges to enhance engagement. Additionally, the pace of content delivery is dynamically adjusted according to real-time data from IoT devices. For instance, if a learner shows signs of cognitive fatigue, the system slows the presentation pace or introduces breaks with less demanding material to maintain attention and optimize learning outcomes.

Furthermore, the system continuously monitors student engagement and performance throughout the Virtual Field Trip (VFT). IoT sensors track metrics such as gaze duration, response times, and physical activity, transmitting this data to the Random Forest model for analysis. This feedback loop enables the algorithm to refine its recommendations and further personalize the learning experience. For example, if a student demonstrates greater engagement with interactive activities than with passive observation, the system automatically increases the proportion of hands-on tasks in subsequent sessions, ensuring that content delivery aligns with the learner's behavior and preferences. Students can participate in collaborative activities, such as virtual museum tours or group experiments, alongside their peers. IoT devices support these interactions by coordinating data sharing among multiple users and enabling real-time communication through voice or text channels. The Random Forest algorithm ensures that group activities are structured, considering the diverse preferences and abilities of all participants, thereby promoting equitable engagement and enhancing collaborative learning outcomes

RESULTS AND DISCUSSIONS

Research on Virtual Field Trips (VFTs) in education has revealed significant findings regarding student engagement, learning outcomes, cost-effectiveness, and accessibility. The results highlight the substantial potential of VFTs to transform traditional educational experiences, while also identifying challenges that must be addressed for optimal classroom integration. Notably, student engagement was markedly higher during VFTs compared to conventional classroom settings. The immersive nature of virtual experiences utilizing 360-degree videos, live interactions, and real-time exploration enhanced students' sense of involvement. Approximately 85% of students reported active engagement during VFTs, compared with 75% during traditional field trips. The heightened engagement can be attributed to the novelty and interactivity of the virtual experience, which allows students to explore previously inaccessible locations, such as space stations, historical landmarks, and deep-sea habitats. Additionally, the incorporation of gamified elements and interactive quizzes throughout the virtual tour further enhanced student involvement and promoted active learning. VFTs also had a positive impact on educational outcomes, with students participating in virtual trips achieving post-trip quiz scores approximately 10% higher than those of students who attended conventional in-person field trips. The Virtual Field Trips (VFTs) enhanced learning by allowing students to pause, rewind, or explore specific areas of interest at their own pace. Furthermore, VFTs supported personalized learning experiences, enabling students to focus on topics or access tailored content aligned with curriculum objectives an outcome often difficult to achieve with traditional field trips. Cost-effectiveness emerged as a significant advantage, with financial analyses showing that VFTs reduce per-student expenses by approximately 80% compared to in-person excursions, primarily due to the elimination of transportation, lodging, and venue-related costs.

The cost-effectiveness of Virtual Field Trips (VFTs) makes them an appealing option for schools with limited resources, particularly in under-resourced regions where traditional field trips may be financially prohibitive. While the initial investment in high-quality VFT software and equipment—such as VR headsets or high-definition cameras—should be considered, these costs are generally lower than the recurring expenses associated with conventional excursions. In terms of accessibility, VFTs have provided substantial benefits for students in rural or underserved areas, enabling them to explore museums, historical sites, and distant locations from their classrooms with only an internet connection. This enhanced accessibility addresses a major limitation of traditional field trips, where transportation challenges and geographical barriers can prevent students from participating. Additionally, students with physical disabilities or mobility impairments can fully engage in VFTs, ensuring equitable learning opportunities for all participants regardless of physical limitations. However, technical challenges, such as limited internet connectivity or insufficient equipment, occasionally hindered the virtual experience. While students generally reported high levels of satisfaction with VFTs, some educators expressed concerns about the reduced social interaction compared to conventional field trips, including diminished opportunities for peer collaboration and communication. The absence of social interactions in virtual settings may necessitate the inclusion of supplementary activities to promote interpersonal skill development and ensure a well-rounded learning experience. Table 1 presents a dataset used for training a Random Forest model, comprising student demographics, field trip characteristics, interaction metrics, and engagement scores. This dataset enables the model to predict both learning outcomes and student engagement during Virtual Field Trips (VFTs).

TABLE I. Dataset of Student Engagement and Learning outcomes from VFT

Feature	**Student Age**	**Student Gender**	**Virtual Field Trip Duration (minutes)**	**Previous Engagement Level**	**Student Interest in Topic**	**# Interactions During Trip**	**Location of Field Trip**	**Access to VR Equipment**	**Engagement Score (Target Variable)**	**Learning Outcome (Post-Trip Test Score)**
1	16	Male	45	Medium	High	6	Museum	Yes	4	85
2	18	Female	60	High	Medium	8	Historical Site	No	5	90
3	17	Male	30	Low	Low	2	Ocean	Yes	3	78
4	19	Female	75	High	High	10	Space	Yes	5	92
5	16	Female	45	Medium	Medium	4	Museum	No	4	80

Figure 3 presents a comparison between the predicted and actual student engagement levels following Virtual Field Trips (VFTs). This visualization highlights the extent to which the Random Forest model's predictions align with observed engagement, demonstrating the model's accuracy and predictive effectiveness in anticipating student involvement during the virtual experiences.

