LearnEase: Adaptive Learning Hub

Submitted in partial fulfilment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

By

Jiten Purswani (D12B/43)

Srimathi Srinivasan (D12B/55)

Laveena Mirani (D12B/30)

Kareena Lachhani (D12B/26)

Name of the Mentor

Prof. Pallavi Saindane

Vivekanand Education Society's Institute of Technology,

An Autonomous Institute affiliated to University of Mumbai

HAMC, Collector's Colony, Chembur,

Mumbai-400074

University of Mumbai (AY 2024-25)

CERTIFICATE

This is to certify that the Mini Project entitled **"LearnEase: Adaptive Learning Hub"** is a bonafide work of **Jiten Purswani (D12B/43), Srimathi Srinivasan (D12B/55), Laveena Mirani (D12B/30), Kareena Lachhani (D12B/26)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

(Prof.Pallavi Saindane)

Mentor

(Prof. Nupur Giri)

Head of Department

(Prof. J.M. Nair)

Principal

Mini Project Approval

This Mini Project entitled "**LearnEase: Adaptive Learning Hub"** by **Jiten Purswani (D12B/43), Srimathi Srinivasan (D12B/55), Laveena Mirani (D12B/30), Kareena Lachhani (D12B/26)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

Examiners

1.…………………………………………
(Internal Examiner Name & Sign)

2.…………………………………………
(External Examiner name & Sign)

Date:

Place:

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ABSTRACT

The current learning systems are more generalised and teacher-centric. The teachers disseminate information equally to all studies using the same methods. But, each student has unique learning styles and preferences. This is a major concern that most students experience. To address this gap in their learning process, we are working on a Adaptive Learning system: LearnEase. This system has an interactive summarizer that can summarise the content that students provide. It also features a quiz module that provides dynamic quizzes based on the summarised content the student has studied. The proposed system also can help students plan by recommending schedules based on their requirements, strengths and weaknesses.

ACKNOWLEDGEMENTS

We would like to express our deepest gratitude to everyone who has contributed during this project. Firstly, we are incredibly thankful to our project mentor and guide, Prof. Pallavi Saindane for constant and unwavering support, thoughtful insights, constant feedback and encouragement throughout. Our project has taken shape and direction under her guidance and advice.

We are really grateful to the Head of Department of Computer Engineering, Prof. Nupur Giri for providing us with the opportunity to work on this project. Similarly, we would like to thank Prof. J.M. Nair, Principal of VESIT for fostering an environment where we could explore our limits and work on such an interesting project.

We would like to extend our thanks to all our professors at VESIT for their constant guidance and unwavering belief and support for us. We are really thankful for all the knowledge and skills that they have imparted to us.

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Finally, we would like to express our gratitude to our family and friends who gave us constant encouragement and emotional support. They helped us to stay motivated and bring this project to fruition.

LIST OF ABBREVIATIONS

Abbreviations	**Definition**
BART	Bidirectional and Auto-Regressive Transformer algorithm
T5	Text-to-Text Transfer Transformer algorithm
ROUGE	Recall-oriented Understudy for Gisting Evaluation
NLP	Natural Language Processing
UI	User Interface
LLM	Large Language Model
PSO	Particle Swarm Optimization

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LIST OF SYMBOLS

LearnEase Logo:

INTRODUCTION

1.1 INTRODUCTION

The scope of tech-based platforms being integrated into the current learning space has been on a steady growth over the past few years. The proposed system is one such platform that will help students to route their learning journey according to their needs and expectations. The proposed system aims to provide a tailored learning experience for each learner.

The proposed system's objective is to use machine learning (ML) algorithms to deliver material that is appropriately structured and tailored to users, increasing their engagement and retention. The system will be responsive, with regular tests and evaluations to improve the recommendations and content sent to users by measuring their assimilation of the information.

Recognizing the diverse needs of students, the proposed system aims to leverage algorithms to provide tailored content summaries to students. This interactive system will allow students to learn at their own pace and repeat topics till they are left with a deeper understanding of the material.

In addition, the proposed system will provide frequent tests and evaluations to gauge the students' retention and assimilation from the above content.[1] This assessment will also aid in understanding the student's strengths and weaknesses that can be further used to recommend a course of action, a schedule according to which they can focus on improving the weaker sections and keep in touch with the other topics.[1] This schedule recommended will be able to aid students to approach their learning in a structured format.

By creating a dynamic work environment which emphasises the student's personality and adapts accordingly, the system seeks to enrich their learning experience. The system will be further improved through frequent feedback and assessment which can help refine the models.

1.2 MOTIVATION

The traditional education system, though lays a foundation, fails to address the personal learning styles of students.[8] We ourselves have observed this gap and thought to develop a technological model to bridge it by integrating ML models.

The recent rise of online learning has boosted the demand for technology powered solutions in the education space. Many platforms are able to offer vast amounts of content but few have the ability to dynamically adapt to user's personal needs and real-time performance. We plan to leverage student data and ML algorithms to provide customised learning paths to fill this gap.

The motivation for developing this system is to ensure that education should be made more accessible and adaptable. It will help students to obtain only necessary materials and information and improve their understanding amidst the information overload available today. This system will help students to set priorities, learn accordingly and then test their knowledge assimilation.

1.3 PROBLEM STATEMENT AND OBJECTIVES

Because of the one-size-fits-all nature of the existing educational system, individual student needs are not met, which results in disengagement and subpar academic performance. Conventional approaches do not take into consideration different learning speeds, tailored content relevancy, or unique learning styles. Real-time, tailored feedback is absent from standardised testing, and time and resource restrictions frequently prevent teachers from giving students the targeted attention they need. Furthermore, there is still underutilization of educational data's potential to improve tailored learning. To increase student engagement and academic achievement, a system that adjusts to each student's particular learning style, pace, and preferences is crucial. Although there are many educational platforms available that offer a plethora of educational content, they are not curated specifically to match learner’s specific needs.

The primary objectives of this system are:

- **Personalised and interactive content:** The proposed system aims to provide personalised content by providing a summarizer that can provide concise information from a file that the student uploads. It can further interact with the learner to provide more information.

- **Real-time assessment:** Once a student is confident with the summarised content, they can attempt a quiz to assess their progress and depth of understanding. This can help them decide to move forward or revisit the topics.
- **Increase learner engagement and retention:** The system will provide an interactive and dynamic environment which will help students to be more engaged and in turn increase their knowledge absorption and retention.
- **Schedule Recommendation:** Implement a data-driven approach to provide students with a personalized schedule based on their strengths and weaknesses. This is analyzed based on their previous engagement and assessments.
- **Scalability:** Assure that the system can scale to accommodate a large number of students and a wide range of requirements while ensuring consistent performance.

1.4 ORGANIZATION OF REPORT

This report aims to provide a comprehensive understanding of the personalised learning app that we are currently developing.

- Introduction: An overview of the system and motivation behind the development of the application. Defining the problem statement and setting the flow for the report.
- Literature Survey: A review of the currently existing systems. A discussion of the flaws of such systems and the current trends in the domain. Identification of a gap in the market for the proposed system to fill.
- Proposed system: An outline of the system architecture and details of the major modules of the system. The algorithmic aspects of the system and process design including prototyping.
- Results: A summary of the findings and work so far. The comparison of various summarization models. Overview of the Figma prototype.
- Conclusion and Future Work: A concluding section highlighting the major points discussed in the report.
- Annexure: A draft of a research paper has been attached as an annexure.
- References: References that have been used are cited at the end of the report

LITERATURE SURVEY

2.1 SURVEY OF EXISTING SYSTEM

Author	Publication	Year	Pros	Cons	Inferences
A. B. F. Mansur, N. Yusof, and A. H. Basori,	"Personalized Learning Model Based on Deep Learning Algorithm for Student Behaviour Analytic," *Procedia Computer Science*, vol. 163, pp [2]	2019	- Large set of attributes. - Automation of Feedback	- Potential risk of overfitting. - No specific context is present.	Need more specific dataset rather than a non contextual for a better understanding of the students.
Y. Ma, L. Wang, and Q. Zhang,	"A Personalized Learning Path Recommendation Method Incorporating Multi-Algorithm," *Applied Sciences*, vol. 13, no. 10, Article 5946 [3]	2023	- Personalized Learning paths - Swarm Intelligence	-Limited real-world testing - Dependencies	The PSO algorithm can be very helpful in creating personalized paths. Have to avoid dependencies.
Muñoz, Juan & Jan, Zohaib & Saavedra, Angelo	"Machine learning for learning personalization to enhance student academic performance." [4]	2021	- Ensemble Learning Approach - Cluster based Classifier	-Potential Overfitting - Dependencies	Cluster based classification is very popular nowadays and its accuracy rate is also very good

Author	Publication	Year	Pros	Cons	Inferences
T. B. Lalitha and P. S. Sreeja,	"Personalised Self-Directed Learning Recommendation System," *Procedia Computer Science*, vol. 171, pp. 583–592, 2020. [5]	2020	- Recommendation module by using collaborative filtering and content based filtering	- Lacks explainability to users how recommendation is generated	We can create a better recommendation model which will allow users as well to have a better understanding.
J. Alanya-Beltran	"Personalized Learning Recommendation System in E-learning Platforms Using Collaborative Filtering and Machine Learning," in *Proc. of the IEEE Conference on Artificial Intelligence (ACCAI)* [6]	2024	- Neural Networks - Decision Trees	- Cold start Problem - Potential Bias	Can implement neural networks which can be used to latent features from user- item interaction data.

