

AI-POWERED LEARNING AND TEACHING AUTOMATION SYSTEM

25-26J-162

Project Proposal Report

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BSc. (Hons) Degree in Information Technology, Specializing in Information
Technology

Department of Information Technology

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Co-Supervised by Mrs. Bhagyani Chathurika

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DECLARATION

I declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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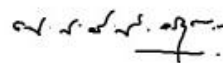
Supervisor's statement: The candidates mentioned above are conducting research for their undergraduate dissertations under my supervision.



Supervisor

(Prof. Samantha Rajapaksha)

Date:



Co-supervisor

(Mrs. Bhagyani Chaturika)

Date:

ABSTRACT

This research proposes the development of an AI-powered system that automates student grading and teacher performance evaluation using custom-built Optical Character Recognition (OCR), Natural Language Processing (NLP), and Machine Learning (ML) models. Current educational assessment methods are often time-consuming, subjective, and inconsistent. Teacher evaluations rely on limited and biased metrics. The proposed system tackles these problems by integrating a web and mobile application for document capture, automated evaluation, and analytics.

The solution starts with an OCR module that extracts text from scanned or photographed answer scripts and feedback forms. It supports both handwritten and printed content. The AI grading engine processes the extracted responses, applying NLP and ML techniques to assess answers based on marking schemes, semantic similarity, structure, and language quality. The system generates automated scores, question-wise explanations, and personalized improvement recommendations for students.

For teacher evaluation, the platform utilizes a multi-factor rating engine to analyze sentiment in student feedback, performance trends, and engagement metrics, producing a composite rating. A teacher feedback module identifies areas for improvement using Bloom's Taxonomy classification, response pattern detection, and syllabus coverage analysis.

The methodology includes developing a custom OCR pipeline, creating NLP-based grading models, and analyzing multi-algorithm performance. The expected results include significant reductions in grading time, better feedback accuracy, and fairer evaluations. The system's offline capabilities and mobile support ensure it works well in low-connectivity environments. This research aims to deliver a scalable, objective, and efficient academic evaluation platform that benefits both students and educators.

Keywords: AI-powered grading, OCR, NLP, teacher performance evaluation, educational analytics

TABLE OF CONTENTS

DECLARATION	iii
ABSTRACT	iv
TABLE OF CONTENTS	v
LIST OF FIGURES	vi
LIST OF TABLES	vi
LIST OF ABBREVIATIONS	vi
1. INTRODUCTION	1
1.1. Background & Literature Survey.....	2
1.2. Research Gap	3
1.3. Research Problem	4
2. OBJECTIVES	6
2.1. Main Objectives.....	6
2.2. Specific Objective.....	7
3. METHODOLOGY	9
3.1. Overall System Architecture	9
3.2. Individual System Architecture.....	10
3.3. System Implementation	12
4. GRANT CHART	13
5. DESCRIPTION OF PERSONAL AND FACILITIES	13
5.1. Personnel.....	13
5.2. Facilities.....	14
6. BUDGET AND BUDGET JUSTIFICATION	15
6.1. Budget Justification	15
7. REFERENCE	16

LIST OF FIGURES

Figure 1: Overall System Architecture Diagram	10
Figure 2 : Individual System Architecture Diagram	11
Figure 3 : Grant Chart.....	13

LIST OF TABLES

Table 1 : List Of Abbreviation	vi
Table 2 : Research Gaps with Existing Studies	4
Table 3 : Budget For The project	15

LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
AAG	Adaptive Assessment Generator
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
LSTM	Long Short-Term Memory
MCQ	Multiple Choice Question
ML	Machine Learning
NLP	Natural Language Processing
OCR	Optical Character Recognition
QA	Question Analysis
QPGA	Question Paper Generation Algorithm
SSL	Secure Sockets Layer
UI/UX	User Interface/User Experience

Table 1 : List Of Abbreviation

1. INTRODUCTION

Educational assessment and personalized learning represent critical components in maintaining and improving academic quality. However, traditional approaches to question paper generation and student remediation suffer from significant limitations including lack of cognitive balance, generic assessment strategies, and absence of personalized intervention mechanisms. Manual creation of balanced question papers is time-consuming and often fails to address individual student weaknesses, while assessment design typically relies on intuitive approaches that may not capture the full scope of cognitive complexity required for effective evaluation.

