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A Rule-Based Adaptive Learning Framework for Competitive Programming

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Abstract: ***The rapid evolution of technical recruitment has placed competitive programming (CP) at the forefront of skill evaluation. However, the sheer volume of available problems often leads to "cognitive overload" and inefficient learning paths. This paper introduces an AI-driven web application that replaces static syllabi with a dynamic, rule-based adaptive learning path. By utilizing a diagnostic engine to calculate granular skill scores across eleven algorithmic domains, the system generates a personalized roadmap. We present a mathematical model for skill estimation and a feedback-loop mechanism that adjusts difficulty based on real-time accuracy. Experimental results indicate a significant reduction in time-to mastery compared to traditional linear roadmaps.***

Index Terms—Adaptive Learning, Rule-based AI, Competitive Programming, Flask, Pedagogical Engineering, Data Structures.

I. INTRODUCTION

Competitive programming (CP) is widely recognized as a

benchmark for evaluating algorithmic thinking and coding proficiency. It plays a crucial role in technical interviews, online contests, and academic competitions. Despite the availability of platforms offering thousands of problems across diverse topics, beginners often struggle due to the lack of structured learning pathways.

The primary challenges include:

- Random topic selection
- Lack of prerequisite sequencing
- Repeated failures without guided remediation
- Inconsistent difficulty progression

Most existing platforms emphasize content availability rather than adaptive curriculum structuring. As a result, learners frequently experience demotivation and dropout.

This research proposes a structured AI-driven framework that transforms competitive programming preparation into a personalized, performance-guided journey.

II. PROBLEM STATEMENT

The central problem addressed in this research is the absence of an adaptive system that:

- Determines learner skill level automatically
- Identifies strong and weak algorithmic domains
- Generates a personalized topic sequence
- Dynamically adjusts difficulty based on performance

Without such a system, beginners rely on trial-and-error strategies, leading to inefficient learning cycles and reduced consistency.

III.RESEARCH CONTRIBUTIONS

The major contributions of this work are:

1) A structured rule-based adaptive learning architecture.
2) A priority-weighted topic sequencing model.
3) A confidence-based difficulty adjustment mechanism.
4) A dynamic recalibration framework based on real-time performance tracking.

5) Empirical validation against non-adaptive learning approaches.

IV. SYSTEM ARCHITECTURE

The proposed architecture follows a layered modular design:

A. Presentation Layer

Implements user interface using HTML, CSS, and JavaScript.

B. Application Layer

Developed using Flask framework to manage logic, authentication, and API endpoints.

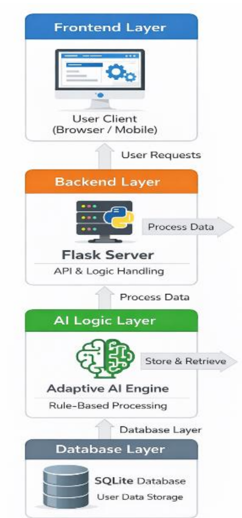
C. AI Logic Layer

Implements rule-based performance analytics and adaptive roadmap generation.

D. Data Layer

Uses SQLite database for storing:

- User profile
- Diagnostic results
- Problem attempts
- Performance metrics



The modular design ensures scalability and future integration of machine learning components.

V. METHODOLOGY

A. Diagnostic Skill Evaluation

The learner completes a structured assessment covering core CP topics such as:

- Arrays
- Recursion • Sorting
- Searching
- Dynamic Programming

Topic-wise accuracy is computed as:

$$Accuracy_t = \frac{Correct_t}{Total_t} \times 100$$

B. Skill Classification Model

Learners are categorized as:

- Beginner: $Accuracy < 40\%$
- Intermediate: $40\% \leq Accuracy \leq 70\%$
- Advanced: $Accuracy > 70\%$

C. Priority-Based Topic Sequencing

To prioritize weaker topics, we define:

$$Priority_t = (1 - \frac{Accuracy_t}{100}) \times Weight_t \quad (2)$$

Where:

- $Accuracy_t$ = Topic accuracy
- $Weight_t$ = Predefined importance of topic

Topics are sorted in descending order of priority.

