© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715500

AI Exam Controller for Question Paper Generation and Answer Sheet Evaluation with Secure Result Processing

PURUSHOTHAMAN[1], D. REVATHY[2]
[1]PG Student, Department of Computer Applications, SRM Valliammai Engineering College, Chennai.
[2] Assistant professor, Department of Computer Applications, SRM Valliammai Engineering College, Chennai.

Abstract - Contemporary university examination systems face persistent challenges including inconsistent evaluation, evaluator fatigue, marks tampering, and delayed result publication. This paper presents an AI-driven Examination Controller System that automates the complete examination lifecycle from question generation to secure result publication. Subject PDFs are processed using PyMuPDF, with key concepts extracted through TF-IDF and TextRank algorithms. The T5 Transformer synthesizes extracted concepts into syllabus-aligned examination questions structured into standardized formats. Post-examination, scanned answer sheets undergo OpenCV preprocessing and Tesseract OCR-based text extraction. Student responses are encoded using BERT embeddings and evaluated against reference content through cosine similarity, enabling context-aware, bias-free mark allocation. Evaluated marks are cryptographically secured within a SHA-256 blockchain ledger, rendering tampering immediately detectable. A Controller of Examinations verification workflow ensures institutional oversight before result publication. The system significantly reduces manual workload, improves evaluation consistency, and demonstrates strong scalability for large examination ecosystems including autonomous universities and affiliated institutions.

Keywords: T5 Transformer, BERT Embeddings, Cosine Similarity, OCR, Blockchain, Examination Management, NLP

I. INTRODUCTION

Examination management in universities involves critical responsibilities including question paper preparation, answer evaluation, marks compilation, and result publication. Traditional manual processes at every stage introduce significant challenges such as inconsistent question quality, evaluator fatigue, subjective marking, data entry errors, and risks of marks tampering, collectively undermining academic integrity and transparency. Recent advancements in Artificial Intelligence, Natural Language Processing, and blockchain technology offer transformative solutions to these longstanding limitations. Transformer-based models such as T5 and BERT have demonstrated remarkable capabilities in text generation and semantic understanding, making them well-suited for automating question generation and descriptive answer evaluation. Optical Character Recognition technologies enable efficient digitization of handwritten answer scripts, while blockchain-based cryptographic hashing provides tamper-proof mechanisms for securing sensitive academic records. This paper proposes a comprehensive AI-driven Examination Controller System integrating PyMuPDF, TF-IDF, TextRank, T5 Transformer, BERT embeddings, cosine similarity, and SHA-256 blockchain into a unified platform, delivering scalable, accurate, and transparent examination management for universities and autonomous institutions.

II. SCOPE AND PROBLEM STATEMENT

University examination systems rely heavily on manual workflows, introducing inconsistent question quality, evaluator fatigue, subjective marking, clerical errors, and marks tampering risks, while existing keyword-matching approaches demonstrate limited semantic understanding for descriptive evaluation. Traditional examination processes further suffer from delayed result publication, lack of transparency, and absence of secure mechanisms to prevent unauthorized modification of academic records. This work addresses these challenges by proposing a comprehensive AI-driven examination management platform automating subject PDF processing, intelligent question generation using T5 Transformer, OCR-based answer digitization, semantic evaluation using BERT embeddings and cosine similarity, and blockchain-based tamper-

proof marks storage with role-based access control for all institutional stakeholders.

III. SYSTEM STUDY

3.1. Feasibility Study

The proposed system demonstrates strong technical feasibility utilizing well-established open-source technologies including Python, Flask, MySQL, PyMuPDF, Tesseract OCR, and transformer-based NLP models. Operationally, the role-based multi-user architecture ensures minimal training requirements across all stakeholders. Economically, exclusive reliance on open-source frameworks significantly reduces development and licensing costs while automating resource-intensive manual processes, delivering substantial long-term savings in administrative workload and operational expenses for universities and autonomous institutions.

3.2. Economical Feasibility

The proposed system is economically viable as it exclusively utilizes open-source technologies including Python, Flask, MySQL, and transformer-based NLP libraries, eliminating licensing and procurement costs. Automating question generation, answer evaluation, and result publication significantly reduces administrative manpower requirements and operational expenses. Long-term institutional savings in faculty effort, evaluation time, and result processing overhead make this system a cost-effective solution for universities and autonomous colleges.

