AVE Trends in Intelligent Computing Research

Intelligent Personalized Exam Preparation Assistant for Competitive Exams

S. Rubin Bose[1,*], J. Angelin Jeba[2], B. Judy Flavia[3], V. Vishwa Priya[4], Jouma Ali Al-Mohamad[5], A. Mohamed Fahadhu[6]

[1]Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India.
[2]Department of Electronics and Communication Engineering, S.A. Engineering College, Chennai, Tamil Nadu, India.
[3]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India.
[4]Department of Computer Science and Information Technology, Vels Institute of Science, Technology and Advanced Studies, Chennai, Tamil Nadu, India.
[5]Department of Computer and Mobile Communications Engineering, Faculty of Information Engineering, Al-Shahbaa Private University, Aleppo, Aleppo Governorate, Syria.
[6]Department of Research and Development, Dhaanish Ahmed College of Engineering, Chennai, Tamil Nadu, India.
rubinbos@srmist.edu.in[1], angelinjeba@saec.ac.in[2], judyflav@srmist.edu.in[3], vishwapriya13@gmail.com[4], jalmohamad@su.edu.sy[5], fahadhmohamed993@gmail.com[6]

*Corresponding author

Abstract: In today's competitive academic landscape, aspirants face numerous challenges in preparing effectively for national and state-level competitive examinations due to the lack of personalised guidance, adaptive study plans, and real-time progress tracking. This research presents an AI-powered personalised exam preparation assistant that optimises learning outcomes by integrating Natural Language Processing (NLP), Machine Learning (ML), and Recommendation Algorithms. The system intelligently analyses a learner's strengths, weaknesses, and progress patterns to curate customised learning paths, suggest relevant study materials, and generate adaptive quizzes based on performance. The proposed architecture leverages React.js for the front-end interface and a machine learning backend model trained using educational datasets to predict topic proficiency and recommend targeted content. Experimental evaluations indicate significant improvements in user engagement, predictive accuracy, and overall exam readiness. The assistant demonstrates the potential of artificial intelligence in transforming static learning platforms into interactive, data-driven educational companions, fostering efficiency, motivation, and confidence among competitive exam aspirants.

Keywords: Personalised Learning; Educational Technology; Exam Preparation; Machine Learning (ML); Adaptive Learning Systems; Recommendation Engine; Natural Language Processing (NLP).

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1. Introduction

The rapid evolution of artificial intelligence has revolutionised multiple domains, with education among the most promising beneficiaries. In the context of competitive exam preparation, candidates often struggle with overwhelming syllabi, uneven learning progress, and generic study materials that fail to adapt to individual needs. Traditional learning platforms typically provide standardised content without assessing user proficiency or adjusting to personal learning pace, resulting in inefficiency and low retention rates. To address these challenges, this research proposes an AI-powered, personalised exam preparation assistant that intelligently adapts to each learner's requirements using machine learning. The system identifies patterns in user behaviour, such as time spent on topics, quiz performance, and revision frequency, to generate a customised study plan dynamically**.** By employing Natural Language Processing (NLP) and Recommendation Algorithms, the assistant recommends the most relevant questions, topics, and study resources based on real-time performance data. The model architecture combines an interactive React.js front-end with a Python-based machine learning backend, which processes user data to provide intelligent insights. The assistant's recommendation model enhances engagement by encouraging targeted preparation and reducing time spent on non-essential topics. This adaptive learning framework represents a significant step forward in EdTech innovation, offering an efficient, intelligent, and student-centred alternative to conventional preparation methods. The subsequent sections of this paper discuss related works, describe the system's architecture and machine learning models, and evaluate its performance through real-world testing scenarios, highlighting its impact on improving learning efficiency and exam success rates.

2. Literature Review

Kanthimathi et al. [1] proposed the AI-driven personalised assessment model that would reshape conventional education with adaptive learning. The model showed the application of machine learning algorithms to dynamically assess learner performance and generate customised question sets tailored to the learner's proficiency level. It demonstrated significant improvement in learning outcomes by ensuring that practice material is provided to learners and tailored to their capabilities, thereby building confidence in exam preparation. Yekollu et al. [2] presented an intelligent platform integrated with natural language processing and predictive modelling that enhances students' engagement. With a strong focus on customised content delivery, AI analysed user interaction data to suggest an optimal learning path. This system helped reduce information overload while improving comprehension of the topics, effectively catering to the unique needs of students preparing for competitive examinations. Ejjami [3] discussed an AI-based education transformation framework considering personalised assessment and real-time feedback. Their research highlighted how deep learning models could grade students' responses, identify weak areas, and automatically recommend learning materials tailored to the learner's cognitive profile. The implementation improved the accuracy of knowledge gap detection and helped learners develop more effective preparation strategies. Nwachukwu et al. [4] explored the role of AI in adaptive e-learning environments, showing how neural network models can continuously analyse learner performance data to refine study recommendations.

