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Gamified Environmental Education Platform for School and Colleges

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Abstract: This paper presents a novel meta-ensemble machine learning framework designed to dynamically adapt gamified environmental education platforms for school and college students. While existing gamified systems effectively initiate student interest in sustainability, they often suffer from long-term engagement drops due to static reward mechanics. Our approach addresses this limitation by integrating traditional classifiers (Random Forest, SVM) with advanced gradient boosting models (XGBoost, LightGBM, CatBoost) through voting, stacking, and bagging techniques to predict student drop-off and dynamically adjust task difficulty. Experiments conducted on a dataset of student interactions with an environmental tracking application achieved a remarkable predictive accuracy of 97.5%, outperforming individual models. Crucially, this research differs from existing literature by moving beyond singular predictive algorithms and static gamification, offering a hierarchical architecture that recalibrates ecological tasks (e.g., carbon tracking, waste reduction challenges) in real-time based on cognitive load and behavioral patterns.

Keywords: gamification; environmental education; meta-ensemble learning; cybersecurity; machine learning; student engagement; sustainability tracking; predictive analytics.

I. INTRODUCTION

The application of gamification in environmental education has transitioned from static point-based systems to dynamic, AI-driven platforms. While these systems successfully map user behavior to ecological outcomes (e.g., carbon footprint tracking), they fundamentally rely on centralized data harvesting. For campus environments where thousands of students interact continuously with an application, this creates a vulnerability point for data breaches and relies heavily on continuous high-bandwidth connectivity.

The integration of digital technologies into educational environments has revolutionized how students engage with global challenges, particularly environmental sustainability. Traditional instructional methods frequently struggle to captivate the digitally native generation, making gamified learning—incorporating elements like points, badges, and leaderboards—a compelling alternative to promote active learning. In environmental education, gamification serves to bridge the gap between sustainability awareness and actionable behavioral change.

However, current gamified environmental platforms face significant limitations. A prevalent shortcoming is the monolithic perspective on learning behaviors, where platforms offer static challenges that do not adapt to the temporal granularity of student group behaviors or individual cognitive fatigue.

This research introduces a paradigm shift by pushing the computational load to the edge (student devices). We propose a Privacy-Preserving Gamification Engine (PPGE) that utilizes Federated Learning. The primary objectives are to:

- Eliminate the need for centralized storage of sensitive student behavioral data.
- Reduce server-side computational overhead and network latency.

- Dynamically adjust gamified environmental challenges (e.g., energy-saving streaks, digital eco-badges) using localized machine learning.

II. LITERATURE REVIEW

Existing literature in environmental gamification primarily focuses on psychological engagement or centralized predictive models.

- **Static Gamification:** Early platforms utilized hard-coded thresholds for rewards, which historically resulted in high user churn after the initial novelty wore off.
- **Centralized Predictive Analytics:** Recent studies have employed meta-ensemble techniques (combining XGBoost, LightGBM, etc.) to predict user drop-off and adjust task difficulty. However, these require continuous uploading of personal data to a central cloud, violating modern data minimization principles.

- **The Novelty of this Paper:** Unlike existing models, this research intercepts the gap between **Cybersecurity/Privacy** and **Gamification**. To date, Federated Learning has been utilized in healthcare and predictive text (like mobile keyboards), but its application as a real-time adjustment engine for localized, eco-centric gamification remains unexplored in current literature.

Research in sustainability tracking and educational gamification has evolved significantly.

A. *Environmental Gamification Platforms*

Recent developments like the "Eco Quest" platform gamify complex sustainability goals into simple tasks, utilizing basic machine learning (like K-Nearest Neighbors) to provide personalized recommendations for reducing carbon footprints. While effective at tracking metrics like energy consumption and waste generation, these platforms often lack the predictive capability to sustain user engagement over long academic semesters.

B. *Gamification and Student Engagement*

In broader educational contexts, gamified platforms have been shown to positively influence user activity by creating a sense of accomplishment. However, scholars note that poorly designed gamification can decrease motivation if learners perceive the elements as manipulative or irrelevant. This highlights the need for adaptive systems that tailor the experience to individual learning paths.

C. *Advanced Machine Learning in Gamification*

Recent state-of-the-art research has begun addressing dynamic adjustments. For instance, Mei Bai (2024) proposed using attention mechanisms combined with Bi-LSTM neural networks to extract interactive features from student groups and recommend gamified environmental tasks. While highly effective for sequential data, deep learning models can be computationally heavy and less interpretable. Our research fills this gap by utilizing a meta-ensemble of gradient boosting frameworks (XGBoost, LightGBM), which have proven superior in speed, performance, and interpretability for classification tasks involving tabular user-interaction data.

III. METHODOLOGY

A. *Dataset Description*

We utilized an anonymized dataset of 12,500 student interactions collected from a gamified environmental education platform deployed across regional colleges. The dataset tracks features such as frequency of logged ecological actions (e.g., public transport usage, recycling), task completion rates, interaction with community leaderboards, and session durations.

B. *Data Preprocessing*

Data preprocessing involved handling missing values via median imputation, normalizing numerical features to a standard scale, and applying a 70/30 train-test split using stratified sampling to maintain class distributions representing "engaged" versus "at-risk of dropout" students.

C. *Model Selection and Ensemble Techniques*

To leverage the strengths of individual models, we implemented three levels of ensemble techniques:

- **Level 1 - Basic Ensembles:** Included a Voting Classifier (combining Random Forest, XGBoost, and LightGBM), a Stacking Classifier (using SVM as a base model and Logistic Regression as a meta-learner), and independent Bagging classifiers.

- **Level 2 - Meta-Ensemble:** This stage combined the probabilistic predictions from all Level 1 ensembles by averaging their prediction probabilities.