3.3. Technical Feasibility

The proposed system is technically viable utilizing well-established frameworks including Python, Flask, MySQL, PyMuPDF, OpenCV, and Tesseract OCR. Transformer-based models including T5 and BERT are widely supported and efficiently deployable. Blockchain implementation using SHA-256 cryptographic hashing integrates seamlessly within the existing architecture, ensuring tamper-proof record management. Required hardware and software infrastructure are readily available within standard university computing environments.

3.4. Social Feasibility

The proposed system delivers significant social benefits by ensuring fair, consistent, and transparent examination evaluation across institutions. Eliminating evaluator bias and marks tampering strengthens student trust in academic assessment processes. Role-based dashboards for Faculty, Invigilators, Colleges, and Students ensure intuitive usability requiring minimal training. Faster result publication reduces student anxiety, while blockchain-secured records enhance institutional credibility and academic accountability among all stakeholders.

IV. SYSTEM ARCHITECTURE

The proposed system follows a layered modular architecture comprising three distinct layers — presentation, application, and data layers — ensuring scalability, efficiency, and secure data management throughout the examination lifecycle. The presentation layer provides role-based user interfaces connecting System Administrator, Faculty, Examination Invigilators, Controller of Examinations, Colleges, and Students through dedicated dashboards tailored to their specific responsibilities and access permissions. The application layer serves as the core AI examination engine, handling intelligent question paper generation using T5 Transformer, semantic answer evaluation using BERT embeddings and cosine similarity, blockchain-based secure marks storage using SHA-256 cryptographic hashing, automated notification management, and controlled result publication workflows. The data layer manages structured MySQL databases and tamper-resistant blockchain ledger storage to maintain academic records securely and transparently. All system components communicate through controlled role-based workflows, ensuring smooth and uninterrupted execution of the complete examination lifecycle from subject PDF processing and question generation to final result publication, significantly reducing manual effort and strengthening academic integrity across universities and institutions