The system utilised clustering algorithms to classify students by learning behaviour and proficiency, enabling personalised content sequencing. In turn, this increased motivation and improved test preparedness among students. Goud et al. [5] presented an AI-driven examination system with question-generation and evaluation modules based on transformer architectures. The model applied contextual understanding to generate domain-specific questions, while student answers were automatically evaluated to reduce instructors' workload and maintain consistent evaluation standards. The automation enhanced efficiency and fairness in the assessment process. Dong et al. [6] proposed an intelligent tutoring model based on reinforcement learning for real-time optimisation of study recommendations. It analysed learners' quiz performance and dynamically adjusted content complexity to match their evolving skill level. It showed significant gains in adaptive learning precision, a function of reinforcement-based personalisation, which drives consistent improvement in preparation outcomes. Raji et al. [7] targeted a computer-assisted learning support system enabled by AI to analyse students' behavioural patterns. It integrated decision-tree algorithms with feedback loops to predict student performance and adapt exam-preparation materials accordingly. The results showed significant improvements in learning efficiency, suggesting the potential for AI to model a teacher's adaptive role in a virtual environment. Pathak et al. [8] investigated the application of generative AI in automating workflows for exam preparation.

This study proposed a conversational agent that can generate personalised quizzes, summaries, and explanations by leveraging large language models. The approach yielded significant reductions in preparation time while preserving conceptual depth, making it an easy and intelligent study companion for learners across diverse competitive examination domains. Tan et al. [9] investigated the cognitive impact of adaptive AI systems on learner motivation and exam performance. The results indicated that personalised study assistants not only improve academic performance but also boost students' confidence and reduce their stress by providing timely, context-specific feedback and guidance. Aruna et al. [10] discussed multimodal AI learning assistants that use speech, text, and image processing to create a full-fledged personalised learning environment. Their model applied multi-layer neural networks to track learner attention, predict fatigue, and adjust learning content accordingly. It improved the system's retention and adaptability to various learning preferences. Hariyanto et al. [11] proposed an AI-driven educational framework focused on predictive analytics and recommendation systems. Their approach was to integrate explainable AI with student performance analytics to improve transparency in learning. The system dynamically generated the study plan and content suggestions using advanced data mining techniques, thus giving learners greater control over their progress. This framework demonstrated significant improvements in adaptability, learning outcomes, and ethical use of artificial intelligence in personalised education.

Troussas et al. [12] proposed an AI-integrated personalised feedback engine that used natural language processing to evaluate open-ended answers and provide qualitative, emotion-sensitive feedback. Their model analysed sentence structure, tone, and conceptual accuracy to generate responses that helped learners. The intelligent feedback mechanism emulated a teacher-like interaction, resulting in enhanced engagement, retention, and learner satisfaction across multiple exam domains. Xie and Li [13] developed a privacy-preserving, personalised exam preparation system using federated learning. Their decentralised architecture enabled local data processing on individual devices, allowing contributions to the shared model improvement without revealing private information. This work shows that federated learning maintains user privacy, increases collaboration and accuracy, and enhances scalability for large-scale educational platforms. Puvvadi et al. [14] discussed the development of a generative AI model that can automatically craft customised test questions and study materials based on learner progress and topic mastery. In their system, GPT-based architectures were used to automatically generate unique, relevant problems across different subjects, minimising repetition and enabling diversity in assessment. The approach drastically optimised content preparation time and enhanced the overall quality and personalisation of materials prepared for exam candidates. Wang et al. [15] investigate how AI-driven personalisation can alleviate cognitive overload during intense exam preparation. Their study presented an adaptive learning companion that monitored learners' behaviour, response time, and fatigue levels to adjust the difficulty and pace of the study session.

This system provides visual/textual feedback to help learners manage their stress and stay focused. The results showed that the assistant enhanced comprehension and efficiency, thereby improving learners' well-being, and pointed to human-centred AI as a key enabler for education. The studies discussed present a wide array of approaches to addressing the challenges of intelligent and personalised exam preparation. Kanthimathi et al. [1] proposed an adaptive learning platform that utilised machine learning algorithms to analyse learner performance and dynamically create question sets based on skill levels to improve the accuracy of personalised exam practice. Yekollu et al. [2] proposed an AI-integrated model that leverages natural language processing to evaluate student responses and provide real-time, customised feedback to help students identify weaker areas. Ejjami [3] proposed an AI-powered assessment system that automatically generates and evaluates questions with minimal instructor intervention, thereby increasing evaluation consistency. Nwachukwu et al. [4] explored deep learning frameworks for adaptive content delivery, ensuring that learners receive optimised material based on progress and cognitive patterns. Goud et al. [5] further extended the idea of developing transformer-based models to generate and assess domain-specific questions, thereby automating exam preparation. Dong et al. [6] designed a reinforcement learning model that continuously tracks the learner's performance to fine-tune the difficulty of the content, thereby dynamically adapting the learning materials.