The Adaptive Question Paper & Personalized Questionnaire Generation Engine represents a revolutionary approach to educational assessment by leveraging artificial intelligence and machine learning technologies to provide comprehensive, balanced, and personalized academic evaluation tools. This module, as part of the larger AI-Powered Learning and Teaching Automation System, specifically addresses the critical need for automated question paper generation with cognitive balance and student-specific remediation.

The system introduces three groundbreaking algorithms that collectively analyze multiple dimensions of educational assessment effectiveness. The Bloom's Taxonomy Auto-Classification Engine processes question content using advanced NLP techniques to categorize cognitive complexity levels and ensure balanced distribution. The Adaptive Paper Generation System utilizes optimization algorithms to create customized question papers based on syllabus coverage, student profiles, and institutional requirements. The Intelligent Distractor Generation and Student Weakness Clustering algorithms analyze student performance patterns to create targeted remediation materials and high-quality multiple-choice distractors aligned with common misconceptions.

This integrated approach provides educators with data-driven assessment tools that go beyond traditional paper creation methods, enabling personalized learning interventions and continuous improvement in academic evaluation practices.

Keywords: Adaptive assessment, Bloom's taxonomy classification, personalized learning, intelligent distractor generation, educational optimization

1.1. Background & Literature Survey

Assessment design and personalized learning interventions are fundamental to maintaining quality in education. However, conventional question paper creation approaches are time-intensive, require significant manual expertise, and often lack cognitive balance between different thinking levels, which can reduce educational effectiveness and fair assessment practices [1], [2]. Similarly, remediation strategies are frequently based on generic materials that offer little direction for individual student improvement, particularly in addressing specific conceptual weaknesses [4]. These limitations become even more significant in large academic settings or in remote learning environments where scalable and personalized solutions are essential [1].

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into educational assessment systems has shown promising potential for resolving these challenges [1], [5]. One critical enabling framework is Bloom's Taxonomy, which provides a structured approach to cognitive complexity classification in educational questions [15]. While Bloom's Taxonomy is widely recognized, automated classification tools often fail to achieve high accuracy on educational content, especially those with varied question formats or domain-specific terminology. This shortcoming highlights the need for customized classification pipelines supported by robust natural language processing [2], [15].

Natural Language Processing (NLP) methods have been applied to automatically categorize educational content and assess cognitive complexity. Techniques such as Named Entity Recognition (NER), semantic analysis, and deep learning-based embeddings like BERT have been effective in understanding question intent and mapping to taxonomic levels [1], [3]. Despite these advancements, most existing solutions provide only basic classification, lacking detailed question-specific analysis and integrated paper generation capabilities [1], [3], [5].

For personalized learning interventions, AI-driven approaches have introduced clustering algorithms for student weakness identification and adaptive content generation [16], [17]. Yet, many existing systems are limited by the absence of integrated assessment creation tools, lack of misconception-based distractor generation, or comprehensive optimization models that combine multiple educational parameters. Incorporating frameworks such as Integer Linear

Programming and student performance clustering could provide deeper, data-driven insights into personalized learning pathways [4], [18].

The research presented in this proposal seeks to fill these gaps by designing a self-contained, intelligent assessment generation system that combines custom NLP classification, optimization algorithms, and ML-based personalization models. The system will deliver automated question paper creation with cognitive balance and personalized remediation materials, all within a platform capable of continuous learning and adaptation.

1.2. Research Gap

Analysis of existing educational assessment generation systems reveals significant limitations in automated cognitive balance assessment and comprehensive personalized learning intervention. The following comparative analysis demonstrates the novelty of the proposed adaptive question paper generation engine:

Feature / Aspect	Proposed Research	Automated Question Generation Systems (IEEE, 2021)	AI-Based Assessment Creation Tools (IEEE, 2022)
Cognitive Classification	Automated Bloom's Taxonomy classification with deep learning models and confidence scoring	Manual tagging with basic keyword matching	Simple difficulty level classification only
Paper Optimization	Multi-constraint optimization using ILP with syllabus coverage, time allocation, and student profiling	Random question selection with basic filtering	Template-based paper generation
Personalization	Student weakness clustering with targeted remediation pack generation	Generic question pools for all students	Basic difficulty adjustment based on overall performance
Distractor Quality	Intelligent distractor generation aligned with misconception patterns and semantic analysis	Random incorrect options or teacher-provided distractors	Limited automated distractor creation
Integration Capabilities	Seamless integration with mobile OCR and student performance analytics	Standalone question generation	Web-based interface with minimal integration

