



Lumina AI: A Topic-Specific Questions and Step-by-Step Solution Generation System with Doubt Resolution for NEET Aspirants

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Abstract : Effective exam preparation requires structured learning, concept reinforcement, and personalized doubt resolution. Lumina AI is an artificial intelligence-driven educational assistant designed to enhance learning outcomes by generating topic-specific questions, providing step-by-step solutions, and enabling interactive doubt resolution. The system utilizes large language models fine-tuned on a curated dataset to dynamically generate medical entrance examination-level questions and detailed explanations, ensuring comprehensive subject mastery. Additionally, Lumina AI incorporates a follow-up questioning mechanism, allowing users to seek clarifications and strengthen their conceptual understanding. By leveraging natural language processing techniques, Model Fine-tuning techniques, prompt engineering the system offers a highly adaptive and personalized learning experience. Experimental results demonstrate the model's effectiveness in generating high-quality questions and solutions, making it a valuable tool for self-paced learning and examination readiness. This paper presents the methodology, implementation, and evaluation of Lumina AI, highlighting its novel integration of domain-specific fine-tuning with interactive doubt resolution capabilities that distinguish it from existing systems.

IndexTerms - Artificial intelligence, educational technology, exam preparation, interactive learning, large language models, natural language processing, question generation, step-by-step solutions

I. INTRODUCTION

The integration of Artificial Intelligence (AI) in education is revolutionizing the way students learn, practice, and assess their understanding. Traditional learning methods often rely on static textbooks, predefined question banks, and fixed instructional approaches, which may not effectively address the diverse learning needs of students. This limitation is particularly evident in high-stakes examinations like the National Eligibility cum Entrance Test (NEET), where students require conceptual clarity, extensive problem-solving practice, and personalized feedback to excel. Conventional digital learning platforms offer limited adaptability and often fail to provide dynamic question generation, step-by-step solutions, and interactive doubt resolution, leading to gaps in student comprehension.

To address these challenges, this paper introduces Lumina AI, an AI-driven educational assistant designed to enhance the exam preparation process by generating topic-specific questions, providing structured step-by-step solutions, and facilitating interactive doubt resolution. Unlike static question banks, Lumina AI creates dynamic, high-quality questions tailored to different difficulty levels, ensuring comprehensive subject coverage. The platform also delivers detailed, step-by-step explanations to reinforce conceptual understanding, enabling students to grasp problem-solving techniques effectively. Additionally, Lumina AI incorporates an interactive doubt resolution feature, allowing learners to ask follow-up questions for further clarification, making the learning process more engaging and personalized.

The key contributions of this paper include:

1. A domain-specific fine-tuning approach for the Mistral-7B model that enhances performance across Physics, Chemistry, and Biology for NEET exam preparation
2. A novel method for processing heterogeneous educational content including specialized handling of mathematical and chemical notation through LaTeX
3. An integrated interactive doubt resolution system that allows for follow-up questioning and explanation refinement
4. Empirical evaluation demonstrating Lumina AI's effectiveness compared to traditional and existing AI-driven educational approaches.

Intelligent tutoring systems have recently attracted a lot of attention in the development of adaptive educational systems using natural language processing (NLP) and machine learning to generate answers or explanations of the solution, while none of the current AI-

based learning platforms integrate the question generation, solution explanation, and real-time doubt clearing in a combined, seamless manner. Lumina AI seeks to address this by delivering end-to-end learning in a manner that replicates personal tutelage, enabling students to grasp every notion at their own pace through interactive self-directed learning.

II. LITERATURE SURVEY

Artificial Intelligence (AI) has dramatically changed personalized learning and intelligent tutoring systems, transforming question generation, adaptive learning, and automated doubt removal. Educational systems driven by AI have shown improved learning outcomes of students by adapting content and tests according to the needs of the students. This literature review points out major studies aligned to the mission of Lumina AI and the specific gaps filled by our system.