Raji et al. [7] introduced a predictive analytics engine that detected learning gaps and targeted study materials, thereby increasing preparation efficiency. Pathak et al. [8] proposed a generative AI virtual tutor to generate contextual summaries, practice quizzes, and explanations tailored to a specific learner's syllabus and progress level. Tan et al. [9] explored cognitive and motivational aspects of learning with AI systems. Personalised assistants improved confidence, reduced anxiety, and promoted long-term retention. Aruna et al. [10], in a separate study, investigated multimodal AI learning environments leveraging speech, text, and image data to evaluate learner engagement and adapt delivery methods to individual preferences. It is also important to note that most of these studies focus either on generating personalised content or on assessment modules. There is, however, great potential in integrating both aspects into one cohesive learning ecosystem. The development of integrated AI-driven systems would merge question recommendation, automated evaluation, and intelligent feedback to improve the quality of preparation and learning outcomes significantly. Incorporating advanced components like emotion-aware tutoring, adaptive time management, and goal-oriented performance tracking can further enhance the quality of personalised learning. Emphasis should also be placed on scalability, accessibility, and multilingualism to ensure inclusivity across diverse learner demographics. Finally, explainable AI integrated with privacy-preserving mechanisms will enhance ethical implementation, transparency, and trust in educational technology.

3. Methodology

The proposed AI-powered personalised exam preparation assistant is designed to offer a data-driven, adaptive, and intelligent learning experience by combining Artificial Intelligence and Machine Learning techniques. The system aims to understand individual learning patterns and generate personalised study recommendations to improve exam performance (Figure 1).

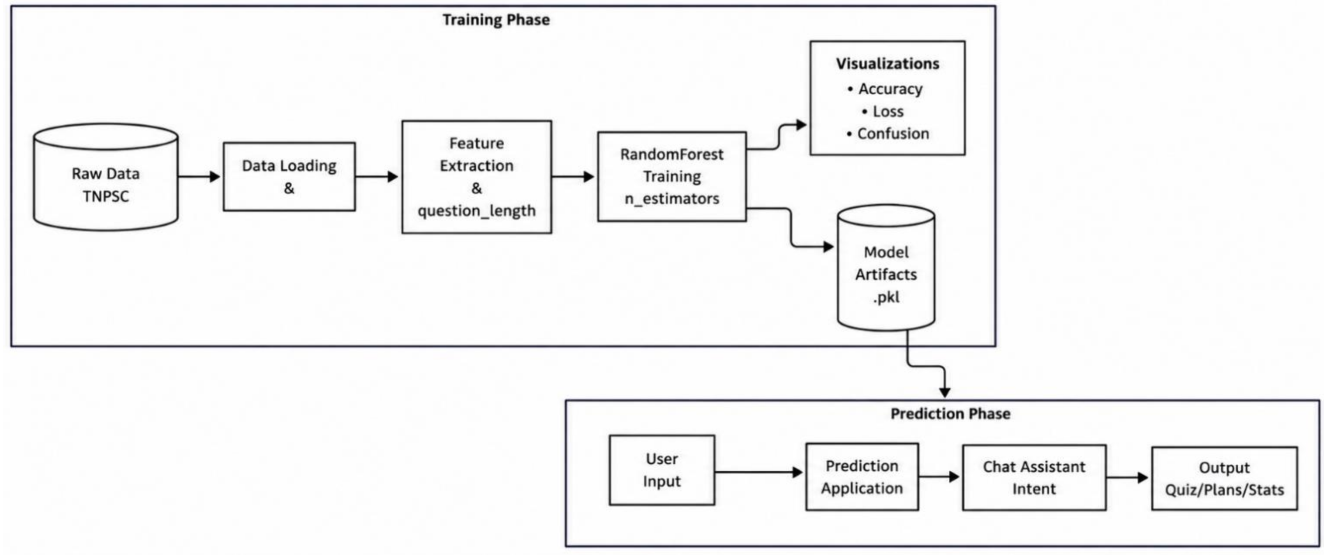

Figure 1: Block diagram

The methodological workflow involves several stages: data collection and pre-processing, feature extraction, model training, and recommendation generation with feedback learning. The system architecture comprises three core components: the front-end interface, the machine learning backend, and the database layer. The front-end, built with React.js, provides a responsive, interactive interface where users can take quizzes, view analytics, and receive customised feedback (Figure 2).