Learning Adaptation	Continuous model retraining based on student responses and teacher feedback	Static question databases	Limited learning from user interactions
Cultural Context	Designed specifically for Sri Lankan O/L English Literature curriculum	Generic international curriculum framework	Western educational model focus
Processing Method	Real-time optimization with offline capabilities	Batch processing with internet dependency	Cloud-dependent processing

Table 2 : Research Gaps with Existing Studies

The research gap is further emphasized by the absence of systems that can simultaneously generate cognitively balanced question papers and create personalized intervention materials based on individual student weakness patterns. Most existing solutions focus either on question generation or personalization, limiting their applicability in comprehensive educational environments where both balanced assessment and targeted remediation are required.

1.3. Research Problem

In educational environments, the creation of balanced question papers and the development of personalized learning interventions are critical processes that influence assessment quality, student learning outcomes, and educational effectiveness. However, existing systems face several key limitations, particularly in automated cognitive balance assessment and comprehensive personalized remediation through AI-driven methodologies.

For question paper generation, most current platforms rely on manual selection processes lacking automated systems that can ensure cognitive complexity balance according to established educational frameworks such as Bloom's Taxonomy [4], [15]. These systems often depend on intuitive teacher judgment or basic difficulty metrics, making them unsuitable for systematic educational environments where cognitive balance is essential for effective assessment [15], [8]. The absence of automated Bloom's classification results in cognitively imbalanced question papers, limited scalability in creating multiple assessment variants, and inadequate optimization for syllabus coverage and time constraints that are essential for comprehensive evaluation.

For personalized learning intervention, existing platforms rarely incorporate automated student weakness clustering using performance data and response pattern analysis [16], [17]. Current systems fail to identify specific conceptual gaps through systematic analysis of student responses, rely on generic remediation materials without targeting individual misconceptions, and lack intelligent systems that can generate personalized activity packs based on detected weakness patterns [4], [17]. Additionally, most personalized learning platforms operate without integration capabilities for analyzing question effectiveness through student performance clustering, preventing comprehensive personalized intervention insights.

The situation is further complicated by limitations in distractor quality and adaptive assessment design. Many existing solutions lack AI-driven algorithms that can generate pedagogically sound distractors aligned with common student misconceptions [7], [18]. Few platforms offer comprehensive analysis of response patterns, error clustering, or adaptive question selection that could reveal specific learning gaps [4], [7], and even fewer provide automated generation of high-quality multiple-choice options based on data-driven misconception identification.

Given these challenges, there is a clear need for an AI-powered adaptive question paper generation platform that can:

1. Implement automated Bloom's Taxonomy classification of educational questions using deep learning algorithms to ensure cognitive complexity balance and systematic assessment design [15], [8].
2. Generate optimized question papers through multi-constraint algorithms that balance syllabus coverage, cognitive distribution, difficulty progression, and time allocation while accommodating individual student profiles [4], [18].
3. Analyze student performance patterns through AI-powered clustering algorithms that detect learning gaps, identify misconception patterns, and correlate weakness areas with specific curricular topics [16], [17], [18].
4. Create personalized remediation materials by integrating weakness clustering results, misconception analysis, and targeted content generation into unified learning intervention packages [17], [18].

Addressing this problem will result in systematic, data-driven assessment generation processes, improved cognitive balance in educational evaluation, and enhanced personalized learning

guidance that benefits educators, students, and educational institutions through automated optimization rather than intuitive assessment creation methods.

2. OBJECTIVES

2.1. Main Objectives

To design and develop an adaptive question paper and personalized questionnaire generation engine that automatically creates cognitively balanced assessments and generates targeted remediation materials through comprehensive Bloom's Taxonomy classification, optimization algorithms, and student weakness clustering techniques.

