

Block Chain Based Digital Certificate Generation and Verification System

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ABSTRACT

The rapid growth of online learning platforms has increased the demand for accurate course recommendation mechanisms and secure digital certification systems. Existing e-learning frameworks typically rely on hybrid filtering, clustering, or ontology-based approaches for personalization and certificate management. However, these systems struggle with dynamic course structures, learner diversity, and weaknesses in centralized certificate verification. To address these challenges, this paper proposes an XGBoost–Integrated Blockchain Certifier Framework that combines a lightweight course recommendation model with a secure blockchain-based digital certification mechanism. The XGBoost model analyzes learner academic history, performance indicators, and skill preferences to generate personalized course recommendations, achieving a correlation value close to 0.99 with low prediction error across multiple training configurations. For certificate security, the framework employs an extended X.509 certificate structure integrated with blockchain-based hashing, ensuring tamper-proof validation and transparent verification. Experimental results demonstrate strong predictive accuracy, stable generalization, and reliable certificate integrity under increasing user load, making the proposed system suitable for modern e-learning environments.

Keywords: Course Recommendation, XGBoost Model, Blockchain, Certificate Verification.

I. INTRODUCTION

Digital learning has become an essential component of modern education as universities, training institutes, and online platforms continue to expand their virtual offerings. Learners increasingly depend on online courses, multimedia content, and self-paced learning modules to enhance their academic and professional skills. As these platforms grow in scale and complexity, there is a rising need for intelligent systems that can guide learners toward suitable courses and provide trustworthy digital credentials upon completion [1,2]. Course recommendation systems and secure digital certification frameworks have therefore become critical components of contemporary e-learning ecosystems.

Despite advancements in this domain, several limitations persist. Many existing recommendation models rely heavily on historical ratings or similarity-based approaches, making them less effective in environments where learner behavior, course content, and skill requirements change frequently [3,4]. Similarly, conventional certificate management systems often depend on centralized storage, exposing them to risks such as data tampering, forgery, and unauthorized access. These challenges limit both personalization and trust in digital learning platforms. Recent studies highlight a clear gap between recommendation accuracy and certificate security. Hybrid filtering and clustering techniques provide limited adaptability, while deep learning-based approaches, although powerful, introduce high computational complexity and scalability issues. On the certification side, many solutions lack

cryptographic verification and transparent storage mechanisms, making digital credentials vulnerable to manipulation [5,6]. To address these issues, this paper proposes an integrated framework that combines accurate course recommendation with secure blockchain-based certificate validation.

The proposed XGBoost–Blockchain Certifier Framework focuses on delivering high prediction accuracy using a lightweight ensemble model while ensuring certificate integrity through blockchain-backed hashing and verification. The remainder of the paper is organized as follows. Section II reviews related work, Section III discusses challenges in existing systems, Section IV presents the proposed methodology, Section V describes the experimental setup, Section VI analyzes results, and Section VII concludes the study.

II. LITERATURE REVIEW

Several researchers have explored course recommendations in e-learning environments using diverse methodologies. Early approaches focused on collaborative filtering and clustering to match learners with relevant courses based on historical behavior and preferences. While these methods improved basic personalization, they struggled with cold-start problems and evolving curricula. Ontology-based systems [7-9] were later introduced to address knowledge representation and semantic relationships among courses and learners. Although effective in reducing cold-start issues, these systems lacked adaptability to behavioral changes across platforms. Reinforcement learning and graph-based models further enhanced personalization by modeling sequential learning paths and complex dependencies, but they introduced significant computational overhead and scalability challenges.

Recent deep learning-based approaches, including LSTM, attention mechanisms, and transformer architectures, demonstrated strong predictive performance by capturing temporal and contextual patterns. However, these models often require extensive training data, high computational resources, and careful parameter tuning, limiting their practical deployment in real-time educational systems [11,12]. On the certification side, blockchain-based frameworks have been proposed to improve trust and transparency in academic credential management. These systems offer immutability and tamper resistance but are often developed independently of recommendation mechanisms. As a result, existing solutions lack unified workflows that integrate personalization with secure credential issuance.

2.1 Challenges in Existing Systems

Although numerous models have been proposed for course recommendation and digital certificate management, practical limitations continue to hinder their effectiveness. Many systems fail to capture complex interactions between learner behavior, academic performance, and course relevance, leading to reduced prediction accuracy. Deep learning and graph-based architectures introduce high computational overhead, making them unsuitable for large-scale or real-time environments. Cold-start issues remain a major concern for new learners and newly introduced courses due to insufficient historical data. Additionally, most existing systems lack adaptability to dynamic curricula, as course content and skill requirements evolve frequently. Cluster-based models often generalize learner behavior excessively, resulting in poor personalization.