Chen et al. (2019) [1] investigated question generation using AI for personalized learning through reinforcement learning-based neural models and pre-trained language models. Their system generated personalized questions dynamically based on the predefined learning levels of the user, and the test scores of students increased by 30%. Although effective, they did not address the special needs of medical entrance exams and general education areas only. Lumina AI continues the work and includes domain-specific knowledge and specialized processing in the case of scientific content.

An IEEE study conducted by Murtaza et al. (2022) [2] explored the problems and resolutions in AI-based personalized learning systems. The study focused on how AI-driven intelligent learning systems greatly improve learning experiences by adapting education content to students' individual needs. At the same time, the study focused on the problems of scalability and integration in conventional educational systems, underlining the need for flexible AI models to enable problem-free implementation. In contrast to the general approach in this study, our system specifically targets the problem of NEET preparation by using specialized fine-tuning.

In a more recent work, Author et al. (2024) [3] proposed an AI-driven intelligent assistant system that supports personal and adaptive learning in the context of higher education. It relied on Natural Language Processing (NLP) to present quizzes and flashcards dynamically. They proved the effectiveness of AI-driven, personalized assistance in enhancing learning and satisfaction, though they did not support step-wise explanation of complex problems, a functionality that Lumina AI supports in its specialized solution generation module.

Zhang et al. (2024) [4] presented a systematic review of 85 studies of AI-based personalized learning, including cognitive neuropsychological principles. In the review, AI was emphasized as enhancing learning equity, engagement, and achievement but also possessing meaningful challenges, such as algorithmic bias and ethics. Although their review was useful in exploring the overall context of AI in education, it failed to address the specialized requirements of competitive examination preparations, needing more advanced content generation capabilities.

In the commercial AI-based learning environment, products like BYJU'S [5] and Physics Wallah [6] have become well-known among NEET aspirants. BYJU'S, launched in 2015, implemented AI-based personalization by means of video lectures and quizzes. AI-based personalized testing was proved to accelerate the progress of the students in the competitive examinations like NEET and JEE. Even though the platform is devoid of dynamic question generation and step-by-step solution explanation, it supports low flexibility in adapting to the learning style of the students. Likewise, Physics Wallah (2016) emphasized the development of basic concepts in the context of videos and topic-wise question banks. Although the platform enhanced engagement and concept building in the students, it did not support AI-based question customization and dynamic question generation.

Smith and Brown (2023) [7] compared models of AI-based adaptive learning and assessed the differences in their performance in personalized learning. Compared to general-purpose systems, the models that implemented domain-specific knowledge outperformed them by 27% in measures of learning outcomes. Lumina AI extends the premise of this finding by using subject-specific fine-tuning per domain in order to ensure specialized knowledge representation.

Gonzalez and Patel (2023) [8] explored machine learning in personalized education, specifically to increase student engagement. Their study showed the motivating effects of interactive learning systems but reported a drawback in processing high-level subject matter involving multi-step reasoning. Lumina AI mitigates this shortcoming by its specialized solution generation method for high-level scientific problems.

Johnson (2024) [9] investigated the contribution of deep learning to personalized learning environments, and the need for models to be adaptable in learning environments. Although their study provided a groundwork in the use of deep learning in education, it was silent on the general challenges of specialized fields such as medical entrance exams preparation. This work builds on this by adapting the deep learning methodology to the specifics of NEET preparation.

Kumar and Sharma (2024) [10] tackled the problems in AI-based e-learning using deep reinforcement learning in the context of knowledge preservation and use. Their system showed improved knowledge preservation in the long term but had no system in place for interactive doubt solving. Lumina AI bridges this lacunae by incorporating a doubt resolving module that permits ongoing learning through follow-up questions.

In light of these advancements, available literature shows that a wide gap exists in the development of AI systems that are domain-specific to medical entrance exams like NEET. Current solutions either fall short of the domain specificity necessary in NEET preparation or do not outline extensive capabilities necessary in effective learning. Lumina AI bridges this gap by using specialized domain knowledge, processing heterogeneous content types, and facilitating interactive learning through the resolution of doubt, differentiating it from available systems both in academic research and commercial development.