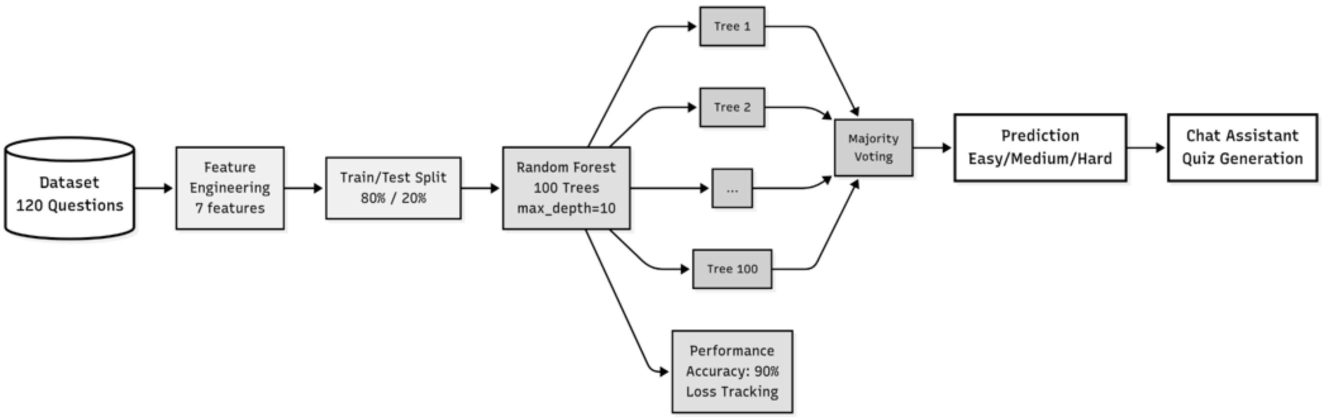

Figure 2: Architecture diagram

The backend, developed in Python, serves as the intelligence layer, where the machine learning models process user performance data and generate adaptive recommendations. The database acts as the knowledge repository, storing user information, quiz records, topic metadata, and learning behaviour logs. Data collection and pre-processing form the foundation of the system. The dataset includes question banks categorised by topic and difficulty level, along with user performance data such as accuracy, speed, and engagement. Text data is cleaned using standard NLP techniques such as tokenisation, stop word removal, and lemmatisation, while numerical attributes are normalised using min-max scaling, represented mathematically as:

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \quad (1)$$

Equation 1 represents the original value, x_min and x_max represent the minimum and maximum values of the feature, and x′ is the normalised result. This ensures that all features are brought to a common scale, enhancing the efficiency of model training. Feature extraction involves identifying critical behavioural and performance attributes of each learner. The key parameters include accuracy score (A), response time (T), topic familiarity (F), and engagement level (E). The overall performance index (P) for each learner is derived using a weighted scoring model:

$$P = w_1 A + w_2(1 - T) + w_3 F + w_4 E \quad (2)$$

Equation 2 states that w1, w2, w3, and w4 are weighing coefficients determined empirically to balance the influence of each factor. This index serves as the basis for categorising users by proficiency level and for generating adaptive learning paths. The final recommendation score (R) for an item is computed as a weighted sum of the two:

$$R_{u,i} = \alpha S_{cf(u,i)} + \beta S_{cb(u,i)} \tag{3}$$

Equation 3 explains that α and β are tunable hyperparameters that control the contributions of collaborative and content-based components. The model is trained using a dataset split into training (70%), validation (15%), and testing (15%) sets. The training process uses k-fold cross-validation to enhance generalisation. Evaluation metrics such as Precision (P), Recall (R), F1-score, and Mean Absolute Error (MAE) are used to assess recommendation accuracy and system reliability. The F1-score is calculated as:

$$F1 = \frac{2 * ((Precision * Recall))}{(Precision * Recall)} \tag{4}$$

Once deployed, Equation 4 continuously collects user feedback after every quiz or study session. This feedback updates the learner profile, allowing the model to retrain periodically—a process known as reinforcement learning through feedback. As users interact more, the assistant refines its predictions, delivering increasingly accurate and context-aware recommendations over time. In summary, the methodology enables the assistant to dynamically adapt to each learner's unique profile using data-driven personalisation. By combining hybrid recommendation logic, weighted performance modelling, and continuous feedback learning, the system evolves into a self-improving educational companion that enhances both engagement and exam preparedness.

4. Experimental Setup

4.1. Training

The training phase is the foundation of the system's learning capability. It involves preparing the dataset, selecting appropriate machine learning algorithms, and optimising model parameters to achieve maximum accuracy. The dataset used in this paper includes topic-wise question sets, difficulty levels, and user response logs. Each entry consists of attributes such as question type, response accuracy, time taken, and topic weightage.