From a security perspective, centralized certificate storage systems are vulnerable to forgery and unauthorized modification. Scalability issues arise as user numbers increase, leading to performance degradation and slower verification. Moreover, recommendation and certification modules are typically treated independently, resulting in fragmented workflows and reduced efficiency.

III. METHODS AND EXPERIMENTATION SETUP

3.1 Proposed Methodology

The proposed framework integrates a lightweight course recommendation engine with a secure digital certification subsystem. It supports the complete learning lifecycle, including registration, course recommendation, performance evaluation, and certificate issuance. The architecture, shown in Fig. 1, illustrates the interaction between the XGBoost-based recommendation module and the blockchain-based certification module.

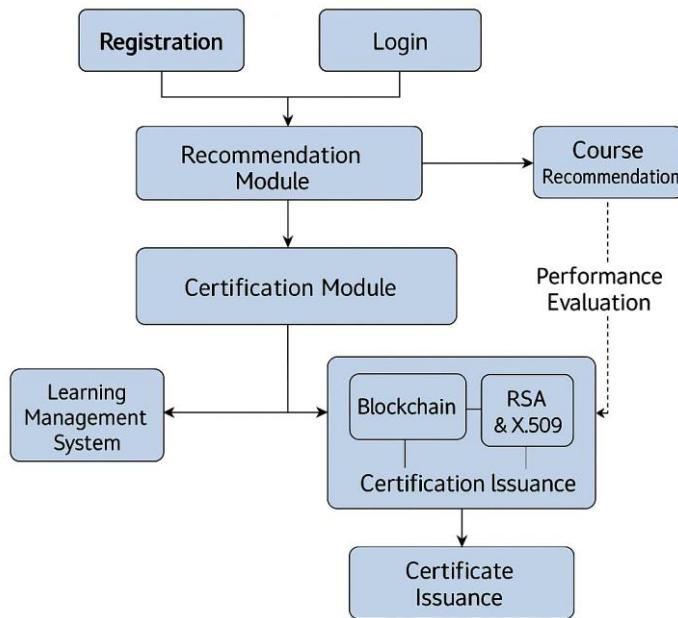


Figure 1: Proposed Framework Using XGBoost

3.2 Registration and Authentication Phase

During registration, learners submit essential personal and academic information. Each user is assigned unique credentials and a blockchain address. RSA-based cryptographic techniques are applied to ensure confidentiality and integrity. Learner data is digitally signed and stored on the blockchain, enabling tamper detection and secure verification during authentication.

3.3 XGBoost-Based Course Recommendation Module

The recommendation module analyzes learner academic history, preferences, and contextual attributes using XGBoost. Data preprocessing includes encoding categorical features and handling missing values. XGBoost automatically performs feature selection through gain-based splits and iteratively refines predictions using gradient boosting. The trained ensemble model outputs course recommendations aligned with learner strengths and interests, as illustrated in Fig. 2.

3.4 Learning Management System Integration

Once a course is recommended, the learning management system assigns instructors and monitors learner engagement and performance. Examination results are validated and securely stored. Identity verification ensures that performance records correspond to the correct learner before certification.

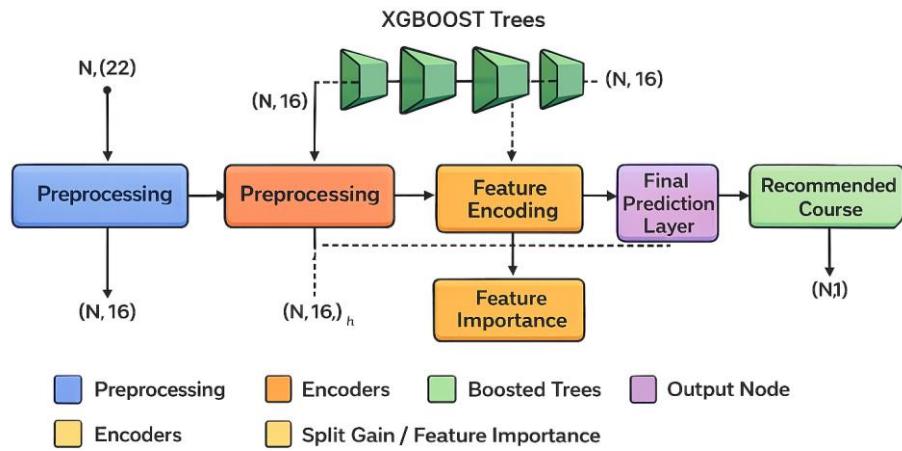


Figure 2: Intelligent Course Recommendation Architecture Using XGBoost

3.5 Certificate Issuance Subsystem

After successful course completion, the system generates a digital certificate following core X.509 v3 fields. The certificate is encoded, hashed using SHA-256, and stored on the blockchain using a Proof-of-Work mechanism. This process ensures immutability, tamper resistance, and transparent verification. Certificates are issued only after successful identity and signature validation.