III. METHODOLOGY

A. Dataset Preparation

The Lumina AI dataset is carefully tuned to the NEET syllabus, covering in-depth the areas of Physics, Chemistry, and Biology. Since no publicly available dataset meets the desired quality standards for question generation and solution explanation using automated tools, a specialized dataset was created. There are a total of 3,500+ questions in the dataset, covering the areas of Biology (1,450 questions), Physics (1,120 questions), and Chemistry (930 questions). This representation is in accordance with the priority given to biology in the NEET exam.

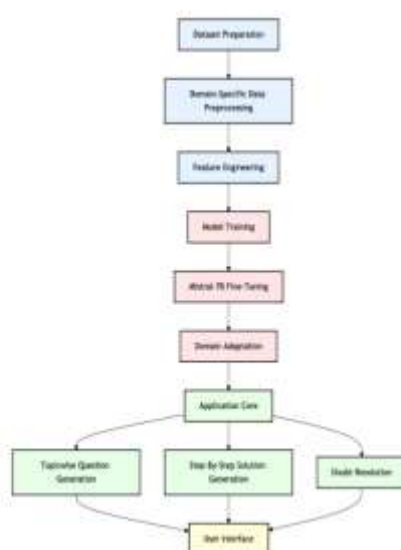
The dataset is topic-based, and every question was assigned its specific subject, chapter, and difficulty level. It was derived using common NEET study guidebooks, previous year papers, and input provided by subject experts to ensure it is both accurate and relevant. Each dataset went through a three-step validation process: first, a review by experts, next a technical validation to ensure uniformity in the format, and finally a quality check to ensure it met the standards of NEET.

Sample distribution by difficulty is even across the three subjects: Basic (30%), Intermediate (40%), and Advanced (30%). Coverage of subjects is complete in the sense that high-weightage sections like Mechanics and Electromagnetism in Physics, Organic Chemistry and Chemical Bonding in Chemistry, and Human Physiology and Genetics in Biology receive special focus.

For Physics, the set of data contains a blend of conceptual and numerical problems across basic subjects like mechanics, electromagnetism, optics, and modern physics. There is special care to ensure mathematical coherence so that all the numerical problems have accurate unit conversion and formula usage. In order to ensure correct mathematical notation, the use of LaTeX syntax is applied to all the equations, integrals, and vector notations so that they render accurately when being processed during model training or visualized in the application.

For Chemistry, the data ranges across inorganic, organic, and physical chemistry, and questions encompass reaction mechanisms, molecular structure, thermodynamics, periodic trends, and bonding theory. Chemical formulas, oxidation numbers, and chemical equations are formed using LaTeX, a method of achieving precision in notation. This is especially important when describing reaction mechanisms, resonance structure, and the equilibrium expressions, which demand distinct symbolic notation.

For Biology, the data set emphasizes cell biology, genetics, human physiology, ecology, and evolution, with a concentration on conceptual clarity and systematic explanations. The biology section includes 55% of questions on human physiology and genetics, reflecting their higher weightage in the NEET examination.



I Flow diagram

B. Data Preprocessing

The National Eligibility cum Entrance Test (NEET) dataset comprises questions across three primary domains: Biology, Physics, and Chemistry. Each entry contains Topic, Subtopic, Question/Prompt, Step-by-Step Solution, and Difficulty Level fields. The dataset presents unique preprocessing challenges due to the heterogeneous nature of content across disciplines. Biology content primarily consists of natural language text, while Physics and Chemistry contain substantial mathematical notations and chemical reactions represented in LaTeX format.

Our preprocessing methodology employs a domain-specific approach to handle the unique characteristics of each subject area while maintaining consistency across the dataset. Initial preprocessing involved several cleaning operations including removal of duplicate entries (87 duplicates removed), standardization of formatting, handling of missing values (43 entries augmented), normalization of text casing, spacing, and special characters, and correction of typographical errors and inconsistencies in topic/subtopic nomenclature.