Table 2.1.1 Literature Survey

2.2 LIMITATION OF EXISTING SYSTEM OR RESEARCH GAP

1. Overfitting risk: Many of the existing systems seem to be prone to overfitting. This limits the generalizability of the models to new, unseen data, which is crucial for designing an effective system that is adaptive.
2. Lack of Contextual understanding: There is a lack of specific, context-aware datasets that capture the nuances of the students' requirements and preferences of individual students. Using generic datasets fail to be applicable for deriving actual learning patterns.
3. Limited Real-world testing: Most studies show limited testing in real-world situations, raising concerns about reliability, scalability and performance of systems in diverse situations. While algorithms may perform well in controlled environments, they often struggle when applied to real-world educational settings as student learning paths can be unpredictable.
4. Explainability Issues: Many systems lack transparency in their decision-making processes. The users are unaware of how or why content is recommended, leading to a lack of trust in the system.
5. Cold start problem: The existing systems face the challenge of cold start problem. This means that, when the system has very little information regarding new users, the recommendations are hampered. This occurs especially in the early stages of system release.
6. Potential Bias: Many algorithms that are used in personalised learning systems are susceptible to biases. This could be because of biased training data or model design. This is a very serious issue as it could lead to recommendation of incorrect or unfair learning paths to students.

2.3 MINI PROJECT CONTRIBUTION

All the members of the team have contributed significantly to the development of this project across the entire semester, leveraging their individual strengths. We have all challenged ourselves, acquired new knowledge, and look forward to further growth alongside our application. Our individual contributions are as follows:

- **Jiten Purswani:** As the team leader, managed the overall vision and ensured seamless collaboration among all members. He played a critical role in the design and enhancement of algorithms, working closely with Laveena to fine-tune the models.

Jiten tested and optimised BART and T5 models, troubleshooting issues and recommending strategic improvements. He also provided detailed analysis of model performance and contributed significantly to the algorithm's further enhancements to meet the project requirements [10].

- **Srimathi Srinivasan:** Primarily responsible for backend integration, she developed a robust connection between the front-end design and backend services, ensuring smooth data flow and interactions. Srimathi also contributed to a portion of the architecture and interface design, laying out the initial framework of some pages. She transformed static designs into dynamic prototypes that demonstrated real-time system interactions and user flows. Srimathi also led the deployment process, configuring the application for production environments and ensuring smooth operations on target systems [11].
- **Laveena Mirani:** Focused on implementing and optimising the Lamini model for summarization. She rigorously tested the model using various evaluation metrics, analyzing performance to fine-tune and improve it. Laveena worked closely with Jiten to enhance the algorithmic efficiency of the summarization models, leading to an informed selection of the best model for the system. She was also responsible for testing the overall system, ensuring it met the functional requirements and performed reliably before deployment [12].
- **Kareena Lachhani:** Designed and fully implemented the Figma-based user interface (UI) of the system, focusing on delivering a highly interactive and aesthetically pleasing UI. Her design ensures both functionality and quality user experience, facilitating easy engagement for learners. She was instrumental in transforming the design into an interactive interface that is ready for the development phase [13].

PROPOSED SYSTEM

3.1 INTRODUCTION

The material summarizer, quiz generator, and schedule recommendation system are the three main parts of the "LearnEase" platform. Advanced machine learning models customised to meet the specific requirements of pupils in Class 9 and Class 10 are used in each of these components.

- Summarizer module: The content summarizer makes difficult academic information easy to understand by simplifying it. Three pre-trained models (BART, LaMini, and T5) were tested; each was refined using datasets pertinent to the Maharashtra Board curriculum. After analysing their performance, we decided to proceed with the BART model.
- Quiz Generator Model: The quiz generator is an intelligent system that generates dynamic and tailored quizzes based on each student's current level of knowledge. It uses clustering techniques to categorise students based on their learning rate and proficiency, resulting in exams suited to their unique needs. The algorithm adjusts the complexity of the questions in real time based on student performance, providing a balance of challenge and fairness.
- Schedule Recommendation System: The schedule recommendation system is intended to assist students properly plan their study time. This method suggests learning schedules that are tailored to each student's progress, learning style, and degree of engagement using a combination of collaborative and content-based filtering.

3.2 ARCHITECTURAL FRAMEWORK/CONCEPTUAL DESIGN

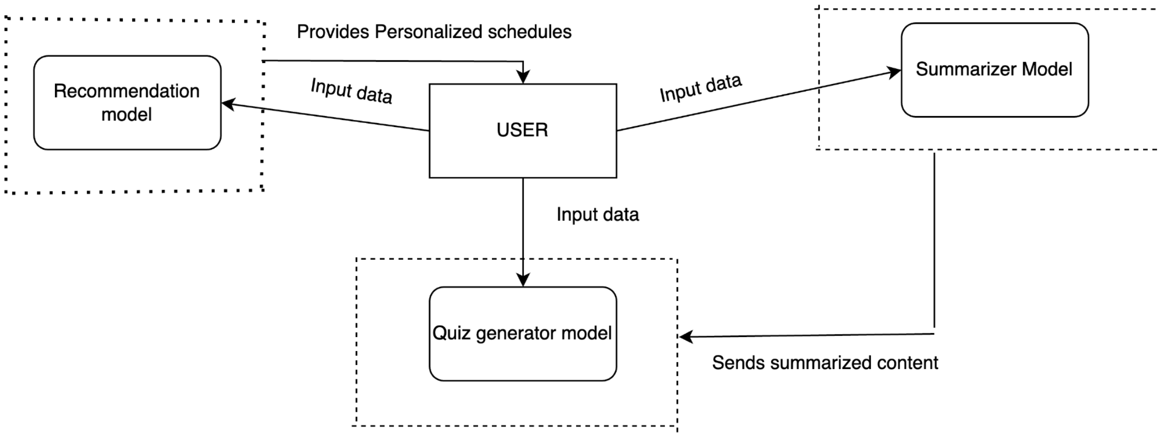

Fig 3.2.1. Block diagram

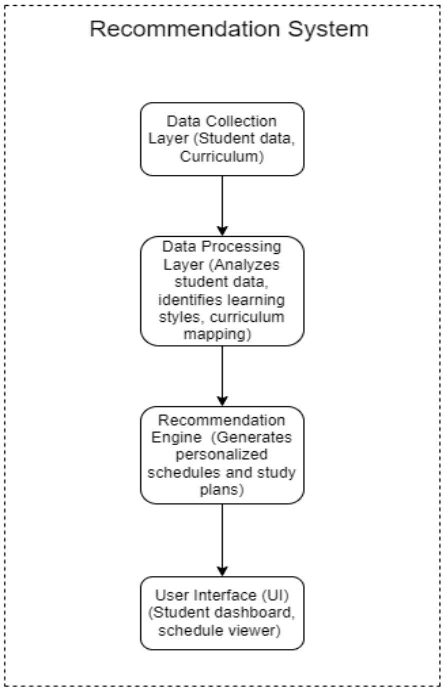

Fig 3.2.2 . Modular Design- Recommendation system

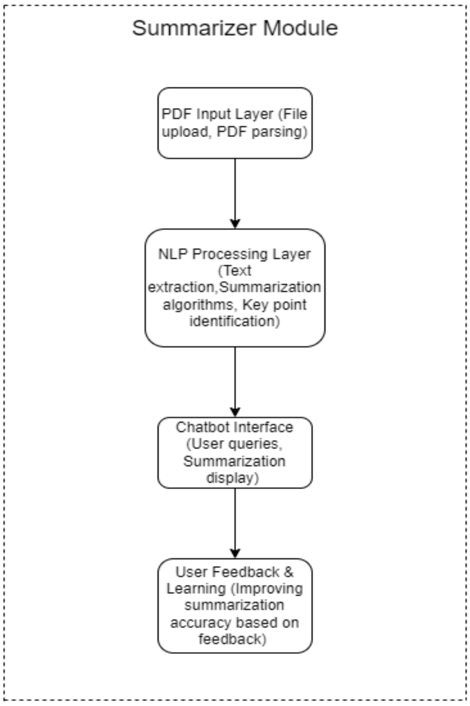

Fig 3.2.3. Modular Design- Summarizer system

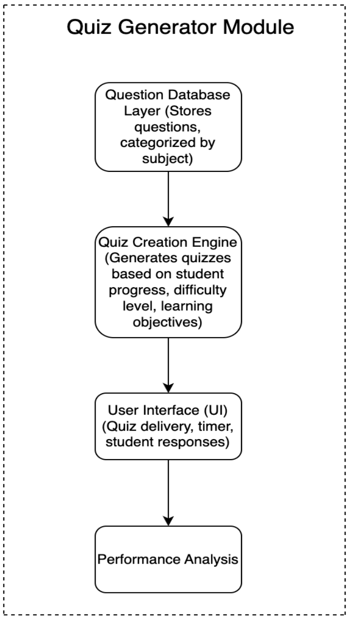

Fig 3.2.4. Modular Design- Quiz generator system

3.3 ALGORITHM AND PROCESS DESIGN

Currently we have worked on the summarizer module of the system. For this, we have trained and tested three summarizing models. Initially we explored the various types of summarizing such as abstractive and extractive. We finally narrowed down to three of the models:

- BART model: BART (Bidirectional and Auto-Regressive Transformers) is a transformer-based model that is pre-trained on denoising autoencoder objectives. It basically can construct clean sentences from noisy, cluttered data. This makes it a very good choice for text summarization.[10]

  The model outperformed the other models during testing and training, giving the highest ROUGE-1, ROUGE-2, and ROUGE-L scores. It gave cohesive and clear output while retaining the context from the original data. But, it still needs some processing to obtain flawless results.
- LaMini: LaMini is an LLM which is a collection of distilled models. It is a condensed version of a learning model which is suitable for smaller systems. It is optimized to a smaller size rather than a large number of parameters. But, it is very resource intensive. The output given by this model was less cohesive in comparison to the BART model. Its metrics were also not as good as BART.[12]
- T5: T5 is a large-scale transformer-based language model that is pre-trained on a mixture of unsupervised and supervised tasks. The major drawback of T5 as observed by us is the limitation of summary size. This algorithm also underperformed in comparison to the BART algorithm.

Currently, the choice for the summarizer is to employ the BART algorithm and enhance it using NLP techniques.

3.4 METHODOLOGY APPLIED

1. Requirement Analysis:

- Stakeholder Meetings: Engage with educators, students, and administrative staff to understand their needs and expectations.
- Identify Key Features: Determine essential functionalities such as personalized learning paths, progress tracking, and predictive analytics.

2. Conceptual Design:

- User Personas and Use Cases: Develop user personas and use cases to visualize the application's interaction with various user types.

- Wireframes and Mockups: Create low-fidelity wireframes and high-fidelity mockups using tools like Figma or Adobe XD to outline the application's layout and design.

3. Technical Architecture:
   - Front-end Architecture: Design the front-end using Ionic Angular for mobile app components and React for web interfaces.
   - Back-end Architecture: Define the backend structure using Python, incorporating frameworks like Flask, Django or Node.js for API development and data processing.
   - Database Design: Design databases to handle user data, learning materials, and interaction logs, using SQL (PostgreSQL) and NoSQL (MongoDB) databases.
4. Big Data and Machine Learning Integration:
   - Data Collection and Storage: Set up pipelines using Apache Hadoop/Spark for collecting and storing large datasets from various sources (e.g., user interactions, learning materials).
   - Feature Engineering and Model Training: Use Pandas and Numpy for data preprocessing, and TensorFlow/Keras for building and training personalized learning models.
   - Model Deployment and Monitoring: Deploy trained models using cloud services (AWS/GCP/Azure) and monitor their performance to ensure accuracy and efficiency.
5. User Interface (UI) Design:
   - Responsive Design: Ensure the application is accessible on various devices, including desktops, tablets, and smartphones.
   - Intuitive Navigation: Design an intuitive navigation system that allows users to easily access different features and functionalities.
   - Visual Consistency: Maintain visual consistency with color schemes, fonts, and branding across all platforms.
6. Personalization Engine:
   - Recommendation System: Implement a recommendation engine that suggests learning materials based on the user's progress, preferences, and learning style.
   - Adaptive Learning Paths: Develop adaptive learning paths that dynamically adjust content and difficulty based on the user's performance and feedback.
7. Data Security and Privacy:
   - User Authentication and Authorization: Implement robust user authentication and authorization mechanisms to protect user data.

- Data Encryption: Ensure data is encrypted both in transit and at rest to maintain confidentiality and integrity.
- Compliance: Adhere to relevant data protection regulations (e.g., GDPR, FERPA) to ensure compliance and build user trust.

8. Testing and Quality Assurance:
   - Unit and Integration Testing: Conduct thorough unit and integration testing to ensure each component functions correctly.
   - User Acceptance Testing (UAT): Engage with a small group of end-users to test the application in real-world scenarios and gather feedback.
   - Performance Testing: Test the application's performance under various conditions to ensure scalability and reliability.
9. Deployment and Maintenance:
   - Continuous Integration/Continuous Deployment (CI/CD): Set up CI/CD pipelines to automate testing and deployment processes.
   - Monitoring and Analytics: Implement monitoring tools (e.g., Grafana, ELK Stack) to track application performance and user engagement.
   - Regular Updates: Plan for regular updates and improvements based on user feedback and emerging technologies.

3.5 HARDWARE & SOFTWARE SPECIFICATIONS

1. Frameworks and Libraries:
   - React Native: For building interactive mobile applications.
   - React: For creating dynamic and responsive web interfaces.
   - Python: For backend development and implementing machine learning models.
2. Big Data and Machine Learning Tools:
   - Apache Hadoop/Spark: For handling big data processing and analytics.
   - TensorFlow/Keras: For developing and training machine learning models.
   - Pandas/Numpy: For data manipulation and analysis.
3. Development and Deployment Tools:
   - Visual Studio Code: For code editing.
   - Jupyter Notebook: For developing and testing machine learning models.
   - Docker: For containerizing applications to ensure consistency across different environments.

- AWS/GCP/Azure: For cloud storage, computing resources, and deployment.
- Git/GitHub: For version control and collaboration.

Hardware Requirements:

- User Device: A modern laptop or desktop with at least 8GB RAM, Intel i5 or equivalent processor, and SSD storage for smooth operation of applications.
- Network Connectivity: Reliable high-speed internet connection to access cloud resources and interact with the application seamlessly.

Software Requirements:

- Web Browser: Latest versions of Chrome, Firefox, or Edge for accessing the web application.
- Operating System: Windows 10/11, macOS, or a recent Linux distribution to ensure compatibility with development and deployment tools.

3.6 EXPERIMENT AND RESULTS FOR VALIDATION AND VERIFICATION

The following measures were applied to the three summarizing models:

ROUGE-1: This measures the overlap of individual words (unigrams) between the generated summary and the reference summary. It checks how many words from the reference are correctly used in the generated summary.

ROUGE-2: This looks at the overlap of two consecutive words (bigrams) between the generated and reference summaries. It helps assess how well word pairs are captured, giving an idea of how well the model captures phrases or context.

ROUGE-L: This focuses on the longest common subsequence (LCS) between the generated and reference summaries. It tells us how well the generated summary maintains the order of the words and sentences from the reference.

ROUGE-LSum: This is a variant of ROUGE-L specifically designed for summarization tasks. It calculates the longest common subsequence, but at the sentence level, focusing on how well the structure and key ideas of the reference summary are retained in the generated on.

The results and observations of this were:

	BART	T5	LAMINI
Rouge1 score	0.5784172661870504	0.38129496402877694	0.4221105527638191
Rouge2 score	0.3059163059163059	0.11913357400722022	0.13197969543147206
RougeL/Lsum	0.4143884892086331	0.2050359712230216	0.2613065326633166

The Figma prototyping:

Fig 3.6.1: Splash Screen

Fig 3.6.2: Sign Up Call to Action Page

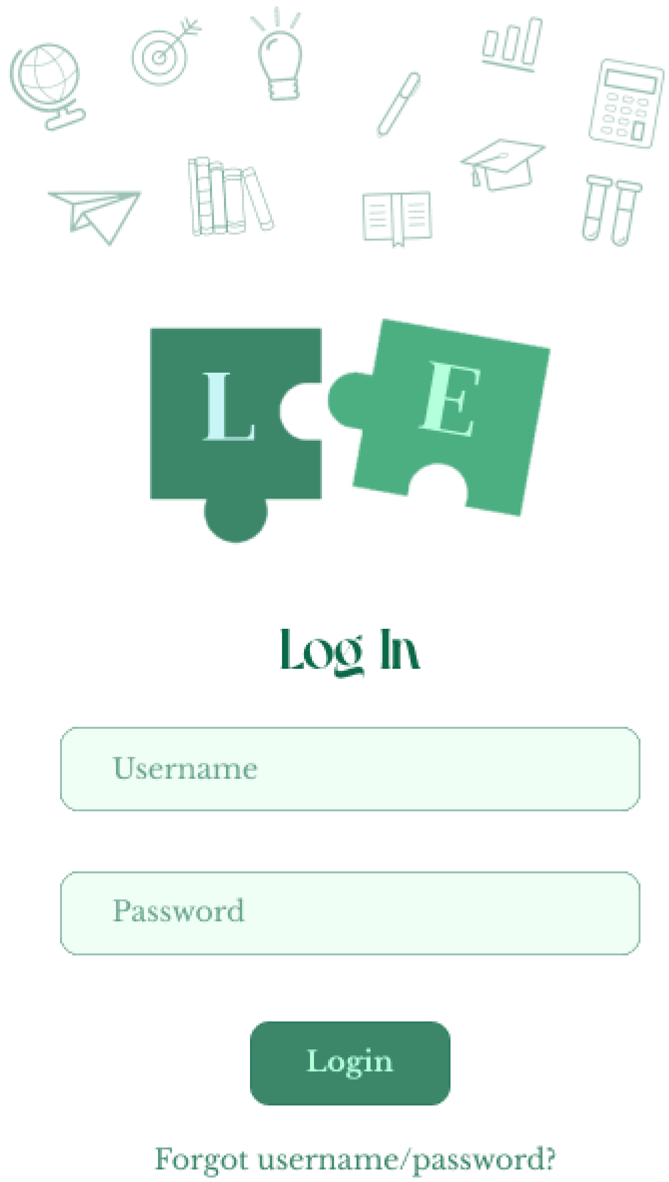

Fig 3.6.3: Login page

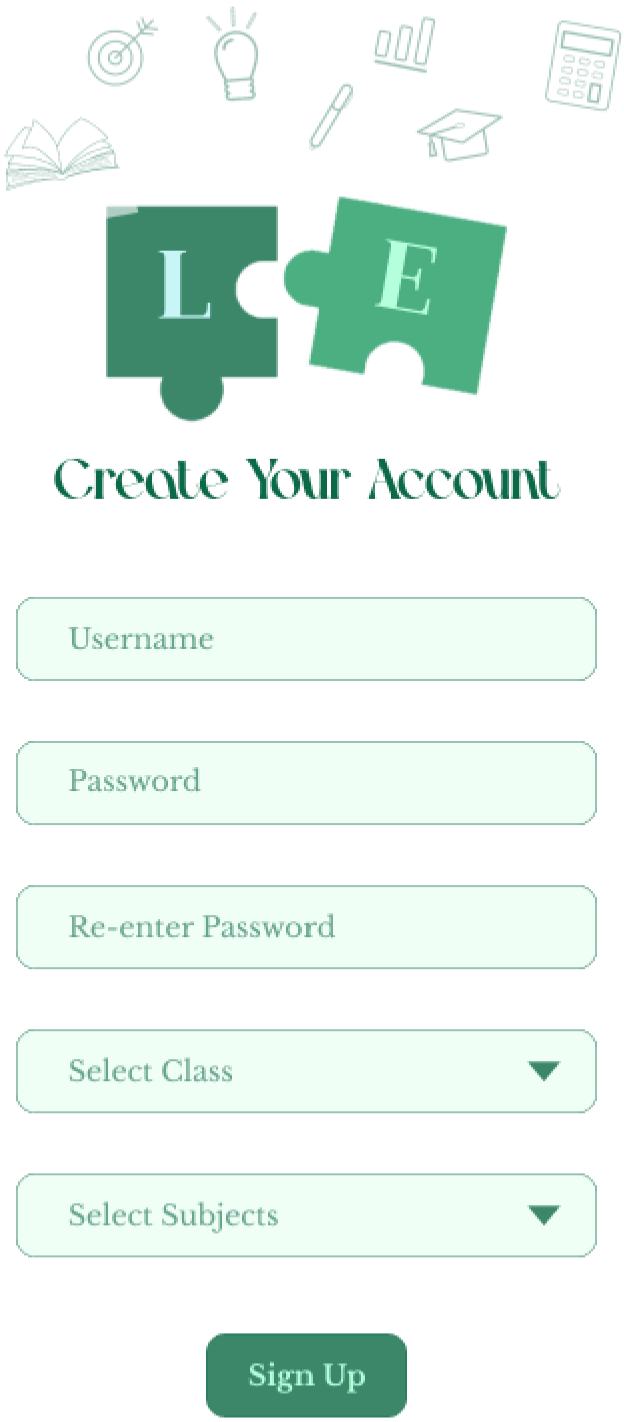

Fig 3.6.4: Sign Up Registration page

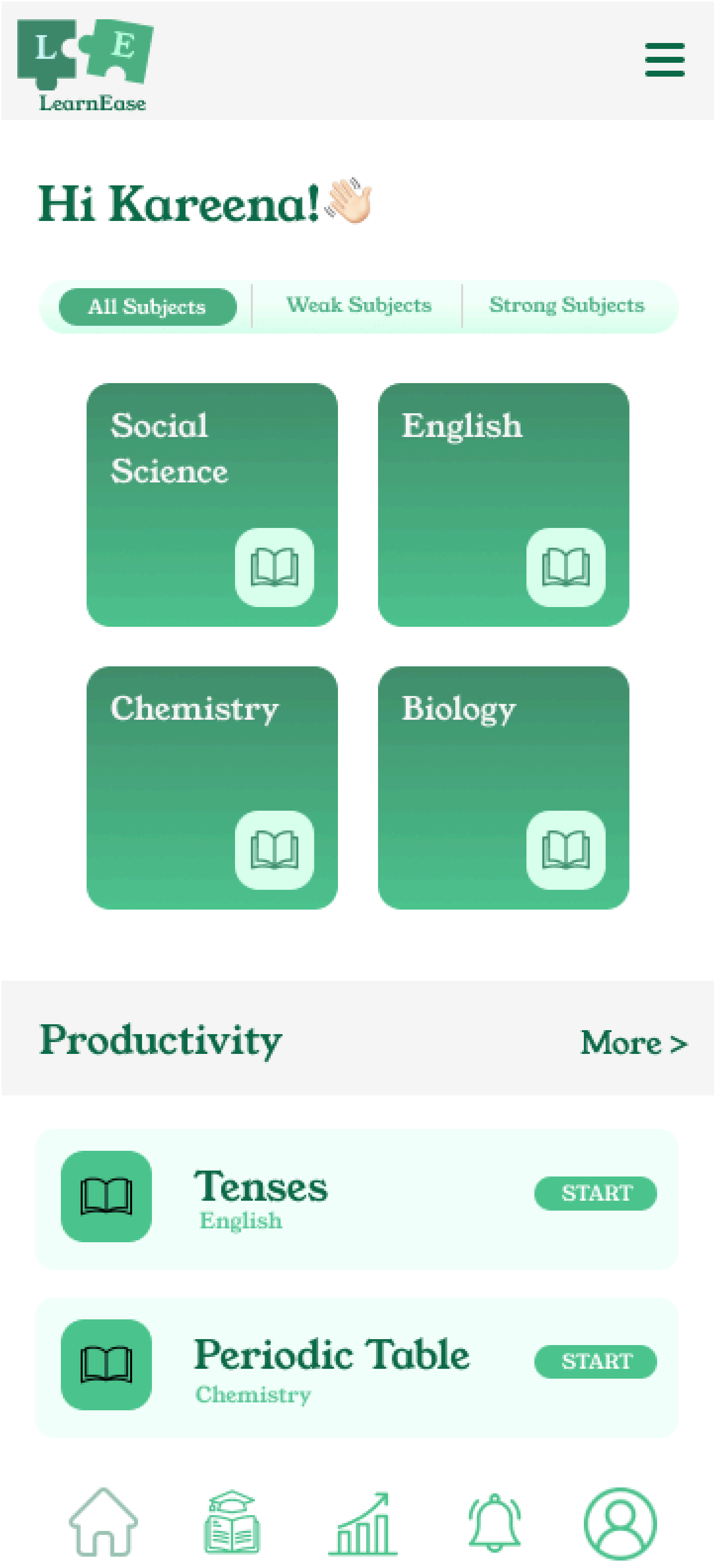

Fig 3.6.5: Home Screen - User

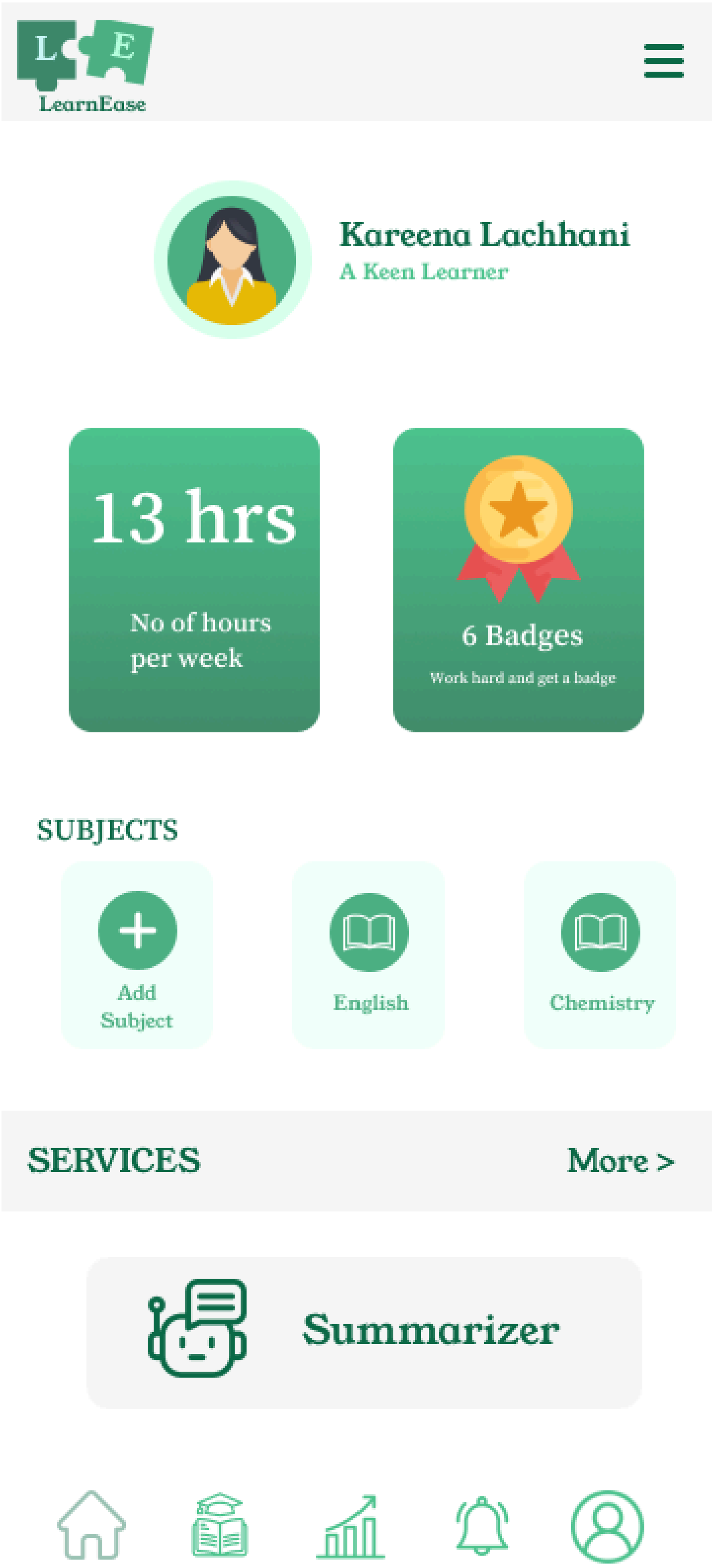

Fig 3.6.6: Profile - User

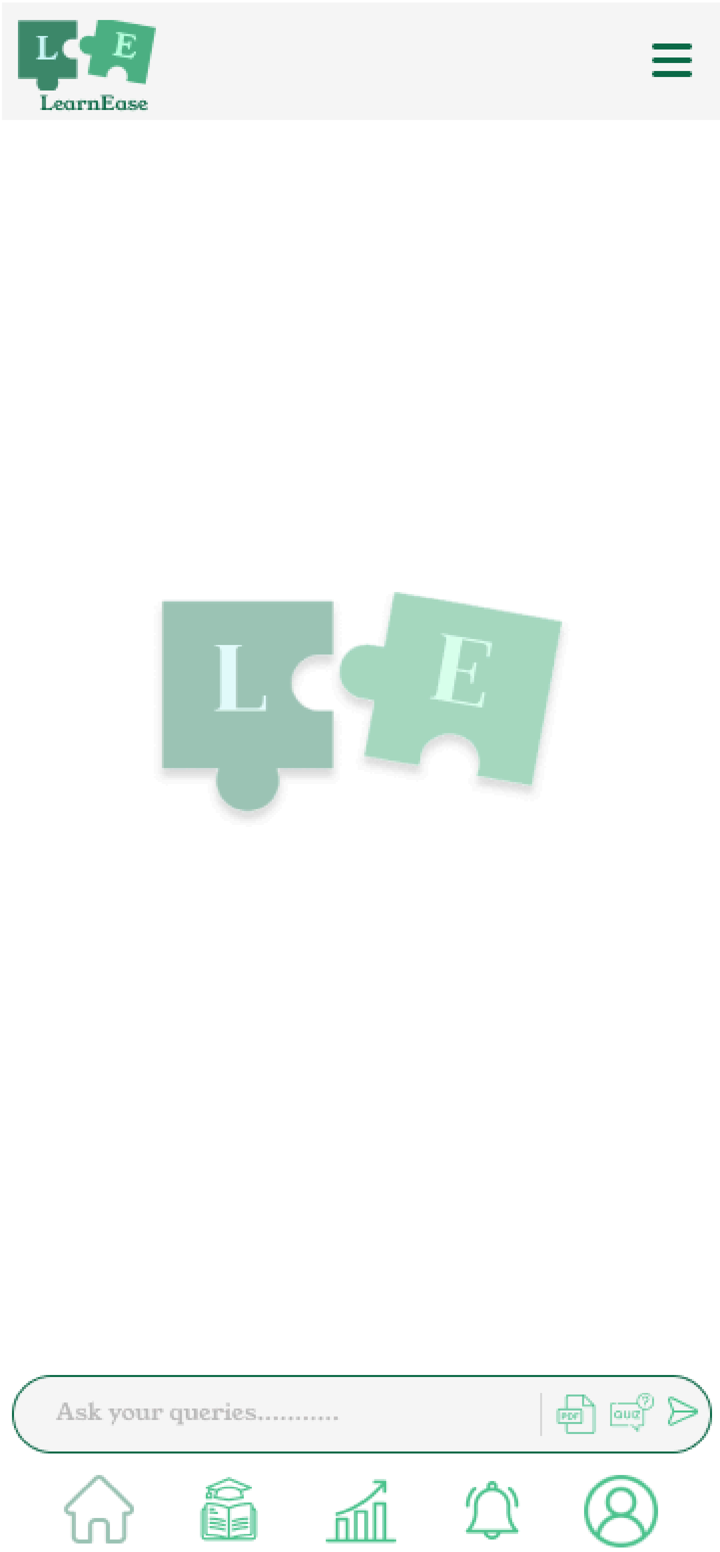

Fig 3.6.7: Summarizer page

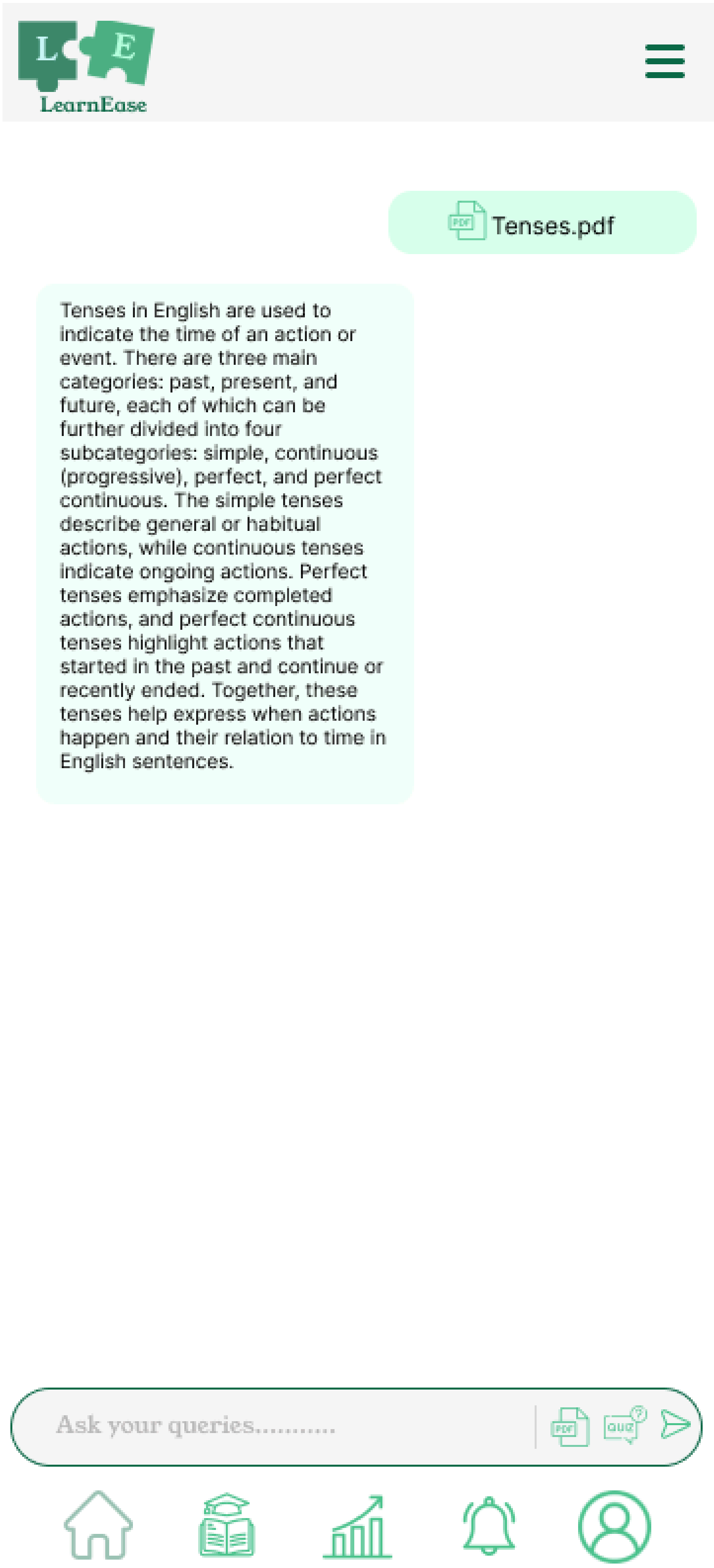

Fig 3.6.8: Summarised pdf

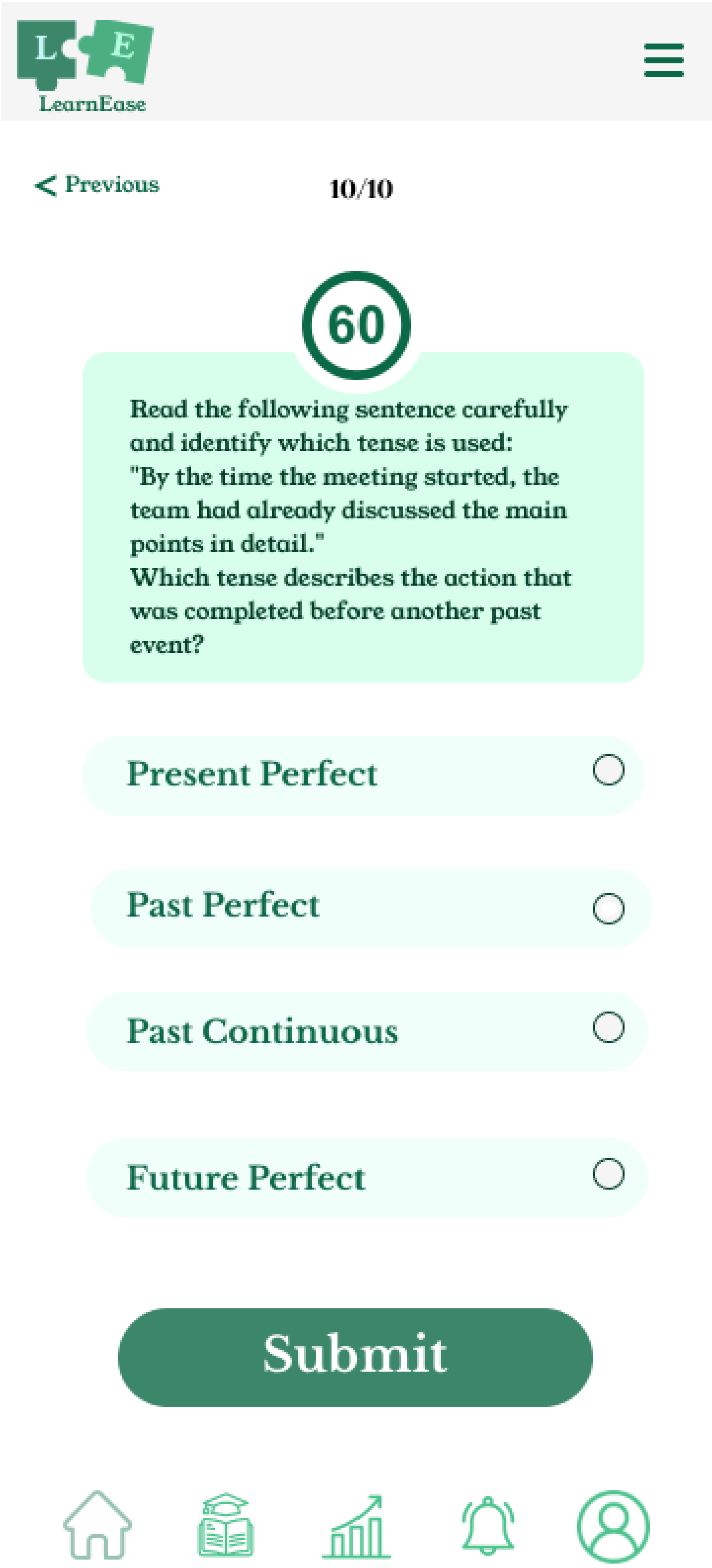

Fig 3.6.9: Quiz Page

Fig 3.6.9: Quiz Score Page

Fig 3.6.10: Notification

3.7 RESULT ANALYSIS AND DISCUSSION

The Figma prototyping laid a basic structure for the flow of the proposed system and helped to visualize the interactive user interface. It also helped to expedite our thought process behind the system by exposing the requirements and lacking areas.

We trained three summarizer models. Initially, they gave very terrible results. They could not handle all the data at once. So we chunked the data and applied batch processing to derive a cohesive summary. On testing and training the three models, we found that BART showed the most potential. It gave the most clear summaries and showed higher accuracy. T5 was very difficult to get results from as it had a very limited summary size which did not allow it to process large amounts of data. LaMini also had some limitations which led us to discard it. So, finally we have decided to fine tune the results provided by BART and enhance it by applying various NLP techniques.