3.6 Experimental Setup

The framework was implemented using Python in a Windows-based environment with sufficient memory and storage resources. XGBoost was configured using standard tree boosting parameters. Two datasets were used for evaluation: a course recommendation dataset containing over 3,500 courses with descriptive attributes, and a student performance dataset comprising academic and demographic features. Model performance was evaluated using Pearson correlation coefficient, Mean Squared Error, Mean Absolute Error, and Root Mean Squared Error. Experiments were conducted across multiple training-test splits and K-fold cross-validation settings to assess stability and generalization.

IV. RESULTS AND DISCUSSION

The experimental evaluation demonstrates that the proposed XGBoost–Blockchain Certifier Framework achieves consistently strong performance across different training configurations and validation strategies. The behavior of the recommendation model was first analyzed by varying the training percentage from 40% to 90%, as illustrated in Fig. 3. The results show a clear and stable improvement in prediction accuracy as the amount of training data increases. Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) steadily decrease with higher training percentages, indicating that the XGBoost model effectively learns meaningful relationships between learner attributes and course outcomes. This trend confirms that the model benefits from increased data availability without exhibiting instability or excessive variance.

The correlation coefficient follows an opposite but complementary trend. At lower training percentages, the correlation remains moderate, reflecting limited exposure to learner-course patterns. However, once the training percentage exceeds 70%, correlation values increase sharply and stabilize between 0.96 and 0.99. This stabilization suggests that the model reaches a saturation point where additional training data yields marginal gains, indicating strong generalization capability rather than

overfitting. The flattening of error curves at higher training splits further supports this observation, showing that the model converges efficiently.