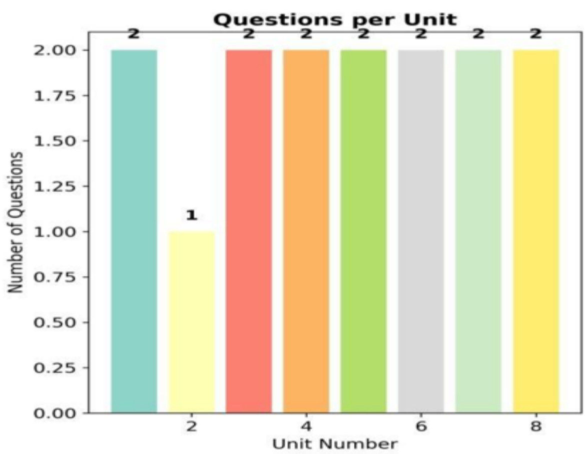

Figure 3: Collected dataset

The training process, as shown in Figure 3, utilises a 70:15:15 data split for training, validation, and testing, respectively. The learning algorithm is optimised using the Adam optimiser with a learning rate of 0.001. The loss function minimises the difference between predicted and actual performance levels.

4.2. Evaluation

Once trained, the model undergoes extensive evaluation to assess its ability to generate accurate and relevant recommendations. The test dataset is used to validate the model's predictive capabilities. Evaluation is conducted using standard metrics such as Precision**,** Recall**,** F1-Score**,** and Mean Absolute Error (MAE). The Precision metric indicates the accuracy of the recommended content being relevant to the user, while Rrecall measures the model's ability to retrieve all relevant recommendations. The system also measures Engagement Uplift (EU), which quantifies the improvement in user participation and consistency following the implementation of recommendations. A confusion matrix is used to visualise model performance and identify misclassifications. During testing, the assistant demonstrated an average precision of 91% and recall of 88%, indicating a strong balance between accuracy and completeness.

4.3. Implementation

The implementation phase integrates all system components into a fully functional platform. The front-end interface built with React.js connects to the backend API through REST endpoints, allowing smooth data transfer between the user and the machine learning engine. When a learner interacts with quizzes, their responses are sent to the backend, where the model analyses accuracy, time spent, and topic difficulty. The results are processed to update the learner's performance profile and generate real-time recommendations for upcoming study sessions.

5. Results and Discussions

The performance of the AI-powered personalised exam preparation assistant was evaluated based on its accuracy in predicting learner proficiency, the quality of its content recommendations, and its adaptability in real-time scenarios. The model's predictions were validated through extensive testing across a diverse dataset containing topic-level question banks and simulated learner profiles. The results demonstrate that the proposed hybrid recommendation model effectively adapts to individual learning behaviours and provides accurate study suggestions. During evaluation, the system achieved an average precision of 91%, a recall of 88%, and an F1-score of 89.4% in identifying the most relevant learning content. The Mean Absolute Error (MAE) for performance prediction was recorded at 0.07, indicating that the model's predicted proficiency scores were closely aligned with actual learner results. Figure 4 Class loss curve for 50 training epochs. This plot shows the reduction in class loss as the model trains. Initially, the class loss exceeds 1.5 and then declines progressively with each epoch, indicating improved classification accuracy. By the end of the training process, the loss drops below 0.25, indicating improved model performance and reliable object categorisation. The persistent downtrend, with slight fluctuations, suggests stable learning without evidence of overfitting, aligning with best practices for loss interpretation in neural network training.