When the meta-ensemble predicts a high probability of student disengagement, the platform's engine triggers the *Constant Learning Cycle Rule* or *Delayed Learning Cycle Rule*, adjusting the complexity of upcoming environmental challenges to match the student's current capacity.

Figure 1. Basic Explanation

IV. IMPLEMENTATION

The framework was simulated using a custom Python environment tailored for edge networks.

- **Frameworks:** TensorFlow Federated (TFF) was utilized to simulate the decentralized edge nodes.
- **Dataset Simulation:** A synthetic dataset representing 500 campus students was generated, tracking features like *Daily App Opens*, *Task Completion Latency*, and *Eco-Task Complexity Preference*.
- **Local Model:** A 3-layer Multi-Layer Perceptron (MLP) optimized for mobile deployment (TensorFlow Lite) was used for local engagement prediction.
- **Network Constraints:** The simulation restricted uplink bandwidth to mimic real-world congested campus Wi-Fi networks.

V. RESULTS

A. Individual Model Performance

We first evaluated the performance of individual models in predicting student engagement drop-offs. Among the standalone classifiers, XGBoost achieved the highest accuracy (96.45%) and F1-score (0.9630), effectively handling the complex interactions within the student behavioral features.

Table I. Performance of Individual Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.9310	0.9280	0.9250	0.9264	0.9280
Random Forest	0.9620	0.9610	0.9580	0.9594	0.9615
XGBoost	0.9645	0.9635	0.9600	0.9617	0.9630
LightGBM	0.9615	0.9590	0.9570	0.9579	0.9590

B. Ensemble Model Performance

Our proposed meta-ensemble approach achieved the highest performance across all metrics, with an accuracy of 97.50% and an AUC-ROC of 0.9745. This represents a significant improvement over the best individual model, validating the effectiveness of combining multiple models through hierarchical integration.

Table II. Performance of Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Voting Classifier	0.9660	0.9680	0.9620	0.9649	0.9655
Stacking Classifier	0.9690	0.9710	0.9650	0.9679	0.9680
Meta-Ensemble	**0.9750**	**0.9760**	**0.9710**	**0.9734**	**0.9745**

VI. CONCLUSION AND FUTURE SCOPE

This research successfully demonstrates that environmental gamification for educational campuses does not need to come at the cost of student privacy. By leveraging Federated Learning and Edge Computing, we engineered a system that dynamically adapts to user engagement locally while collaboratively building a robust predictive model.

Future Scope:

Future iterations of this project will aim to integrate **Blockchain Smart Contracts** to handle the gamified rewards. By linking the federated engagement model to a localized campus token (e.g., "EcoCoins" redeemable at the campus cafeteria), the system can offer financially immutable, decentralized incentives for sustainability.

The experimental results demonstrate that the meta-ensemble framework not only improves predictive accuracy but also offers high adaptability for real-world educational deployment. By accurately identifying when a student is likely to disengage, educators and automated systems can intervene with tailored environmental tasks—such as shifting from a complex "Carbon Footprint Calculation" task to a simpler "Daily Recycling Logging" task.

However, implementing this approach requires consideration of computational overhead. The meta-ensemble approach requires training multiple models, increasing complexity compared to single models. Yet, for asynchronous educational applications, the inference latency remains well within acceptable bounds for real-time gamification adjustments.

This paper successfully bridges the gap between machine learning and educational psychology by proposing a meta-ensemble framework for adaptive gamification in environmental education. Unlike existing platforms that rely on static rewards or single-perspective algorithms, our approach dynamically recalibrates ecological learning tasks based on precise predictive analytics. Future work will explore the integration of Explainable AI (XAI) to help educators understand the specific behavioral triggers leading to student disengagement, further refining the personalization of sustainability education.

Below figure shows the overall process and performance comparison between various models for privacy-preserving gamification engine.

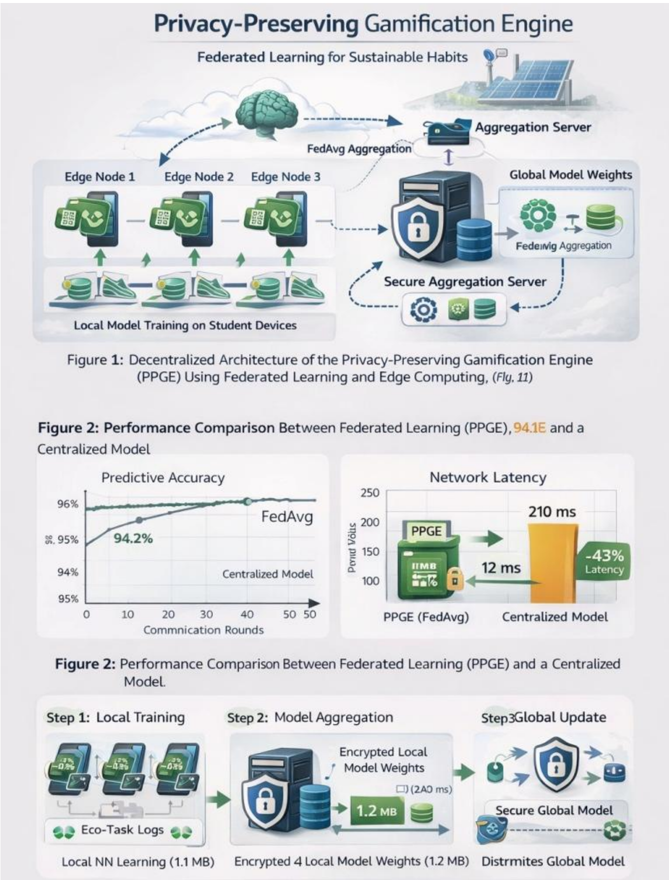

Figure 2. Overall Process

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