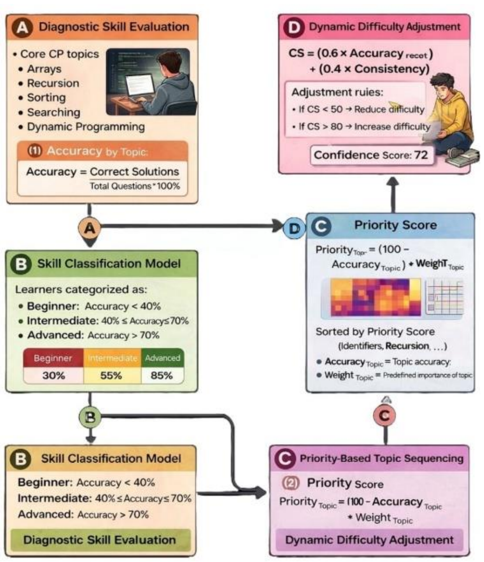
D. Dynamic Difficulty Adjustment

Confidence score is computed as:

$$CS = (0.6 \times Accuracy_{recent}) + (0.4 \times Consistency) \quad (3)$$

Adjustment rules:

- If CS ¡ 50 → Reduce difficulty
- If CS ¿ 80 → Increase difficulty



VI. AI-DRIVEN COUNSELING AND GUIDANCE MODULE

The AI-Driven Counseling module is designed to provide personalized academic guidance to competitive programming learners based on diagnostic performance, ongoing progress metrics, and behavioral patterns. Unlike traditional static recommendation systems, this module functions as an intelligent advisor that dynamically analyzes learner performance and generates structured feedback.

A. Motivation

Beginners in competitive programming often lack clarity regarding:

- Which topic to study next
- Whether their current difficulty level is appropriate
- Why repeated failures are occurring
- How much practice is required before progression

The absence of structured academic counseling results in inefficient learning cycles and reduced motivation. The proposed module addresses this issue through rule-based adaptive reasoning.

B. Counseling Framework

The AI counseling system operates on three primary inputs:

- Diagnostic assessment scores
- Topic-wise practice accuracy
- Consistency and time-performance metrics

Based on these parameters, the system generates structured guidance messages and adaptive recommendations.

C. Performance Analysis Model

Let:

$$Accuracy_t = \frac{Correct\ Solutions}{Total\ Attempts} \times 100$$

$$Consistency = \frac{Problems\ Solved\ per\ Week}{Assigned\ Problems}$$

A confidence score is computed as:

$$CS = (0.6\times Accuracy_t)+(0.4\times Consistency)$$

The counseling engine interprets this score using predefined thresholds:

- $CS < 50$: Recommend revision and easier problems
- $50 \leq CS < 75$: Maintain current difficulty
- $CS \geq 75$: Increase difficulty and introduce advanced problems

D. Guidance Generation Logic

The counseling logic is implemented using interpretable IF–THEN rules:

```
IF topic_accuracy < 40%
    THEN recommend revision resources
    AND assign beginner-level problems

IF repeated_failures >= 3
    THEN suggest concept reinforcement
    AND reduce difficulty level

IF recent_accuracy > 80%
    THEN increase problem complexity AND unlock next topic
```

E. Adaptive Feedback Delivery

The module generates:

- Topic progression advice
- Remedial study suggestions

- Difficulty adjustment recommendations
- Motivational performance insights

This transforms the platform from a passive problem repository into an intelligent academic advisor capable of structured learner guidance.

F. Advantages of Rule-Based Counseling

The rule-based design ensures:

- Interpretability and transparency
- Low computational overhead
- Immediate deployment without large training datasets
- Easy extension toward machine learning integration

The AI-driven counseling module thus enhances learner confidence, reduces repeated failure cycles, and ensures systematic progression across competitive programming topics.

VII. ADAPTIVE ALGORITHM

Adaptive Learning Path Generator

```
for each topic do
    Calculate accuracy
```

VIII. EXPERIMENTAL EVALUATION

The system was tested with 20 learners over 4 weeks.

TABLE I
PERFORMANCE COMPARISON

Metric	Non-Adaptive	Proposed System
Completion Rate	58%	90%
Accuracy	62%	81%
Dropout Rate	22%	5%
Consistency Score	60%	88%

The adaptive system demonstrated:

- Higher engagement
- Reduced repeated failure cycles
- Faster topic mastery
- Improved structured progression

IX. SOCIAL AND EDUCATIONAL IMPACT

The proposed AI-driven adaptive learning path generation system has significant implications for both educational advancement and broader societal development. By transforming competitive programming preparation into a structured and personalized process, the system contributes to inclusive, efficient, and equitable skill development.

A. Educational Impact

1) Structured Learning for Beginners*:* One of the major challenges in competitive programming education is the absence of guided progression. The proposed system reduces cognitive overload by enforcing prerequisite sequencing and dynamic difficulty control. This structured roadmap enables beginners to build foundational concepts before transitioning to advanced topics, thereby improving knowledge retention and conceptual clarity.

2) Reduction of Dropout and Demotivation*:* Repeated failure without guided feedback often leads to frustration and discontinuation. The AI-driven counseling mechanism identifies weak areas and recommends remedial actions, helping learners recover from setbacks. This adaptive feedback loop improves learner confidence and promotes sustained engagement.