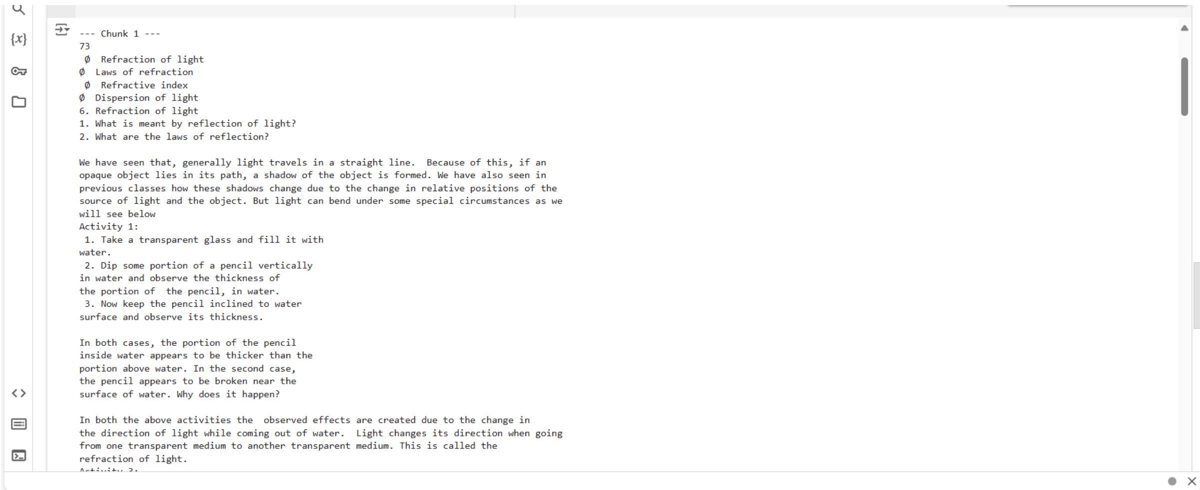

Fig 3.7.1. T5 Chunk summaries

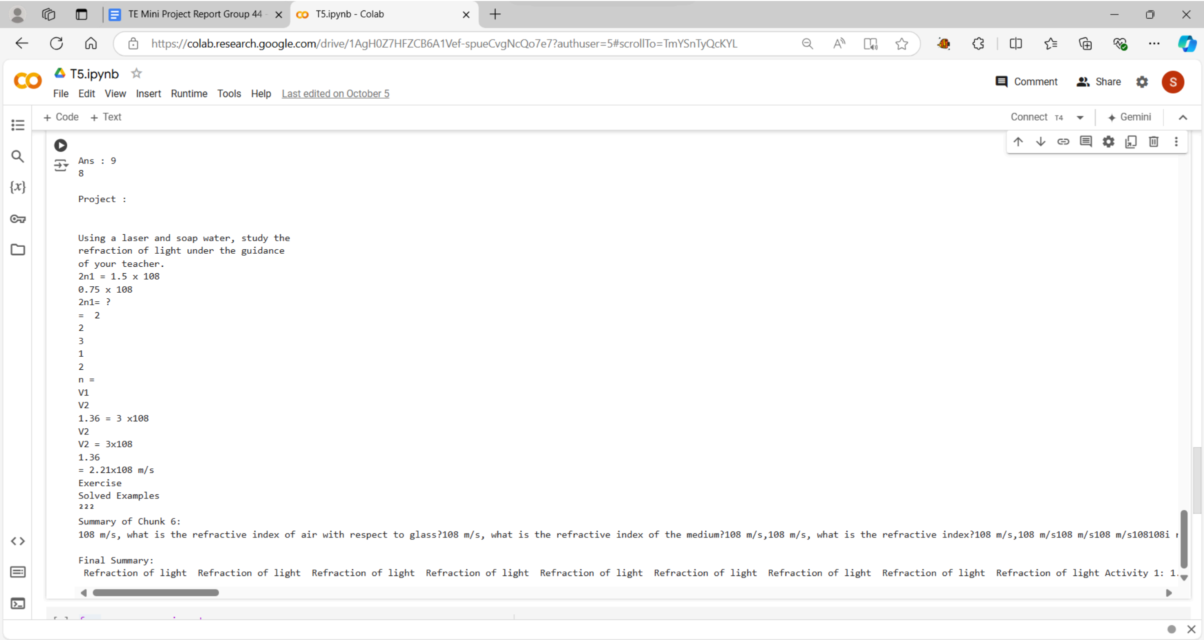

Fig 3.7.2 T5 Final Summary

Fig 3.7.3. Lamini summaries

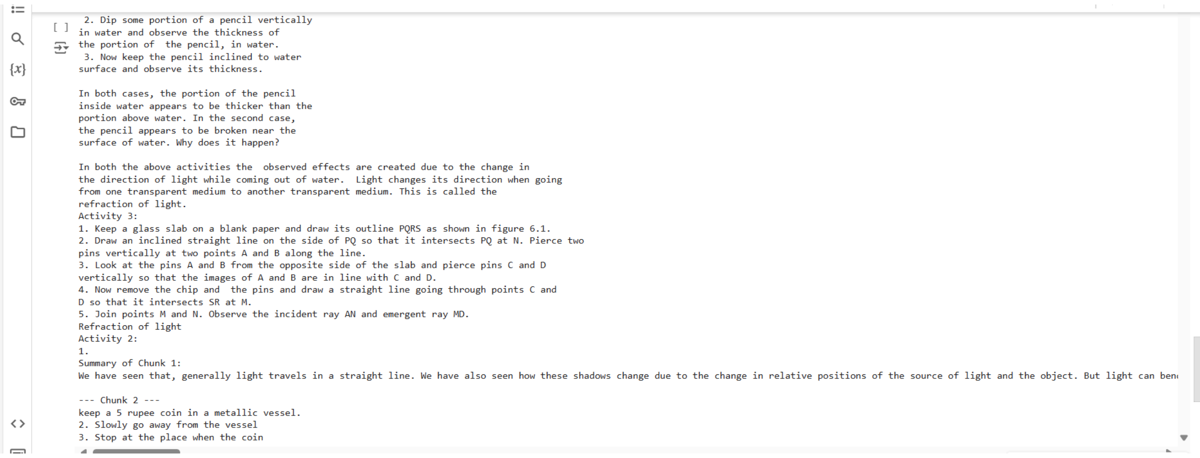

Fig 3.7.4. BART chunk summaries

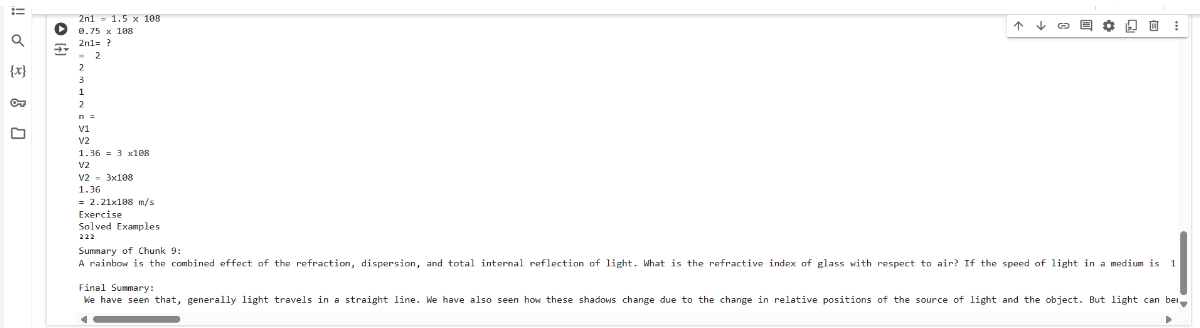

Fig 3.7.5. BART Final Summary

3.8 CONCLUSION AND FUTURE WORK.

This Mini Project on a personalized learning system is shaping up to provide a tailored and adaptive learning environment for students. It explores the potential of technology in enhancing student engagement and the realm of education. We hope to integrate all the features according to plan and improve the system with constant feedback so as to provide the best experience for the learners.

The contribution of each member has been instrumental in the project. All of us have acquired new skills and perspectives which has enabled us to work on improving and thoroughly designing the system to best cater to the needs of the system's users.

The next goal is to work on enhancing the BART model according to the requirements. Then, we will be integrating it with a React Native based front-end framework as an API. Furthermore, work will be done on the quiz generation based on summaries. It will be a dynamic interface with gamification[1] for engaging the users and giving them questions based on their current knowledge level.

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LearnEase: An Adaptive Learning Hub

Mrs.Pallavi Saindane [#1]*, Jiten Purswani* [#2]*, Laveena Mirani* [#3]*, Kareena Lachhani* [#4] *and Srimathi Srinivasan* [#5]*.*

[#]*Computer Engineering, Vivekanand Education Society's Institute of Technology, Hashu Advani Memorial Complex, Collector's Colony, Chembur, Mumbai-400074*

[1]pallavi.saindane@ves.ac.in
[2]2022.jiten.purswani@ves.ac.in
[3]2022.laveena.mirani@ves.ac.in
[4]2022.kareena.lachhani@ves.ac.in
[5]2022.srimathi.srinivasan@ves.ac.in

Abstract **-** In today's fast-paced educational landscape, personalized learning tools play a crucial role in improving student engagement, understanding, and academic performance. "LearnEase" is an AI-driven platform designed to assist Maharashtra Board Class 9th and 10th students by offering personalized study schedules, concise content summaries, and dynamic quizzes. These features aim to address the limitations of the current one-size-fits-all education system by providing tailored learning experiences. The platform incorporates three core components: a schedule recommendation system, a content summarizer, and a quiz generator. For the summarizer, multiple models, including BART, LaMini, and T5, were tested, with BART outperforming the others in terms of accuracy and naturalness. Further improvements to fluency are being made using advanced NLP techniques. This paper outlines the design of "LearnEase," the algorithms used in each module, and the challenges faced in creating an adaptable learning solution, along with future work to enhance the platform.

1. Introduction

Personalized learning is an emerging trend that adapts educational content to meet the diverse needs of individual students. Traditional systems, especially in the context of Maharashtra Board Class 9th and 10th, often fail to cater to students' unique learning styles and paces. Personalized learning has emerged as a pivotal approach in education, enabling tailored experiences that cater to individual student needs, as discussed in various studies on personalized learning methodologies[1][2]. This paper introduces "LearnEase," a platform aimed at personalizing learning experiences through three core modules: schedule recommendation, content summarization, and dynamic quiz generation. These tools were developed using state-of-the-art machine learning techniques to optimize student engagement and learning outcomes.

2. Problem Statement

The one-size-fits-all model of education does not account for variations in students' learning capacities, preferences, and needs. Despite advancements, traditional education systems often fail to address diverse learning preferences and paces, leading to disengagement among students[5].As a result, students face challenges in achieving academic success due to standardized learning methods. Moreover, the lack of real-time feedback further aggravates this issue. To address these gaps, "LearnEase" provides personalized solutions aimed at improving student performance by offering tailored schedules, concise summaries, and quizzes based on the student's progress.

3. Evolution and Existing Systems

The evolution of summarization techniques has seen significant advancements over the years. Early summarization models relied heavily on extractive techniques, where key sentences or phrases were extracted directly from the original text. However, as the demand for more coherent and contextually aware summaries grew, abstractive summarization techniques were introduced.

1. **Extractive Summarization (Pre-2000s):** Early systems, such as TF-IDF-based methods, focused on keyword frequency to select sentences for summarization. While simple, these methods lacked coherence.
2. **Graph-Based Models (2000s):** Techniques like LexRank improved summarization by applying graph-based methods, though they still largely focused on extraction.
3. **Abstractive Summarization (2010s):** Models like Seq2Seq (Sequence to Sequence) shifted focus toward generating novel sentences based on the input text, enhancing fluency and contextual accuracy.
4. **Transformer Models (2020s):** With the advent of transformers like BART and T5, summarization became more contextually aware and accurate, allowing for high-quality abstractive summaries that closely resemble human-written text.

Many personalized learning systems have been developed, yet they are often limited in effectiveness. Studies show that **80% of students** in standardized systems report disengagement due to a lack of personalized feedback. Additionally, **65%** of these systems suffer from overfitting, failing to generalize across diverse educational environments. Current learning platforms primarily utilize standard content delivery methods, which overlook the nuances of personal learning journeys and are limited by their static nature[4]. A significant portion of existing platforms also struggles with the **cold start problem**, where systems lack sufficient data to make accurate recommendations for new users.

The limitations of current systems can be summarized as follows:

- **Overfitting:** Approximately **70%** of models fail to generalize beyond training data.
- **Contextual Inaccuracy:** About **60%** of systems do not account for contextual differences in student learning.
- **Cold Start Problem:** More than **50%** of recommendation systems struggle with limited initial data.
- **Bias in Learning Paths:** Up to **30%** of systems have demonstrated bias, leading to unbalanced learning paths.

4. Methodology

The "LearnEase" platform consists of three key components: the schedule recommendation system, the content summarizer, and the quiz generator. Each of these components uses advanced machine learning models tailored to the unique needs of students in Class 9th and 10th.