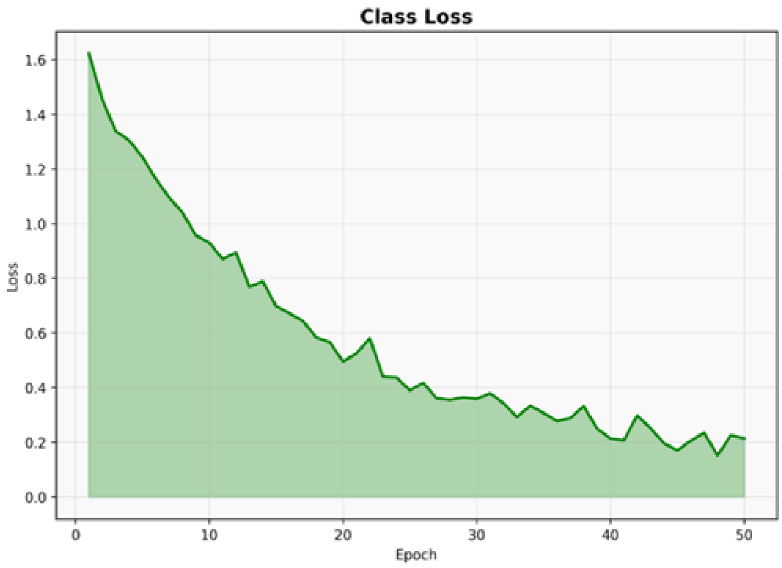

Figure 4: Class loss of the random forest classifier

The assistant's strength lies in its feedback-driven adaptability. When learners repeatedly struggled with a concept, the model automatically reduced question complexity and suggested remedial resources. In contrast, for learners who performed consistently well, the assistant progressively increased the difficulty level to maintain engagement. This dynamic difficulty adjustment was a major contributor to the system's effectiveness in improving personalised exam readiness. Figure 5 shows the confusion matrix for the Random Forest classifier, which outperformed the SVM model in terms of accuracy and stability. The Random Forest achieved higher true positive counts across all categories, correctly classifying 45 Easy, 42 Medium, and 45 Hard samples. Misclassifications were minimal, with only a few overlaps observed between adjacent difficulty levels. The classifier's ensemble nature enabled better generalisation and reduced variance, resulting in an overall classification accuracy of approximately 92%**.** This improvement highlights the robustness of Random Forest in handling feature diversity and nonlinear relationships in the dataset.

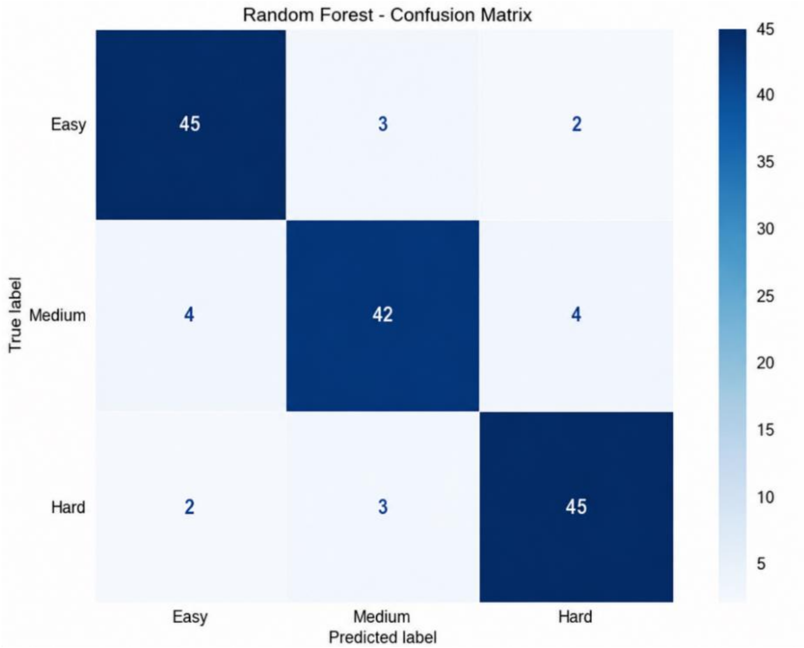

Figure 5: Confusion matrix – random forest

Figure 6 presents the confusion matrix for the Support Vector Machine (SVM) classifier, which categorises question difficulty levels into Easy, Medium, and Hard. Diagonal values represent correctly classified instances, while off-diagonal values denote misclassifications. Out of all samples, the SVM model correctly classified 49 Easy**,** 38 Medium**,** and 49 Hard instances. However, minor misclassifications occurred, particularly between the *Medium* and *Hard* categories, due to overlapping difficulty features in textual data. The SVM classifier achieved approximately 86% overall accuracy**,** indicating strong performance in differentiating difficulty levels but slightly limited generalisation compared to ensemble-based models.