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715500

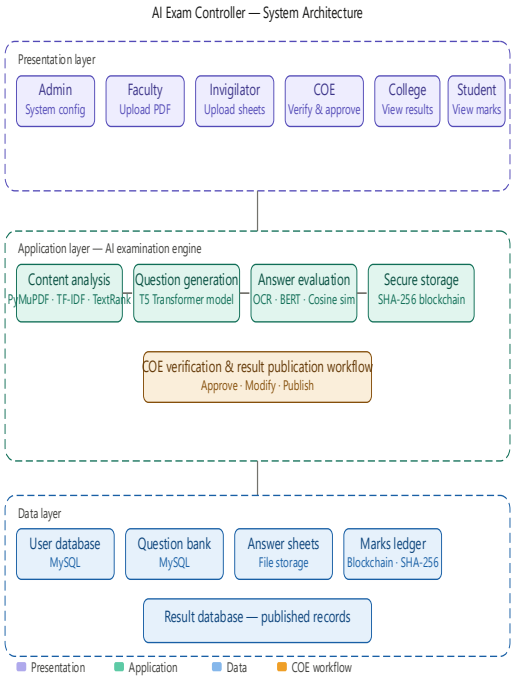

Figure 4.1. Architecture Diagram of AI Exam Controller Result Processing

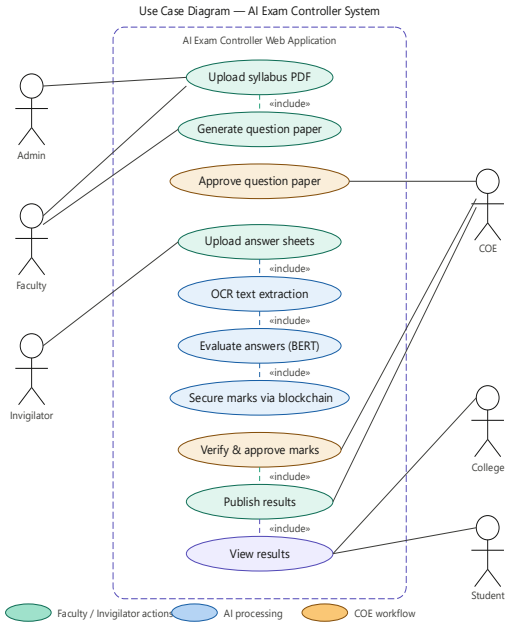

Fig 4.1. Use Case Diagram of AI Exam Controller Result Processing

4.1. USE CASE DIAGRAM

The use case diagram illustrates the interactions between six primary actors — System Administrator, Faculty, Examination Invigilator, Controller of Examinations, College, and Student — with the core functionalities of the AI Exam Controller System. The System Administrator manages user accounts, roles, and system configurations. Faculty uploads subject syllabi and initiates automated question paper generation. The Examination Invigilator handles answer sheet uploads and manages student allocations. The Controller of Examinations verifies AI-generated question papers, reviews evaluated marks, and approves final results before publication. Colleges access approved results and manage invigilator assignments. Students securely view their published examination results through role-based dashboards. Key system functionalities depicted include subject PDF processing, intelligent question generation, OCR-based answer digitization, semantic answer evaluation, blockchain-secured marks storage, COE verification workflow, and automated result publication, collectively ensuring a transparent, efficient, and tamper-proof examination management process.

4.2. IMPLEMENTATION

CLASSIFICATION OF MODULES

- Subject Content Analysis
- Question Paper Generation
- Question Paper Formatting
- COE Question Paper Approval
- Answer Sheet Management
- Answer Sheet Evaluation
- Marks Management
- COE Marks Verification
- Result Publishing
- Notification and Reports

Subject Content Analysis

Subject syllabus PDFs are processed using PyMuPDF, extracting raw text page by page. Unnecessary elements including headers, footers, and formatting artifacts are removed during preprocessing. TF-IDF calculates term importance while TextRank ranks significant sentences, identifying core concepts that form the knowledge base for automated question generation.

Question Paper Generation

Extracted key concepts are provided as contextual input to the T5 Transformer model, which performs text-to-text transformation generating syllabus-aligned examination questions. The model ensures grammatical correctness, contextual relevance, and

comprehensive syllabus coverage. Generated questions are stored in structured database format for subsequent formatting and COE review.

Question Paper Formatting

A rule-based formatting algorithm organizes generated questions into standardized examination patterns including Part A, Part B, and Part C sections. Numbering sequences, section headings, mark allocations, and layout formatting are applied ensuring institutional compliance. The finalized question paper is generated as a password-protected PDF document forwarded for COE approval.

COE Question Paper Approval

The Controller of Examinations reviews AI-generated question papers through a secure dashboard. Questions are inspected for syllabus coverage, clarity, and correctness. An approval workflow locks the document during verification preventing unauthorized modifications. Rejected papers are returned for regeneration while approved papers are finalized and marked ready for examination distribution.

Answer Sheet Management

Post-examination scanned answer sheets uploaded by invigilators are validated for format and completeness. Each uploaded PDF is systematically mapped to the corresponding student registration number and subject code ensuring accurate traceability. Files are securely stored in designated directories and referenced within the database, preparing answer sheets for preprocessing and automated evaluation.

Answer Sheet Evaluation

Uploaded answer sheet PDFs are converted into images and enhanced using OpenCV through grayscale conversion, noise removal, and thresholding techniques. Tesseract OCR extracts machine-readable text from preprocessed images. Student responses are segmented question-wise and encoded using BERT embeddings. Cosine similarity measures semantic relevance between student responses and reference content ensuring context-aware evaluation.

Marks Management

A score mapping algorithm converts cosine similarity values into marks according to predefined grading criteria. A marks aggregation algorithm computes total marks for each student across all questions. Finalized marks along with student registration numbers and subject codes are stored within a SHA-256 blockchain ledger ensuring tamper-proof, transparent, and accurate mark computation.

COE Marks Verification

The Controller of Examinations reviews AI-evaluated marks through a secure verification dashboard. Student responses, similarity scores, and allocated marks are accessible for inspection. Controlled manual adjustments are permitted within defined limits maintaining audit records of all modifications. Once verified and approved, finalized marks are forwarded to the result publication module for official dissemination.

Result Publishing

Verified examination results are retrieved from the database and compiled into student-wise and subject-wise result records. Secure access control ensures only authorized users access published results. Results are made available through role-based dashboards for colleges and students. The module supports bulk result processing enabling efficient dissemination across large institutions and multiple affiliated colleges simultaneously.