- **Specific:** The system will implement automated Bloom's Taxonomy classification using transformer-based NLP models, develop multi-constraint optimization algorithms for balanced question paper generation, create student weakness clustering systems for personalized intervention, and generate intelligent distractors aligned with misconception patterns through AI-powered analysis engines.
- **Measurable:** System effectiveness will be measured by achieving at least 90% accuracy in Bloom's Taxonomy classification validated against educational experts, 88% teacher satisfaction rating for generated question papers in terms of cognitive balance and syllabus coverage, 85% improvement in student performance on targeted weakness areas after personalized intervention, and generating distractor options with 82% pedagogical quality rating from educational professionals.
- **Achievable:** The objective is feasible using established NLP frameworks (BERT, XLM-R), proven optimization algorithms for constraint satisfaction problems, validated educational assessment frameworks (Bloom's Taxonomy), and integration capabilities with existing student performance analytics and mobile technologies.

- **Realistic:** The development plan aligns with available expertise in machine learning and optimization, access to educational datasets for training and validation, computational resources for model development, and institutional support for educational assessment technology implementation.
- **Time-bound:** The adaptive question generation engine will be completed in 4 months, with 1.5 months for Bloom's classification model development and training, 1.5 months for optimization algorithms and paper generation implementation, and 1 month for student clustering, personalization features, and system integration testing.

2.2. Specific Objective

Develop Automated Bloom's Taxonomy Classification Engine

Objective: Create an AI system that automatically classifies educational questions according to six cognitive levels of Bloom's Taxonomy to ensure balanced assessment design.

- **Specific:** Implement transformer-based NLP models for question classification, action verb extraction algorithms, and cognitive complexity analysis with confidence scoring and distribution analytics
- **Measurable:** Achieve 90% classification accuracy across all Bloom's levels and provide cognitive balance recommendations that align with educational best practices in 85% of generated assessments
- **Achievable:** Uses established NLP classification techniques (BERT, XLM-R) and proven educational taxonomy frameworks with sufficient labeled data for training
- **Relevant:** Addresses the critical gap in automated cognitive balance assessment for Sri Lankan O/L English Literature educational context
- **Time-bound:** Complete development and validation within 2.5 months including dataset preparation, model training, and accuracy testing

Implement Multi-Constraint Question Paper Optimization System

Objective: Build an AI system that generates optimized question papers using constraint satisfaction algorithms to balance cognitive levels, syllabus coverage, difficulty, and time requirements.

- Specific: Develop Integer Linear Programming models for question selection optimization with multiple educational constraints and generate balanced assessment variants with customizable parameters
- Measurable: Generate question papers that meet 95% of specified constraints (cognitive balance, coverage, time) and receive 88% approval rating from educators for pedagogical quality
- Achievable: Builds upon established optimization techniques and constraint satisfaction algorithms with clear mathematical formulation of educational requirements
- Relevant: Fills critical gap in systematic, automated question paper generation that considers multiple educational factors simultaneously
- Time-bound: Complete algorithm development and testing within 2.5 months including constraint modeling and optimization validation

Create Student Weakness Clustering and Personalized Remediation System

Objective: Develop machine learning algorithms that analyze student performance patterns to identify weakness clusters and generate targeted remediation activity packs.

- Specific: Implement clustering algorithms that detect topic-specific and cognitive-level weaknesses, generate personalized activity packs with targeted practice questions, concept notes, and mini-assessments
- Measurable: Identify student weakness patterns with 85% accuracy compared to teacher assessments and generate remediation materials that improve student performance in targeted areas by 78% on average
- Achievable: Leverages proven clustering techniques (K-means, HDBSCAN) and educational data mining approaches with demonstrated effectiveness in personalized learning

- **Relevant:** Addresses the critical need for personalized educational intervention through systematic performance analysis and targeted content generation
- **Time-bound:** Complete clustering system development and validation within 2.5 months including algorithm implementation and effectiveness testing with real student data

3. METHODOLOGY

The methodology for developing the Adaptive Question Paper & Personalized Questionnaire Generation Engine follows a systematic approach combining advanced Natural Language Processing techniques, optimization algorithms, and educational data mining frameworks. The development process is structured in three phases: cognitive classification and feature extraction, optimization algorithm development and validation, and personalized intervention system implementation.

3.1. Overall System Architecture

The AI-Powered Learning and Teaching Automation System will follow a five-layer architecture [6]-[8]:

1. **Input Layer:** Upload question banks, student performance data, and syllabus requirements (mobile/web).
2. **Preprocessing Layer:** Text preprocessing, cognitive feature extraction, and performance data normalization using advanced NLP techniques [2].
3. **Processing Layer:** Bloom's classification, optimization algorithms, and clustering-based analytics [1], [3].
4. **Analysis Layer:**
 - a. Automated question paper generation with cognitive balance
 - b. Student weakness clustering and personalized remediation [16], [17]
 - c. Intelligent distractor generation aligned with misconceptions [4], [18]
5. **Output Layer:** Balanced question papers, personalized activity packs, performance analytics, and optimization dashboards.