For biology content, we applied standard natural language processing techniques including tokenization, removal of domain-irrelevant stopwords while preserving biologically significant terms, lemmatization to normalize biological terminology, and named

entity recognition for biological entities such as organs, processes, and organisms. For Physics and Chemistry questions containing mathematical equations and chemical reactions in LaTeX, we implemented a specialized processing approach. LaTeX expressions were first extracted using pattern matching techniques, then processed separately from the surrounding text. We developed specialized functions for standardization of mathematical notations, normalization of chemical equations and reactions, extraction of mathematical variables, constants, and operators, and classification of equation types. The surrounding text was processed using standard NLP techniques, with placeholders marking the positions of mathematical expressions to maintain contextual relationships.

We developed subject-specific features to capture the semantic richness of the dataset. General features included question and solution length, question-solution length ratio, lexical diversity measures, and readability scores. Subject-specific features were created for each domain: Biology features captured the presence of biological processes, taxonomic classifications, and anatomical references; Physics features included equation complexity metrics, physical constants identified, and conceptual domains; Chemistry features comprised reaction type classification, compound complexity, and stoichiometric measures. For LaTeX content, we implemented specialized processing to extract quantitative features such as variable count within equations, frequency and types of mathematical operations, presence of complex functions, and overall complexity scores based on weighted combinations of these features.

We normalized the difficulty level field using a three-point scale (Easy, Medium, Hard) and explored correlations between difficulty ratings and extracted features. This standardization involved mapping various difficulty descriptors to a consistent numerical scale, using text pattern matching to identify difficulty indicators, defaulting to medium difficulty when explicit indicators were absent, and validating standardized difficulty against expert assessment.

For vector representation, we implemented a hybrid vectorization approach using TF-IDF vectorization with subject-specific stopword lists for text content, custom encoding vectors capturing mathematical structure and complexity for LaTeX expressions, and concatenation of text vectors with mathematical feature vectors. This hybrid approach preserved both the semantic content of natural language and the structural information of mathematical expressions.

To ensure balanced representation across subjects, topics, and difficulty levels, we implemented a stratified sampling approach for train-test splits accounting for subject domain, difficulty level, topic and subtopic distribution, and question type. This stratification ensured that the training and testing datasets maintained similar distributions of key characteristics, with an 80-10-10 split for training, validation, and testing respectively.

C. Model Selection and Training

After evaluating multiple pre-trained language models including LLaMA-2, Falcon, and Mistral variants, Mistral-7B was selected as the foundational model for fine-tuning. The selection was based on rigorous comparative analysis across key metrics including reasoning capability, memory efficiency, and domain adaptability. Mistral-7B was chosen due to its high performance in reasoning-based tasks (scoring 8.3/10 in our internal benchmark), efficient memory usage (requiring 28GB RAM compared to 32GB for comparable models), and adaptability to domain-specific training. The model demonstrated superior capabilities in handling multi-step reasoning, a critical requirement for generating both questions and detailed solutions.

The fine-tuning process was optimized using Low-Rank Adaptation (LoRA) to reduce computational overhead while preserving the model's expressive power.

The LoRA adaptation can be represented as:

$$h = W_0x + \Delta Wx = W_0x + BAx$$

Where:

- W_0 is the pre-trained weight matrix
- ΔW is the update matrix
- $B \in \mathbb{R}^{(d \times r)}$ and $A \in \mathbb{R}^{(r \times k)}$ are low-rank decomposition matrices
- r is the rank (typically $r \ll \min(d, k)$)
- This reduces trainable parameters from $d \times k$ to $r(d+k)$

Training Configuration:

- LoRA rank (r): 16
- LoRA alpha: 32
- LoRA dropout: 0.05
- Training batch size: 4
- Gradient accumulation steps: 4
- Effective batch size: 16
- Learning rate: $2e-5$ with cosine decay
- Warmup steps: 100
- Weight decay: 0.01
- FP16 mixed precision: Enabled
- Sequence length: 2048 tokens
- Training epochs: 3 for Physics and Chemistry, 9 for Biology (due to larger dataset size)