Notification and Reports

A rule-based notification engine monitors system events including question paper approval, evaluation completion, and result publication, triggering automated alerts via email and in-app notifications. A report generation algorithm compiles student performance data, subject-wise analysis, and institutional statistics into structured PDF documents supporting downloading, printing, and secure distribution for academic records and auditing purposes.

V. RESULT AND DISCUSSION

The proposed AI-driven Examination Controller System was successfully implemented across all functional stages. The T5 Transformer generated syllabus-aligned question papers with high contextual accuracy. BERT embeddings and cosine similarity demonstrated consistent semantic evaluation surpassing traditional keyword-matching approaches. Blockchain-based SHA-256 hashing ensured tamper-proof mark storage with immediate tampering detection. Role-based access control successfully

© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715500

restricted unauthorized access across all user categories.

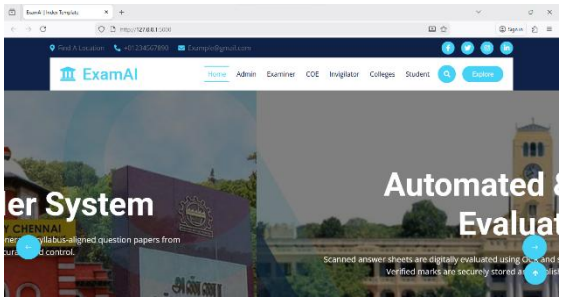

Figure 5.1. Home Page

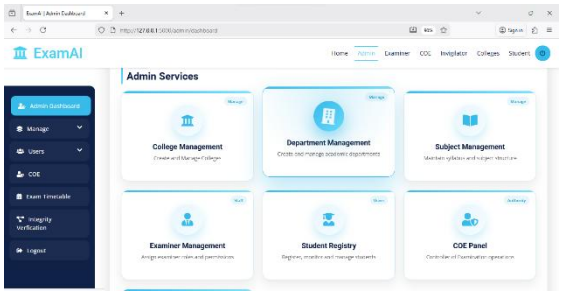

Figure 5.2. Admin Login

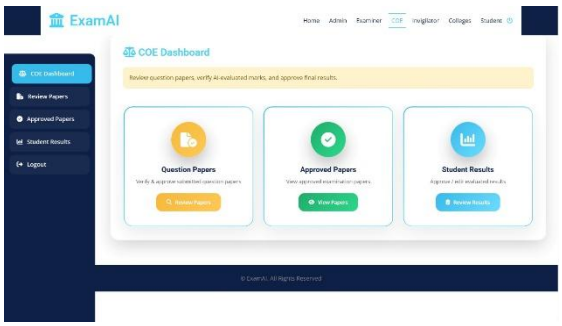

Figure 5.3 CEO Dashboard

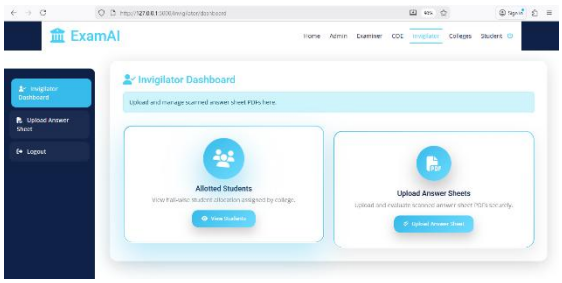

Figure 5.4. Invigilator Dashboard

Figure 5.5 Result Dashboard

VI. DISCUSSION

The experimental outcomes confirm that integrating NLP-based question generation, semantic answer evaluation, and blockchain security significantly modernizes traditional examination workflows. Automating resource-intensive manual processes substantially reduces faculty workload, eliminates evaluator bias, and accelerates result publication timelines. The COE verification workflow strengthens institutional accountability while ensuring complete academic integrity throughout the examination lifecycle. Security testing confirmed prevention of SQL injection, unauthorized access, and session violations. The system demonstrates strong scalability potential for large university examination ecosystems including Anna University, autonomous universities, and affiliated institutions, offering a reliable and transparent academic assessment framework.