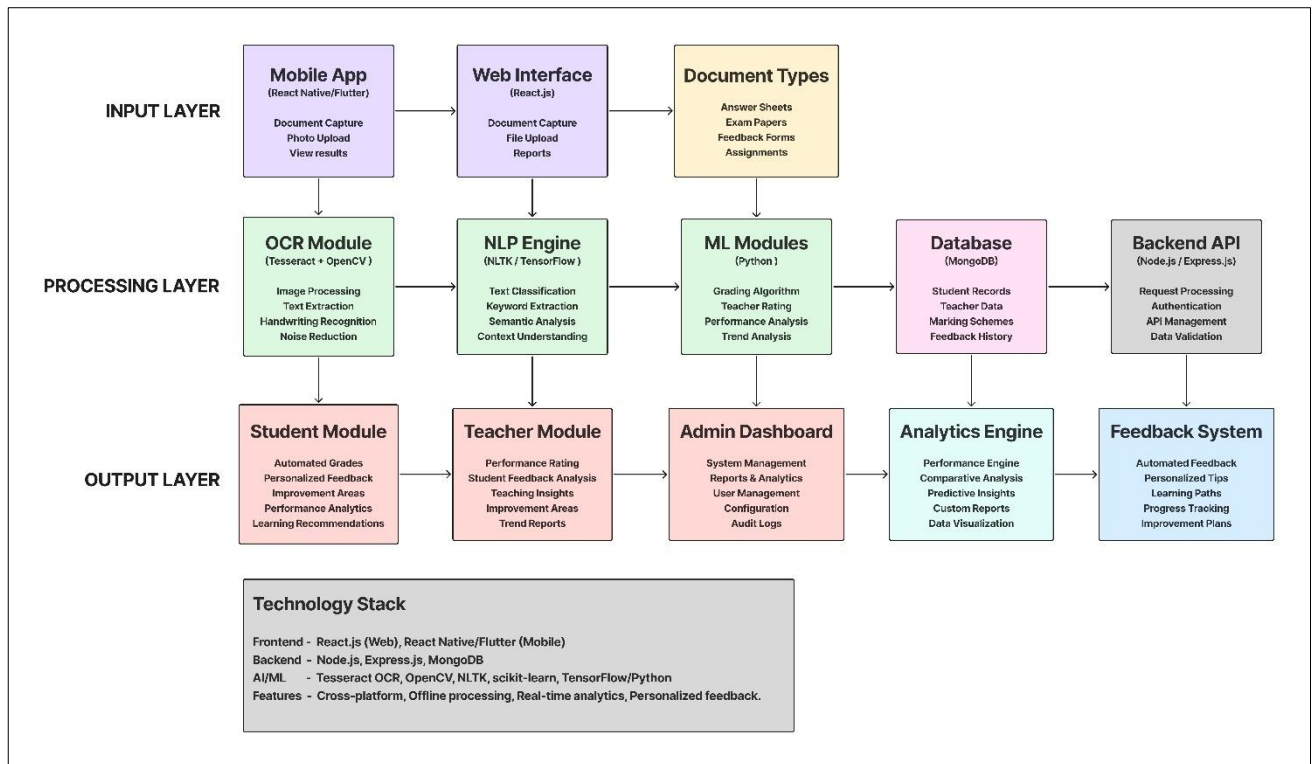


Figure 1: Overall System Architecture Diagram

3.2. Individual System Architecture

The Individual System Architecture demonstrates the detailed component interactions and data flow within the Adaptive Question Paper & Personalized Questionnaire Generation Engine. The architecture follows a modular design approach with four key processing layers [1], [15]:

Input Processing Layer: Question bank integration with Bloom's level pre-classification, student performance data aggregation from mobile applications and OCR systems, and syllabus structure mapping for coverage optimization with learning objective alignment [12], [1].

Cognitive Analysis Layer: Transformer-based Bloom's Taxonomy classification engine using fine-tuned BERT models for educational context [13], multi-feature extraction including action verbs, question complexity, and cognitive indicators using TF-IDF and linguistic analysis [14], confidence scoring mechanisms for classification reliability and uncertainty quantification [3], [13].