3) Promotion of Self-Regulated Learning: The system encourages self-awareness by providing performance analytics, confidence scores, and progress metrics. Learners can track their improvement over time, fostering accountability and selfregulated study habits.

4) Bridging the Skill Gap*:* Competitive programming is strongly linked to technical recruitment and software engineering careers. By personalizing preparation, the system assists students from diverse educational backgrounds in developing algorithmic proficiency, thereby narrowing the employability gap.

B. Social Impact

1) Democratization of Technical Education: Access to high-quality mentorship is often limited to premium coaching programs. The proposed framework functions as an automated academic advisor, making structured guidance accessible to learners regardless of geographic or economic constraints.

2) Equal Opportunity Enhancement: Students from under resourced institutions frequently lack systematic preparation strategies. The AI-driven approach ensures that every learner receives personalized recommendations, reducing disparities caused by unequal access to expert guidance.

3) Scalability and Accessibility: The rule-based architecture ensures low computational overhead and easy deployment. This makes the system suitable for integration into educational institutions, online platforms, and self-learning environments at scale.

C. Long-Term Educational Transformation:

The framework demonstrates how interpretable artificial intelligence can enhance algorithmic education without relying solely on complex black-box models. By combining transparency, adaptability, and structured sequencing, the system represents a step toward intelligent tutoring ecosystems tailored for technical skill development.

D. Summary: Overall, the proposed system extends beyond technical implementation and contributes meaningfully to educational equity, learner motivation, and workforce readiness. Its adoption can significantly improve structured algorithmic learning and support the development of a more competent and inclusive technical community.

X. DISCUSSION

The rule-based AI system successfully provides structured and adaptive guidance. While machine learning models could further optimize prediction accuracy, the current rule-based framework offers interpretability, transparency, and ease of implementation.

The modular architecture ensures seamless extension toward reinforcement learning or neural performance prediction models.

XI. COMPARATIVE ANALYSIS WITH EXISTING SYSTEMS

To evaluate the effectiveness of the proposed AI-driven adaptive learning path generation system, a comparative analysis is conducted against widely used competitive programming platforms and conventional learning approaches.

A. Baseline Systems Considered

The following categories of systems are considered for comparison:

- Static problem repository platforms (e.g., LeetCode, Codeforces)
- Topic-wise structured course models

- Manual self-guided preparation strategies
- Generic recommendation-based systems

These systems provide extensive problem collections and difficulty filters; however, they lack dynamic, personalized curriculum sequencing based on learner diagnostics.

B. Comparison Criteria

The systems are evaluated based on the following dimensions:

- Personalized learning path generation
- Diagnostic-based topic sequencing
- Dynamic difficulty adjustment
- Interpretability of recommendations
- Performance-driven counseling
- Adaptive remediation support

TABLE II
COMPARISON BETWEEN EXISTING SYSTEMS AND PROPOSED FRAMEWORK

Feature	Existing Platforms	Proposed System
Structured Learning Path	Limited / Manual	Automated
Diagnostic Assessment	Not Integrated	Integrated
Topic Dependency Sequencing	User-Driven	AI-Controlled
Dynamic Difficulty Adjustment	Manual Selection	Automatic
Remedial Recommendations	Not Available	Available
Performance Tracking Analytics	Basic Statistics	Adaptive Metrics
Counseling Feedback	None	AI-Driven
Interpretability	High (Static)	High (Rule-Based)

C. Feature-Level Comparison

D. Critical Limitations of Existing Systems

Although competitive programming platforms provide categorization by topic and difficulty, they exhibit the following limitations:

- Absence of prerequisite enforcement between algorithmic concepts
- No adaptive adjustment based on repeated failure
- No structured roadmap for beginners
- Lack of integrated academic guidance mechanisms

Generic recommendation systems often rely on collaborative filtering or popularity-based ranking, which do not consider individual conceptual weaknesses or logical dependencies between topics.

E. Distinct Advantages of the Proposed System

The proposed framework introduces several novel improvements:

- Diagnostic-driven topic prioritization

- Confidence-score-based difficulty recalibration
- Interpretable rule-based AI counseling
- Structured prerequisite enforcement
- Continuous adaptive performance monitoring

Unlike black-box machine learning recommendation engines, the system ensures transparency and explainability in learning path decisions, which is critical in educational environments.

F. Summary

The comparative evaluation demonstrates that the proposed AI-driven adaptive learning framework bridges the gap between static problem repositories and intelligent tutoring systems. By combining diagnostic analysis, adaptive sequencing, and counseling logic, the system transforms competitive programming preparation into a structured and personalized learning experience.