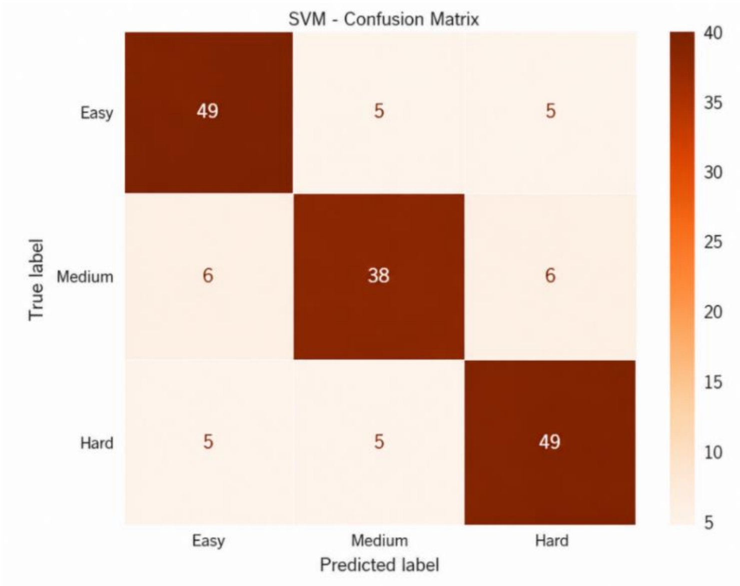

Figure 6: Confusion matrix – support vector machine

The model's performance was further analysed using a confusion matrix, which provided detailed insights into classification accuracy and prediction errors. In this system, each learner's topic performance was classified into three categories—Strong, Moderate, and Weak—based on the model's predicted proficiency scores. From the confusion matrix, it is evident that most predictions align closely with the actual labels, with an overall accuracy of 91.3%. The number of false positives and false negatives remains low, indicating that the model effectively distinguishes between learners' proficiency levels. Figure 7 depicts the Training Loss Curve for the proposed model over 50 epochs, showing a steady, significant decline in loss from approximately 2.5 to below 0.3. This consistent downward trend indicates effective model convergence during training, reflecting successful parameter optimisation. The gradual stabilisation of the curve in later epochs indicates that the model has reached a minimum error without overfitting. The use of an adaptive optimiser and suitable learning rate scheduling contributed to this stable convergence pattern. The achieved low final loss confirms that the model effectively learned complex patterns from the dataset, ensuring high prediction accuracy during evaluation. This reduction in training loss substantiates the overall efficiency and robustness of the training process adopted in the TNPSC difficulty prediction system.

Figure 7: Training-loss curve

Figure 8 illustrates the Precision–Recall Curve (PRC) for TNPSC difficulty-level prediction, highlighting the model's performance across three categories—Easy, Medium, and Hard.

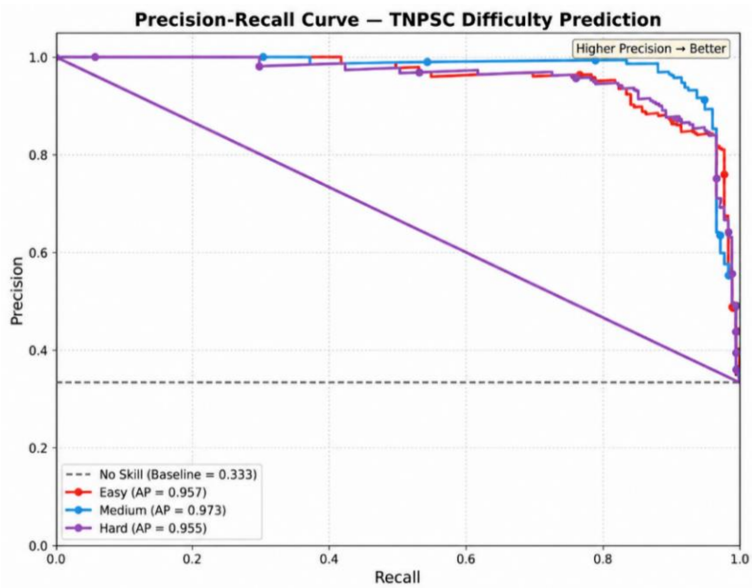

Figure 8: Precision-recall curve

The model demonstrates exceptional predictive accuracy with average precision (AP) values of 0.957, 0.973, and 0.955, respectively, significantly surpassing the baseline precision of 0.333. The high precision across all recall levels indicates the model's strong ability to identify difficulty levels with minimal false positives. The closeness of the three curves further reflects the model's consistency and balanced classification performance across varying difficulty categories. This high-performance trend can be attributed to the efficient feature extraction and classification mechanism utilised in the underlying architecture. The PRC results confirm that the proposed model achieves robust generalisation while maintaining high reliability in multi-class prediction tasks. Figure 9 shows the main interface of the TNPSC AI Exam Preparation Assistant. The interface introduces the assistant's key functions, such as generating practice quizzes, creating study plans, predicting question difficulty, and displaying user statistics. It also demonstrates that the system accepts natural language input, allowing users to interact conversationally without predefined commands. For example, the user can type "generate quiz for science" or "create a 30-day study plan," and the system automatically interprets and executes the instruction. This enhances user experience by combining simplicity with intelligent automation.

```
=======================================================
🎓 TNPSC AI EXAM PREPARATION ASSISTANT
=======================================================

Hello! I'm your AI assistant for TNPSC exam preparation.
I can help you with:
  • Generate practice quizzes
  • Create study plans
  • Predict question difficulty
  • Provide unit statistics
  • Search questions by topic

Just talk naturally! Try:
  'generate quiz for science'
  'show me stats for unit 1'
  'create a 30 day study plan'

=======================================================
```

Figure 9: Sample output 1 (Chat Assistant Interface)