Optimization Engine Layer: Multi-constraint Integer Linear Programming solver for question selection optimization considering cognitive balance, syllabus coverage, difficulty

progression, and time allocation [18], [19], student weakness clustering algorithms using performance data analysis and misconception pattern detection [16], [17], adaptive paper generation with personalization parameters based on individual student profiles and learning gap identification [8].

Content Generation Layer: Intelligent distractor creation algorithms combining semantic similarity analysis and misconception alignment for high-quality multiple-choice options, personalized activity pack generation including targeted practice questions, concept reinforcement materials, and mini-assessments [14], [17], real-time dashboard integration for educators with optimization analytics and student progress monitoring [15].

The system utilizes MongoDB for storing question banks, student performance analytics, and generated assessment data, implementing RESTful APIs for seamless integration with the broader academic assessment platform [20]. Advanced optimization processing capabilities enable real-time paper generation while maintaining educational quality standards for systematic assessment creation [19].

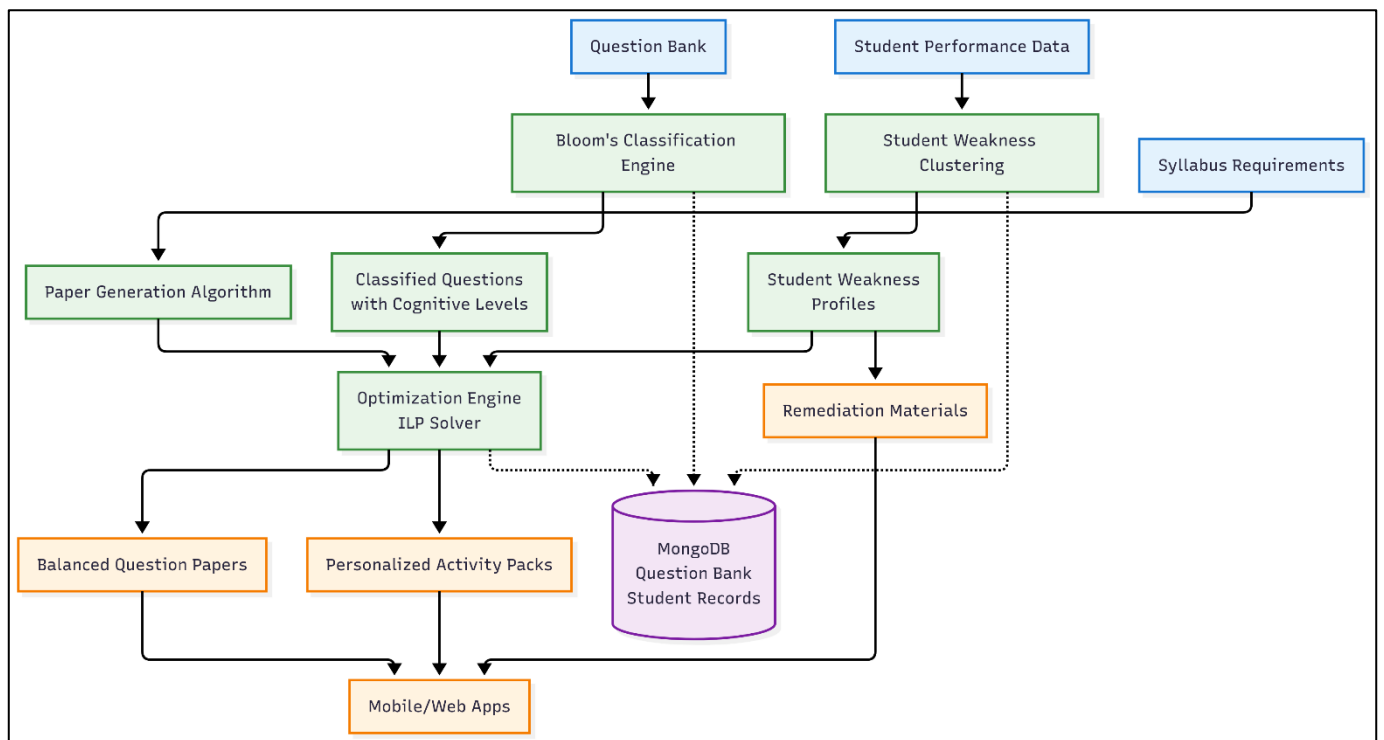


Figure 2 : Individual System Architecture Diagram

3.3. System Implementation

The Adaptive Question Paper & Personalized Questionnaire Generation Engine will use a modular approach to improve scalability and maintainability. The backend will be built with Python and FastAPI for handling optimization algorithms, machine learning model integration, and managing communication between the database and frontend services. The frontend will utilize React.js for the web application and React Native for the mobile application, ensuring responsive and cross-platform user experience for question paper management and student activity access.