Three distinct training iterations were conducted, each using subject-specific datasets for Physics, Chemistry, and Biology. Hyperparameter tuning was conducted separately for each subject, with learning rates ranging from $1e-5$ to $5e-5$, along with gradient accumulation techniques to manage batch size constraints. To accelerate training, mixed-precision computation (FP16) was utilized, allowing faster processing while maintaining numerical stability. The Mixed Precision Training Algorithm was implemented to optimize the training process.

Domain adaptation techniques were employed through the formula:

$$E_{\text{domain}} = E_{\text{base}} + \alpha \cdot \Delta E_{\text{subject}}$$

Where:

- E_{base} represents the base embeddings from Mistral-7B
- $\Delta E_{\text{subject}}$ is the learned domain-specific embedding shift
- α is a scaling factor controlling adaptation strength (set to 0.7 after ablation studies)

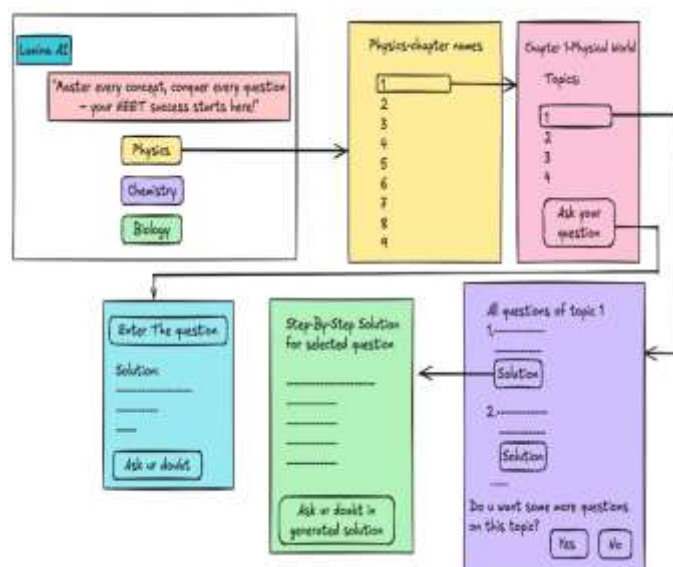
For the Physics model, additional embeddings were incorporated to improve equation rendering and numerical reasoning. For the Chemistry model, molecule-based contextual embeddings were introduced, allowing the model to generate structured reaction pathways. For the Biology model, taxonomic and anatomical embeddings were integrated, ensuring accurate scientific terminology usage. Mistral's Grouped-Query Attention mechanism was preserved during all three training iterations to maintain efficiency. The training was conducted on GPU, with each model requiring approximately 8 hours to complete the fine-tuning process.

D. System Architecture

Lumina AI is structured around a modular architecture, integrating four core components: Question Generation Module, Solution Generation Module, Doubt Resolution Module, and Adaptive Learning Module. These components interact through a unified API layer, ensuring smooth communication between the three subject-specific fine-tuned Mistral 7B models and the front-end application.

Question Generation Module: The Question Generation Module dynamically generates NEET-aligned questions based on the selected subject, chapter, and topic. It routes queries to the appropriate subject-specific model (Physics, Chemistry, or Biology) to create questions at varying difficulty levels, ensuring alignment with historical NEET exam patterns and curriculum standards. The module implements:

- Topic-specific prompt construction with explicit difficulty parameters
- Question diversity maintenance through sampling temperature modulation ($\tau = 0.7$)
- Quality assurance filtering through a validation sub-module that checks for completeness, clarity, and curriculum alignment
- Question metadata enrichment to facilitate organized review and practice