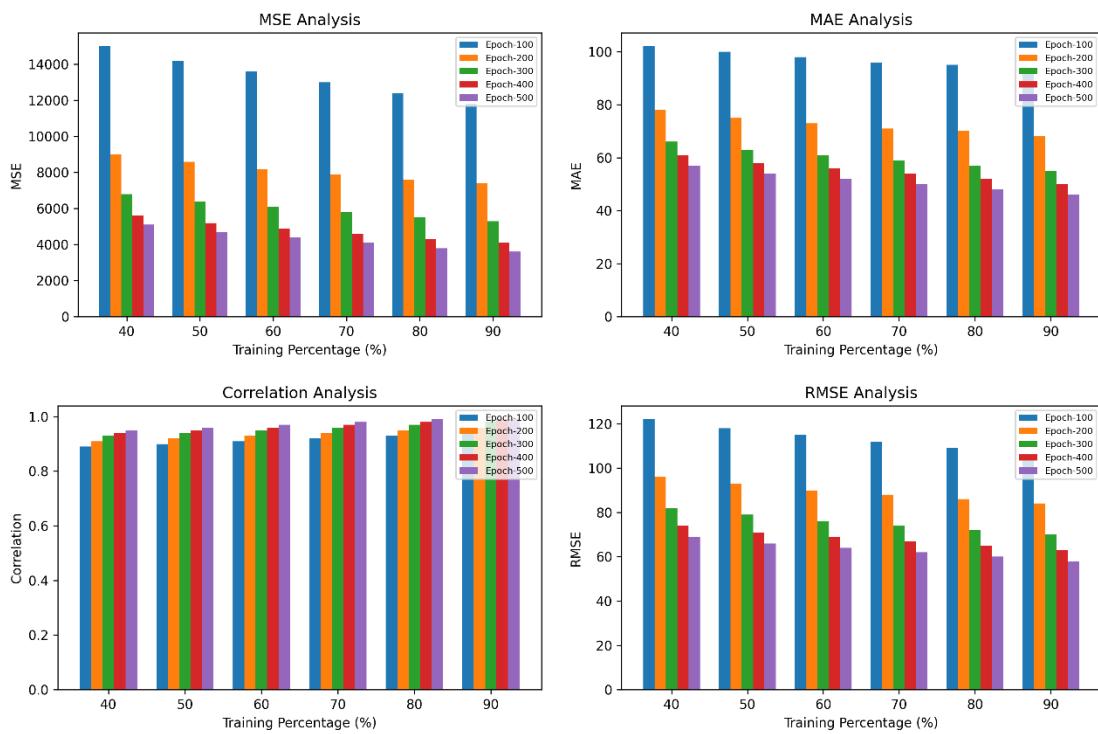


Figure 3: Model Performance Trend Analysis Using Error Metrics and Correlation

To evaluate robustness, K-fold cross-validation was performed using K values of 6, 8, and 10, with results summarized in Fig. 4. Across all folds, the XGBoost model maintains stable performance with minimal variation between training and validation subsets. Correlation values remain consistently above 0.94 for all K values, confirming that the model's predictive capability is not dependent on a specific data partition. RMSE values also remain within a narrow range, demonstrating resistance to overfitting and sensitivity to data reshuffling. These results indicate that the ensemble nature of XGBoost effectively reduces variance while preserving accuracy.

A comparative analysis with baseline methods further highlights the effectiveness of the proposed framework. As shown in Table 1, the proposed XGBoost-based approach outperforms several state-of-the-art models, including RL-MDP, TP-GNN, Hybrid DNN, KT-Transformers, and LSTM-based architectures. The proposed model achieves the highest correlation value of approximately 0.99, along with lower MSE and RMSE values compared to most baselines. While certain deep learning models achieve competitive performance, they do so at the cost of higher computational complexity and longer training times. In contrast, the proposed framework delivers superior accuracy with significantly lower resource requirements, making it more practical for real-world e-learning environments.

The blockchain-based certificate subsystem was evaluated under varying user loads to assess its security and scalability characteristics. As illustrated in Fig. 5, the Genuine User Rate (GUR) gradually decreases as the number of users increases. This reduction is expected due to increased transaction verification overhead and network contention. However, even at higher loads, the system maintains acceptable verification accuracy, demonstrating its robustness in multi-user environments. Transaction

time increases moderately with user count, remaining within practical limits for academic certificate verification workflows.