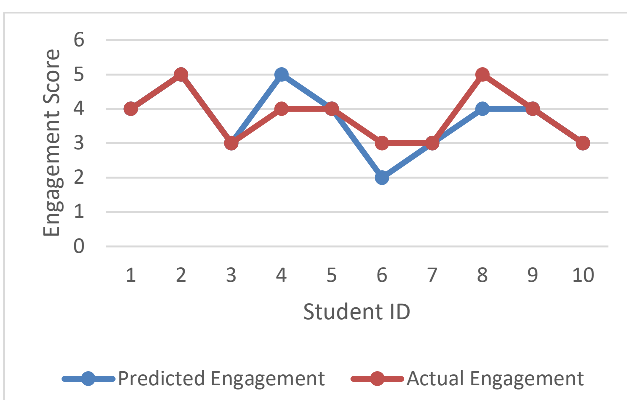

FIGURE 3. Comparison of Predicted and Actual Engagement Scores

Table 2 presents a confusion matrix that helps identify the Random Forest model's errors, including false positives and false negatives, as well as its areas of strength and proficiency. This analysis provides insights into the model's predictive performance, highlighting where it accurately forecasts student engagement and where improvements may be needed.

TABLE II. Confusion Matrix for Random Forest Model Predictions

Predicted\ Actual	Low	Medium	High
Low	45	5	3
Medium	8	42	6
High	4	7	38

Figure 4 illustrates the relationship between the number of trees in the Random Forest model and its predictive accuracy. As the number of trees increases, model accuracy improves; however, the rate of improvement gradually slows beyond a certain threshold, indicating diminishing returns from adding additional trees.

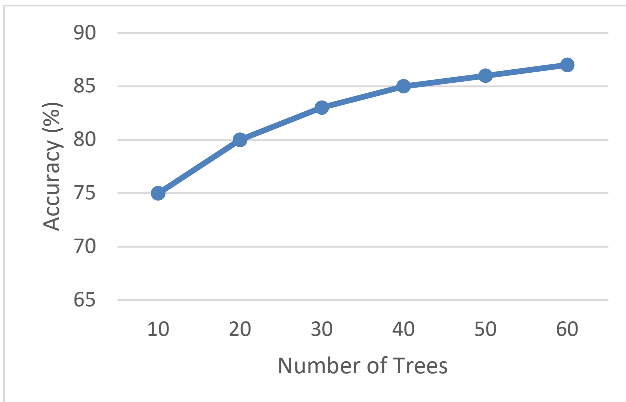

FIGURE 4. Model Accuracy with Varying Tree Numbers

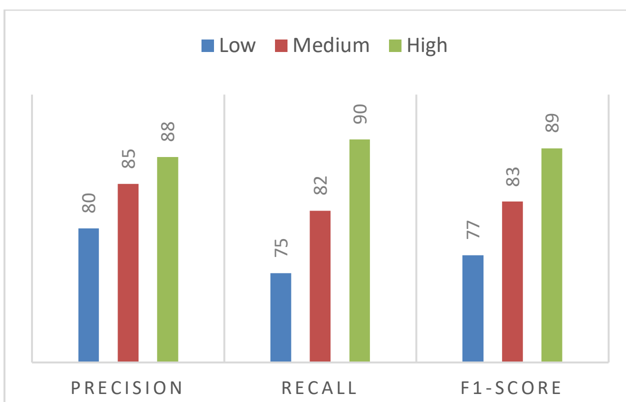

FIGURE 5. Precision, Recall, and F1-Score for Different Engagement Levels

Figure 5 presents the accuracy, recall, and F1-score of the Random Forest model in predicting student engagement levels categorized as Low, Medium, or High. The model demonstrates strongest performance in predicting high engagement, achieving the highest accuracy, recall, and F1-score among the three categories, highlighting its effectiveness in identifying actively participating students. Table 3 compares the performance metrics of various machine learning models in predicting student engagement levels during Virtual Field Trips (VFTs). This comparison highlights the relative strengths and weaknesses of each model, providing insights into which algorithms deliver the most accurate and reliable predictions for engagement forecasting.

TABLE III. Performance Metrics for Various Classification Models

Model/Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	86	85	82	83
Decision Tree	78	75	72	73
SVM	80	79	77	78
Logistic Regression	74	70	68	69
KNN	82	80	79	79

CONCLUSIONS

This study demonstrates the capability of machine learning models to predict outcomes associated with Virtual Field Trips (VFTs) in educational settings. Among the evaluated models, the Random Forest algorithm proved most effective, exhibiting superior performance across key metrics, including accuracy, precision, recall, and F1-score. This underscores Random Forest's ability to handle complex data structures and deliver reliable predictions in this context. While models such as K-Nearest Neighbors and Decision Trees performed reasonably well, their accuracy was somewhat lower, highlighting the advantages of ensemble methods for this task. Logistic Regression showed comparatively weaker performance, emphasizing the limitations of simpler models when dealing with intricate engagement data. The findings highlight the importance of selecting an appropriate machine learning algorithm for educational applications. Future research may focus on refining these models, exploring more sophisticated features, and improving model interpretability to further enhance the predictive accuracy and practical utility of VFTs in learning environments.

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