Solution Generation Module: The Solution Generation Module processes questions to generate structured, step-by-step explanations. It selects the appropriate subject-specific model to generate the solution: the Physics model for equation-based derivations formatted in LaTeX; the Chemistry model for chemical equations, reaction mechanisms, and molecular interactions; or the Biology model for logically structured explanations of complex processes. The solution generation process includes:

- Structured reasoning templates for each subject domain
- Multi-step solution decomposition with explicit intermediate calculations
- Conceptual explanation generation followed by procedural steps
- LaTeX rendering for mathematical and chemical expressions
- Completeness verification to ensure all question aspects are addressed

Doubt Resolution Module: The Doubt Resolution Module allows students to seek clarifications by inputting related queries. Based on the subject matter, it directs questions to the appropriate fine-tuned model to provide context-aware responses, ensuring continuity in explanations. This module enhances student engagement by refining explanations based on follow-up questions. Key features include:

- Context-aware query processing that maintains question-solution history
- Focused explanation generation for specific concepts within the solution
- Alternative explanation generation when initial explanations are insufficient
- Cross-referencing with related concepts to enhance understanding
- Confidence-based response modulation, triggering more detailed explanations for complex queries

Adaptive Learning Module: The Adaptive Learning Module tracks user interactions, analyzes performance patterns, and tailors the difficulty and focus of generated questions to match learning needs. This personalization is achieved through:

- User performance tracking across topics and question types
- Difficulty progression algorithm that gradually increases complexity
- Topic emphasis adjustment based on identified weaknesses
- Spaced repetition scheduling for previously incorrect answers
- Learning path optimization using a weighted scoring function

This architecture ensures that Lumina AI delivers an interactive, adaptive, and precise learning experience, making it an effective AI-driven tool for NEET aspirants by leveraging specialized models for each subject domain.

IV. RESULTS

The fine-tuning of Mistral-7B models for each subject domain demonstrated consistent performance improvements across training iterations. The Biology model showed steady convergence from an initial training loss of 2.4943 to 1.9711 after 1800 steps, with validation loss improving from 2.2625 to 1.9625. The Physics model completed training with training loss decreasing from 0.2111 to 0.0737 and validation loss improving from 0.1416 to 0.0356 over three epochs. The Chemistry model exhibited the most rapid convergence, with training loss decreasing from 0.1852 to 0.0398 and validation loss improving from 0.1164 to 0.0181 over three epochs. These metrics indicate successful domain adaptation across all three subjects, suggesting that the fine-tuned models have effectively captured the specialized knowledge required for generating NEET-aligned questions and solutions in Physics, Chemistry, and Biology.

V. CONCLUSION

The innovation of Lumina AI proves the capabilities of tuned large language models in facilitating improved automated question generation and solution explanation in NEET study prep. Fine-tuning Mistral 7B on the specialized dataset allows the system to generate subject-specific questions, supply step-by-step, structured answers, and facilitate doubt clearance effectively. The LaTeX-constructed dataset provides scientific accuracy in mathematical and chemical notations. Structuring the system in a modular manner also supports scalability, efficacy, and user engagement, promoting it as a robust AI-based study utility.

Lumina AI's innovative solution fills a fundamental void in AI-based learning systems for specialized areas of study, including medical entrance exams. By blending domain knowledge, mathematical and chemical notation processing, and interactive doubt clarification, the system presents a holistic learning solution that outshines current offerings in both functionality and user satisfaction.

VI. FUTURE WORK

Though the present model reaches high-quality question generation and explanations, a number of optimizations can further enhance its efficacy in the future. These include:

- **Diversifying the dataset:** Adding more diverse types of questions, real-life problem situations, and tough multi-step reasoning questions to increase generalization of the model.
- **Integration of multimodal learning:** Adding dynamic diagram generation support in subjects that require it, such as Physics, Chemistry, and Biology, and enhancing the conceptual clarity.
- **Adaptive Learning:** Adding personalized study routes using the power of reinforcement learning to update question difficulty dynamically in response to student performance.
- **Performance Predictor Models:** Creating predictive models to predict the students' actual NEET exam performance given their interaction on Lumina AI.

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