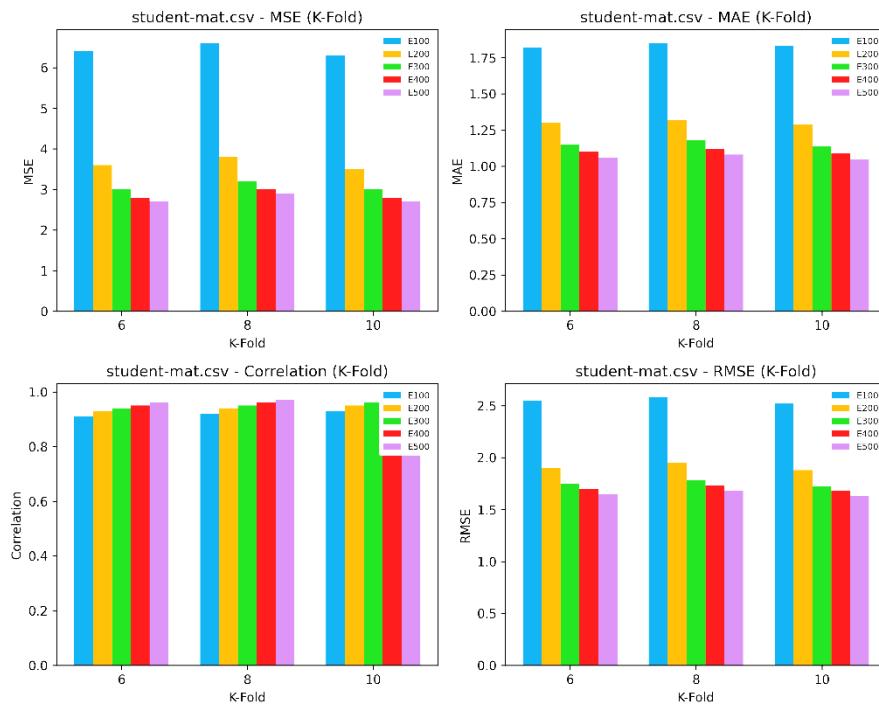


Figure 4: Comparative K-Fold Performance Analysis of the XGBoost Certifier Model

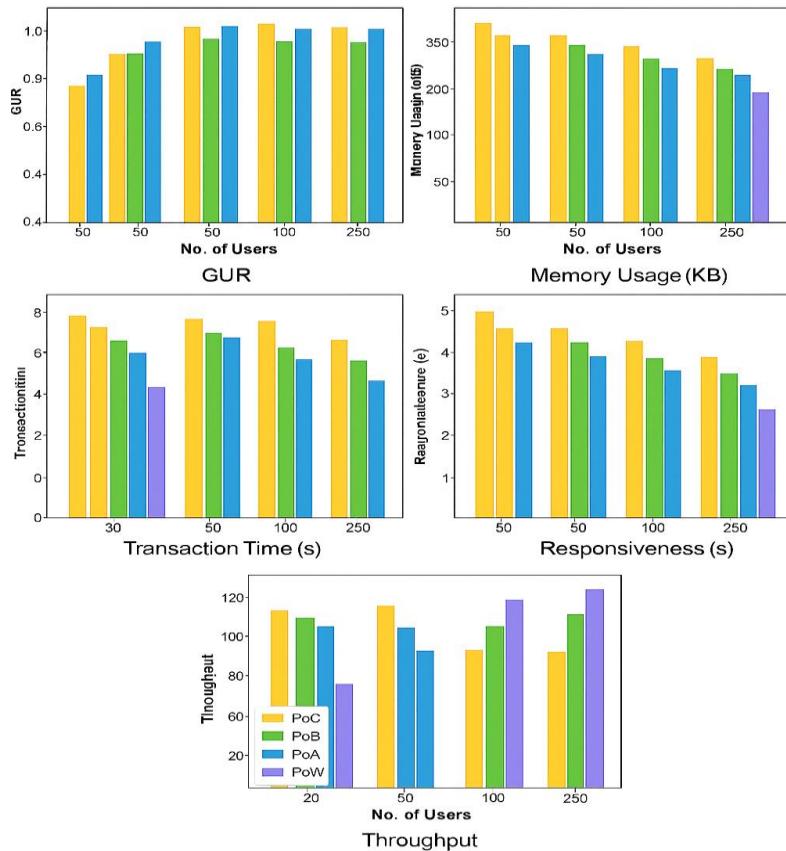


Figure 5: Security Evaluation of the XGBoost-Integrated Certificate Framework

The use of a Proof-of-Work mechanism ensures that each certificate hash is securely embedded within the blockchain, preventing unauthorized modification or duplication. The inclusion of cryptographic hashing and chained block validation provides strong guarantees of immutability and transparency. These properties directly address the weaknesses of centralized certificate systems, where records can be altered or forged without detection. The experimental results confirm that the proposed certificate subsystem maintains security without introducing excessive latency.

The results indicate that XGBoost requires significantly less training time and computational resources than LSTM-Attention, Hybrid DNN, and transformer-based models. This efficiency is primarily due to XGBoost's parallel tree construction and avoidance of iterative backpropagation. As a result, the proposed framework scales effectively with dataset size while remaining suitable for deployment on standard institutional hardware.

Overall, the experimental findings validate that the proposed XGBoost–Blockchain Certifier Framework successfully balances accuracy, efficiency, and security (Fig. 6). The strong recommendation performance addresses limitations related to adaptability and overfitting observed in existing systems, while the blockchain-backed certification mechanism ensures trust and integrity in digital credentials. By integrating these components into a unified workflow, the framework demonstrates clear advantages over fragmented and computationally intensive solutions commonly reported in the literature.

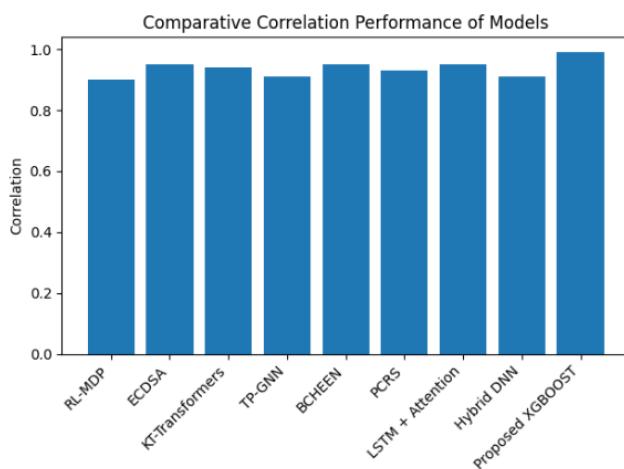


Figure 6: Quantitative Comparison with State-of-the-Art Baseline Models

V. CONCLUSION

This paper presented an integrated XGBoost–Blockchain Certifier Framework for personalized course recommendation and secure digital certificate management in e-learning environments. The framework achieves high predictive accuracy, stable generalization, and reliable certificate verification while maintaining low computational overhead. By unifying recommendation and certification within a single workflow, the system addresses key limitations of existing solutions. Future work will focus on evaluating the framework on large-scale MOOC datasets, exploring energy-efficient blockchain mechanisms, and incorporating real-time analytics to further enhance scalability and security.

VI. REFERENCES

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