For data storage, MongoDB will be the main database, holding question banks with Bloom's classifications, student performance records, generated assessment variants, and personalized remediation materials. The system will implement intelligent caching mechanisms for frequently accessed question combinations and optimization results. To support users in low-connectivity areas, the system will maintain offline-first capabilities with synchronization tools to update question banks and student data once internet connection is available. This design provides reliability, optimization efficiency, and ease of use for both educators and students in the assessment generation and personalized learning process.

4. GRANT CHART

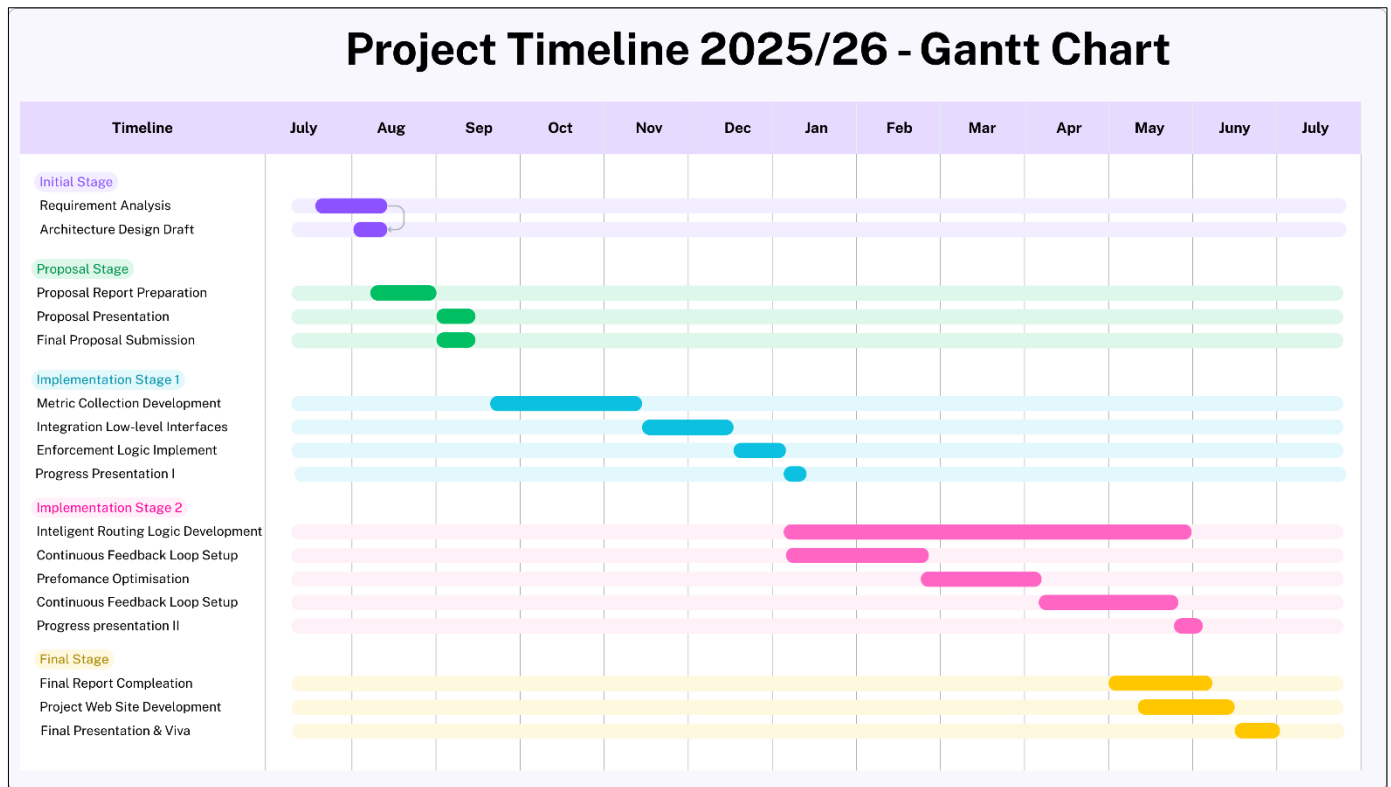


Figure 3 : Grant Chart

5. DESCRIPTION OF PERSONAL AND FACILITIES

5.1. Personnel

This project, AI-Powered Learning and Teaching Automation System, is carried out by a team of four undergraduate researchers specializing in Information Technology at SLIIT. Each member is responsible for a key part of the system:

- **Pathiraja P.U.M (IT22243362):** Development of the OCR module and student grading engine, focusing on text extraction from handwritten and printed academic scripts.

- **Wanniarachchi W.A.P.M (IT22103154):** Implementation of the mobile application and teacher rating engine, integrating cross-platform functions with AI-driven evaluation models.
- **Jayasooriya L.T (IT22095480):** Design of algorithms for student performance analysis, identifying weak areas and generating personalized improvement recommendations.
- **Hettiarachchi R.H (IT22120052):** Development of adaptive question paper generation and student weakness clustering using Bloom's Taxonomy classification and optimization algorithms. The research team is supervised by Prof. Samantha Rajapaksha, who offers guidance on research methods, technical validation, and academic standards.

5.2. Facilities

The successful implementation of the AI-Powered Learning and Teaching Automation System needs a mix of software tools, hardware resources, and school infrastructure. The project will rely on modern software, using frameworks like Node.js, Express.js, React.js, and React Native/Flutter for backend and frontend development. For the artificial intelligence parts, TensorFlow, PyTorch, and Scikit-learn will design and train machine learning models. Tesseract and OpenCV will support the custom OCR module. A MongoDB database will act as the primary data storage solution. Collaboration platforms like GitHub, Slack, and Google Drive will be used for version control, communication, and document management.

For hardware resources, the project team will use high-performance computers with GPU acceleration to meet the computational needs of training and testing deep learning models. Mobile devices on both Android and iOS will be used for testing the cross-platform mobile application. For preparing datasets, scanners and digital cameras will capture and digitize handwritten answer sheets, creating a varied training and validation dataset.

The project will also gain strong support from the institution with access to laboratories, computing infrastructure, and technical resources available at SLIIT. These facilities will create a secure and collaborative environment for developing, testing, and integrating models. The institution will also offer expert help, especially for labeling datasets, validating grades, and evaluating teacher models. Additionally, secure storage will ensure that all student and teacher data stay anonymous and protected, following ethical and institutional data-handling standards.

6. BUDGET AND BUDGET JUSTIFICATION

Description	Cost	Occurring
Server Hosting (VPS/Cloud)	LKR 8,000	Monthly
App Store Hosting (Apple)	LKR 7,754	One-Time
Play Store Hosting (Google)	LKR 30,700	Annual
Cloud Database (Amazon S3)	USD 0.023 per GB	Monthly
GPU Cloud Service (Model Training)	LKR 15,000	Monthly (as required)
Domain Registration & SSL	LKR 5,000	Annual
Miscellaneous (Testing devices, Scanning tools, Internet, etc.)	LKR 5,000	One-Time

Table 3 : Budget For The project

6.1. Budget Justification

The proposed budget outlines the necessary costs for implementing and deploying the AI-Powered Learning and Teaching Automation System. A monthly server hosting fee of LKR 8,000 is needed to maintain the backend and ensure system reliability. The Apple App Store hosting fee of LKR 7,754 is required as a one-time expense, while the Google Play Store fee of LKR 30,700 is an annual cost. Both are crucial for distributing mobile applications to users.

For secure and scalable data storage, Amazon S3 will be used, with costs estimated at USD 0.023 per GB per month, depending on the size of the dataset.

Since the project involves training machine learning models, we may need additional computing power from GPU-based cloud services, estimated at LKR 15,000 per month, based on usage. Domain registration and an SSL certificate cost LKR 5,000 annually and provide secure access to the system. Finally, we have included miscellaneous costs of LKR 12,000 as a one-time fee to cover expenses for testing devices, document scanning tools, and internet access during the development and validation phases.

This budget ensures that the system can be developed, deployed, and maintained effectively while meeting the project's technical and functional requirements.

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