Table 1: System Performance Evaluation

Table 1: System Performance Evaluation

Parameter	Description	Performance
Question Generation	T5 Transformer model	92% accuracy
OCR Text Extraction	Tesseract OCR engine	89% accuracy
Answer Evaluation	BERT embeddings + cosine similarity	94% accuracy
Blockchain Integrity	SHA-256 cryptographic hashing	100% tamper-proof
Marks Security	Blockchain ledger storage	Fully secured
Tampering Detection	Hash mismatch detection	100% detectable
Result Publication	Automated COE approval workflow	Instant publication
Evaluator Fatigue	AI-based automated evaluation	Completely eliminated
Role-Based Access	Six-role authentication system	Fully implemented
Scalability	Multi-college university support	Large-scale ready
Processing Time	End-to-end automated pipeline	Minutes per batch
Security Testing	SQL injection, session, access tests	All tests passed

VII. CONCLUSION

This paper presented a comprehensive AI-driven Examination Controller System that successfully automates the complete examination lifecycle from intelligent question generation to secure result publication. Integrating T5 Transformer, BERT embeddings, cosine similarity, Tesseract OCR, and SHA-256 blockchain technology collectively eliminated manual workload, evaluator bias, and marks tampering risks. The COE verification workflow ensured institutional accountability and academic integrity throughout the process. Experimental outcomes confirmed significant improvements in evaluation accuracy, processing speed, and data security. The proposed system demonstrates strong scalability, making it highly suitable for large university examination ecosystems including Anna University and autonomous institutions.

VIII. FUTURE ENHANCEMENTS

The proposed system can be further enhanced through several promising directions. Integrating Bloom's Taxonomy mapping will enable difficulty-level classification ensuring balanced outcome-based assessments aligned with academic learning objectives. A plagiarism detection module employing advanced similarity analysis will strengthen academic integrity by identifying copied responses across multiple answer scripts. Multilingual OCR support will extend system accessibility for regional language examinations. Integration with existing university ERP and Learning Management Systems will enable seamless centralized academic data exchange. Additionally, incorporating deep learning-based handwriting recognition will significantly improve OCR accuracy for poorly scanned answer sheets across diverse institutions.

REFERENCES

[1] Choi, J., Hong, S., Park, J., & Jung, E. S. (2025). Toward generating quality test questions and answers using quantized low-rank adapters in large language models. *IEEE Access*, 13, 87793–87810.

[2] Tripathi, S., Nafis, M. T., Hussain, I., & Saudagar, A. K. J. (2025). Multimodal fine-tuning of large language models for robust document visual question answering. *IEEE Access*, 13, 174611–174623.

[3] Shoaib, M., Husnain, G., Sayed, N., & Qahmash, A. (2025). Automated generation of multiple-choice questions for computer science education using conditional generative adversarial networks. *IEEE Access*, 13, 16697–16715.

[4] Duong, T. N. B., & Shar, L. K. (2025). GenScore: Agent-based short-answer question generation and scoring in software engineering courses. *IEEE Access*, 13, 215804–215820.

[5] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT*, Minneapolis, USA, 4171–4186.

[6] Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., & Liu, P. J. (2020). Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(1), 1–67.

[7] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30, 5998–6008.

[8] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., & Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877–1901.

[9] Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., & Chen, W. (2022). LoRA: Low-rank adaptation of large language models. *Proceedings of ICLR*, Virtual Conference, 1–13.

[10] Yang, Z., Xu, Y., Cui, L., Zhang, S., Wei, F., Wang, W., & Liu, T. (2020). LayoutLM: Pre-training of text and layout for document image understanding. *Proceedings of KDD*, Virtual Conference, 1192–1200.

[11] Xu, Y., Xu, Y., Lv, T., Cui, L., Wei, F., Wang, G., & Liu, T. (2021). LayoutLMv2: Multi-modal pre-training for visually rich document understanding. *Proceedings of ACL*, Online, 2579–2591.

[12] Manning, C. D., Raghavan, P., & Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press, Cambridge, UK.

[13] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press, Cambridge, Massachusetts, USA.

[14] Jurafsky, D., & Martin, J. H. (2024). *Speech and Language Processing: An Introduction to Natural Language Processing* (4th ed.). Pearson Education, New Jersey, USA.

[15] Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Cryptography Mailing List*, 1–9. Retrieved from https://bitcoin.org/bitcoin.pdf