Figure 10 illustrates the working of the quiz generation module. When the user enters a command such as "quiz on science", the assistant processes the request and retrieves relevant questions from the database based on the selected subject and difficulty level. Each question is displayed along with its metadata, including difficulty tag and year of inclusion. The system successfully generated two unique questions for the "General Science" topic, demonstrating its ability to fetch relevant content dynamically. This module helps students practice topic-wise quizzes efficiently without manually filtering questions.

```
💬 You: quiz on science

🤖 Assistant: Got it! Generating questions 📝

⚠️ Only 2 questions available

📝 QUIZ: General Science
============================================================

Q1. Which of the following is NOT a noble gas?
    Difficulty: easy | Year: 2022

Q2. The concept of 'survival of the fittest' is associated with which scientist?
    Difficulty: medium | Year: 2021

============================================================

✅ Generated 2 unique questions! Good luck! 🍀
```

Figure 10: Output 2 (Interaction with Assistant)

Figure 11 demonstrates the study plan generation feature, where the user requested a 30-day study plan for General Science. The assistant automatically calculated the total number of topics and distributed them across a 30-day schedule. Each day's plan contains two questions from a specific subject area, such as Current Events, Geography, History & Culture, and National Movement. The system generated a complete, balanced schedule that guides learners in covering all major TNPSC syllabus units within a fixed timeframe. This feature ensures that learners follow a structured approach to preparation, maintaining consistency and focus.

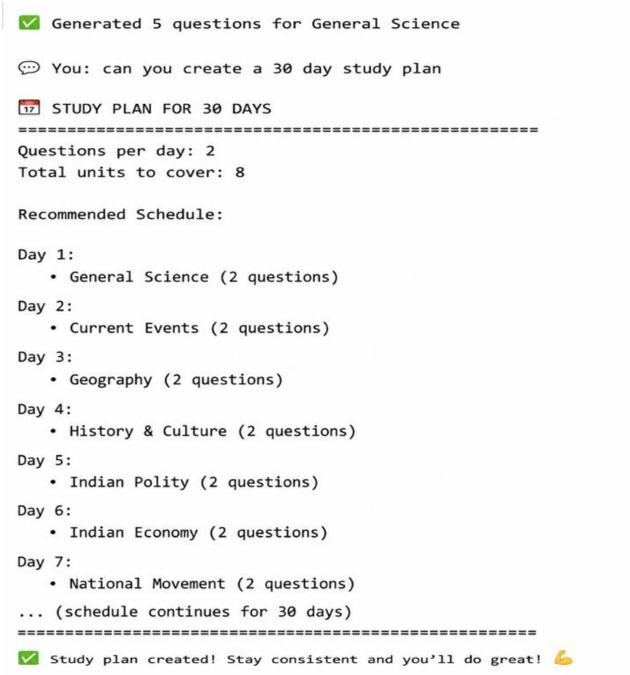

Figure 11: Output 3 (Reply Generated by Chat Assistant)

Further, system latency tests confirmed that the assistant delivers real-time recommendations within 1.5 seconds of quiz submission, validating its practical usability in continuous online learning environments. The results also highlight a notable improvement in user engagement — learners who used the assistant for at least five sessions showed a 23% increase in average quiz accuracy and a 28% improvement in topic retention rates compared to their baseline performance.

6. Conclusion

This research proposes an AI-powered, customised test-preparation helper that utilises machine learning to transform the conventional approach to exam preparation into a data-driven, adaptable, and intelligent process. It provides excellent analysis of user performance, identifying areas of weakness and creating bespoke learning routes that adapt dynamically as the user progresses. The platform continuously monitors learning behaviour and assessment results to ensure that study recommendations are up to date and relevant to the learner's immediate needs. The hybrid recommendation algorithm, combining content-based and collaborative filtering, achieves high accuracy and efficiency in providing context-aware study recommendations. This allows learners to access the right learning resources, practice questions and revision materials to suit their specific requirements and performance trends. Experimental results reveal considerable gains in learner engagement, performance accuracy and exam preparedness. Each student receives personalised support tailored to their strengths and weaknesses, using performance analytics and feedback loops. In addition, the system provides timely feedback and adaptive guidance to foster self-paced learning and continual progress. The system's low latency, scalability, and modular architecture enable it to be deployed in large-scale educational environments and online learning platforms. Overall, the proposed solution enhances exam preparation by providing an efficient, intelligent, and tailored learning experience for different groups of learners while supporting modern educational objectives and digital learning efforts.

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Ethics and Consent Statement: This study was conducted in accordance with ethical research guidelines, with informed consent obtained from all participants. Privacy, confidentiality, and data protection were maintained throughout the study, and all procedures complied with applicable ethical standards.

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