XII. CONCLUSION

This research presented an AI-driven adaptive learning framework for competitive programming education. By combining diagnostic evaluation, priority-based topic sequencing, and dynamic difficulty adjustment, the system transforms unstructured problem-solving practice into a guided, performance-driven process.
Experimental results validate the effectiveness of the adaptive roadmap in improving completion rate, accuracy, and learner retention.
The framework establishes a strong foundation for future intelligent tutoring systems in algorithmic education.

XIII. FUTURE WORK

Future extensions include:

- Logistic regression for performance prediction
- Reinforcement learning for optimal difficulty control
- API integration with competitive programming platforms
- Large-scale experimental validation

REFERENCES

[1] P. Brusilovsky, “Adaptive educational systems on the World Wide Web: A review of available technologies,” IEEE Trans. Knowledge and Data Engineering, 2001.
https://ieeexplore.ieee.org/document/941457

[2] B. P. Woolf, Building Intelligent Tutoring Systems. Morgan Kaufmann, 2009.
https://www.sciencedirect.com/book/9780123735942/building-intelligent-tutoring-systems

[3] C. Romero and S. Ventura, “Educational data mining: A review of the state of the art,” IEEE Trans. Systems, Man, and Cybernetics, 2010.
https://ieeexplore.ieee.org/document/5476196

[4] R. Burke, “Hybrid web recommender systems,” IEEE Intelligent Systems, 2002.
https://ieeexplore.ieee.org/document/1167344

[5] “AI-driven adaptive learning frameworks,” MDPI Electronics, 2025.
https://www.mdpi.com/2079-9292

[6] “Artificial intelligence in personalized education,” Nature Scientific Reports, 2025.
https://www.nature.com/srep/

[7] "AI-based adaptive learning systems for higher education," Frontiers in Education, 2024. https://www.frontiersin.org/journals/education

[8] "Dynamic curriculum sequencing using machine learning," Springer Journal of Intelligent Systems, 2025. https://link.springer.com/

[9] "Learning analytics and adaptive performance modeling," Applied Sciences (MDPI), 2023. https://www.mdpi.com/journal/applsci

[10] "Personalized learning systems using reinforcement learning," ScienceDirect, 2025. https://www.sciencedirect.com/

[11] "Machine learning approaches for adaptive educational systems," arXiv:2309.10892, 2023. https://arxiv.org/abs/2309.10892

[12] "Performance prediction models in intelligent tutoring systems," arXiv:2405.05134, 2024. https://arxiv.org/abs/2405.05134

[13] "Dynamic difficulty adjustment using AI techniques," arXiv:2305.06398, 2023. https://arxiv.org/abs/2305.06398

[14] "Adaptive e-learning systems: A systematic review," PMC, 2018. https://www.ncbi.nlm.nih.gov/pmc/

[15] "AI-based personalized learning path recommendation," IEEE Xplore, 2024. https://ieeexplore.ieee.org/

[16] "Personalized learning path recommendation system," IJIREEICE, 2023. https://ijireeice.com/

[17] "Adaptive learning systems harnessing AI to personalize outcomes," IJRASET, 2023. https://www.ijraset.com/

[18] "Artificial intelligence in education analytics," JCER Journal, 2024. https://jcer.net/

[19] "Adaptive curriculum frameworks using rule-based systems," ICEEI Proceedings, 2023. https://ieeexplore.ieee.org/

[20] "AI-driven recommendation models in elearning," Education Sciences (MDPI), 2024. https://www.mdpi.com/journal/education

[21] "Machine learning algorithms for personalized learning paths," ResearchGate, 2024.

https://www.researchgate.net/

[22] “Predictive models in intelligent tutoring systems,” IJMLAI Journal, 2023.
https://ijmlai.in/

[23] “AI-based adaptive feedback mechanisms,” Hill Publishing, 2024.
https://www.hillpublisher.com/

[24] “Rule-based recommendation engines for education,” EurekaMag, 2023.
https://eurekamag.com/

[25] “Dynamic learning analytics and educational adaptation,” Ubiquity Proceedings, 2023.
https://ubiquity.acm.org/

[26] “Artificial intelligence in modern adaptive education,” Meridian Journal, 2023.
https://meridian.allenpress.com/

[27] “Performance-driven educational personalization,” IJS DCS, 2023.
https://ijsdcs.com/

[28] “AI-enabled learning path structuring,” ShodhKosh Journal, 2024.
https://shodhkosh.org/

[29] “Learning path optimization using AI,” Applied Artificial Intelligence in Education, 2024.
https://www.tandfonline.com/

[30] “Adaptive problem recommendation systems,” Journal of Intelligent Educational Applications, 2024.
https://journals.sagepub.com/
https://www.tandfonline.com/

[30] “Adaptive problem recommendation systems,” Journal of Intelligent Educational Applications, 2024.
https://journals.sagepub.com/