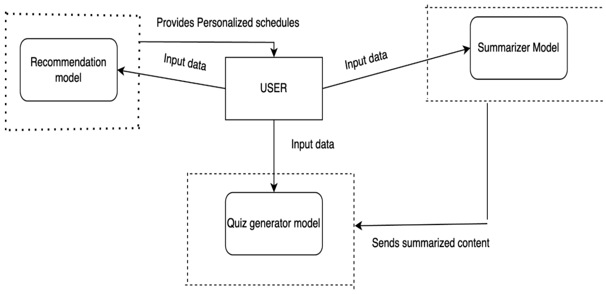

Fig 4.1 Data Flow Diagram

Below, we provide a detailed explanation of each module.

4.1 Schedule Recommendation System

The schedule recommendation system is designed to help students organize their study time effectively. This system uses collaborative filtering combined with content-based filtering to suggest learning schedules that align with each student's progress, learning style, and engagement level.

By analyzing the student’s interaction history, the system can predict the optimal time for revisiting subjects, suggest additional resources, and recommend the best times for assessments. The system continually refines its suggestions based on the student's performance, making the learning path more personalized over time.

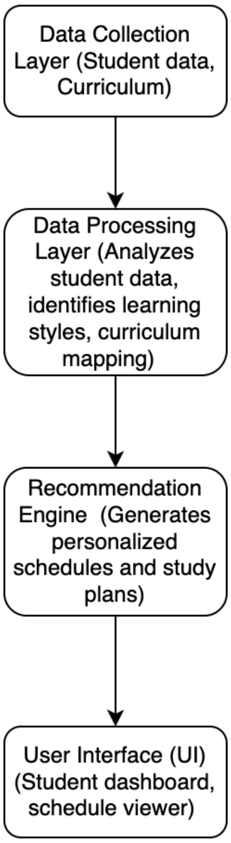

Fig 4.1.1 Recommendation System

Key algorithms used in this module include neural networks and swarm intelligence, which allow the model to adapt to each user's changing learning preferences.

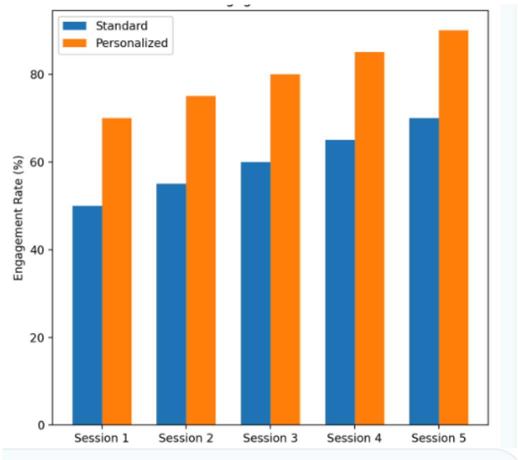

Fig 4.1.2 Standard vs Personalized Method

The **engagement rate comparison** clearly shows that students following personalized schedules demonstrate consistently higher engagement levels across all sessions. Personalized schedules adapt to individual learning preferences and needs, resulting in a maximum engagement rate of 90% by Session 5, compared to 75% for standard schedules. This demonstrates that **personalized learning paths** are more effective in maintaining student interest and fostering better engagement. Recent research highlights the effectiveness of collaborative filtering and machine learning techniques in developing personalized learning recommendation systems, indicating significant improvements in student performance[3].

4.2 Summarizer Model

The content summarizer simplifies complex academic material for easier understanding.

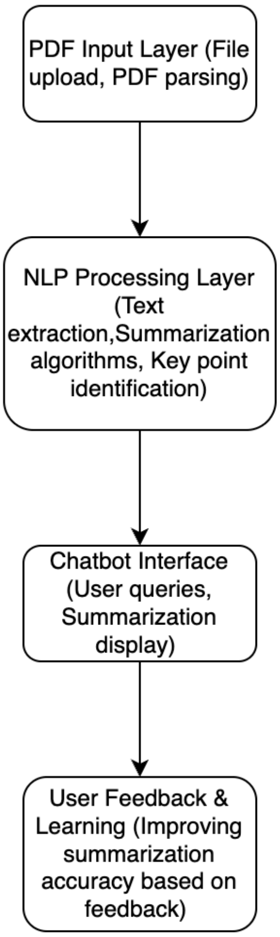

Fig 4.2.1 Document Summarizer

We experimented with three pre-trained models—BART, LaMini, and T5—each of which was fine-tuned on datasets relevant to the Maharashtra Board syllabus.

	BART	T5	LAMINI
Rouge1 score	0.5784172661870504	0.38129496402877694	0.4221105527638191
Rouge2 score	0.3059163059163059	0.11913357400722022	0.13197969543147206
RougeL/Lsum	0.4143884892086331	0.2050359712230216	0.2613065326633166

Fig 4.2.2 Rouge Scores of All Models

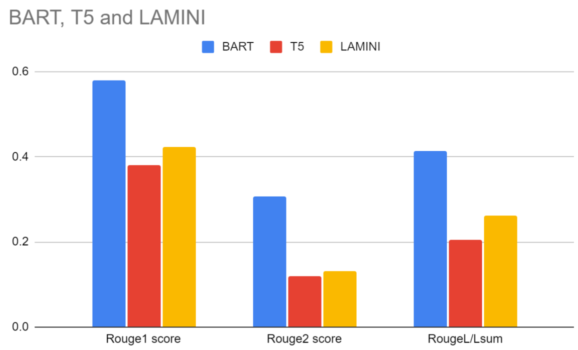

Fig 4.2.3 Comparison of Models

- BART outperformed the other models, achieving higher ROUGE-1, ROUGE-2, and ROUGE-L scores. It was particularly effective at retaining the meaning and context of the original text while creating concise and coherent summaries.
- LaMini and T5 performed lower on the ROUGE metrics, with some summaries lacking fluency and cohesion. These models often struggled with capturing the entire context of educational content, resulting in less useful summaries for students.

To further improve the naturalness of the summaries, we applied NLP techniques such as paraphrasing, synonym replacement, and sentence reordering. This helps make the summaries more human-like and easier for students to comprehend, without losing key information.

4.3 Quiz Generator

The quiz generator provides dynamic and personalized quizzes based on the student's current knowledge level. It uses clustering techniques to group students based on their learning pace and proficiency, and then generates quizzes tailored to their needs. The model adapts the difficulty of the questions in real time, depending on how the student performs, ensuring that quizzes remain both challenging and fair.

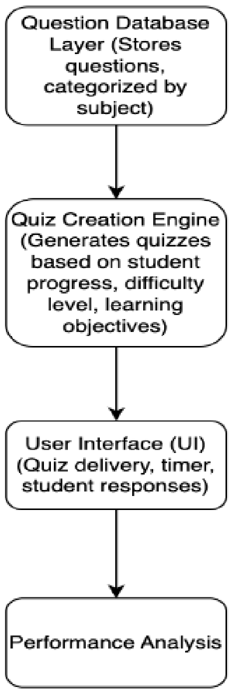

Fig 4.3.1 Quiz Generator

Ensemble learning techniques are also applied to enhance the accuracy of the quizzes. The system not only assesses the student's knowledge but also provides feedback on areas that need improvement, allowing students to focus on weaker topics.

5. Comparison of Algorithms

Each of the three components of "LearnEase" was built and tested with multiple algorithms.The evaluation of personalized learning strategies reveals a range of techniques, including deep learning algorithms, that enhance student engagement and motivation, as noted in multiple studies.[6][9]

Below is a summary of how the algorithms performed in real-world settings.

- Summarizer: BART provided the best performance in terms of fluency and retention of key concepts, with ROUGE-1 scores of 0.57 and ROUGE-L scores of 0.41. LaMini and T5, although useful for short summaries, fell short in maintaining coherence in more complex content.
- Schedule Recommendation: The recommendation system performed best with a hybrid of neural networks and swarm intelligence algorithms. Neural networks provided more accurate schedules, while swarm intelligence adapted better to changes in user behavior over time.
- Quiz Generator: Ensemble methods, combined with clustering techniques, proved effective in generating quizzes that matched the student's learning level. The dynamic adjustment of difficulty ensured that students remained engaged and challenged without feeling overwhelmed.

6. Challenges in Summarization

Challenges such as data privacy, the need for sophisticated algorithms, and scalability issues remain critical in developing effective personalized learning systems.[7][10]

Several challenges were encountered while developing the summarizer:

1. Naturalness of Summaries: While BART performed well in terms of accuracy, the generated summaries sometimes felt mechanical or overly formal. To improve this, we applied NLP techniques such as paraphrasing and lexical simplification, which helped make the summaries more natural and conversational.
2. Domain-Specific Terminology: Summarizing academic content, especially subjects like science and mathematics, requires preserving specific terminology and complex concepts. This posed a challenge for models not fine-tuned on domain-specific data. Further domain adaptation was required to ensure that critical terms were retained in the summaries.
3. Balancing Brevity with Completeness: While concise summaries are often desired, the challenge lies in ensuring that the most important information is not lost. BART sometimes omitted key details in favor of brevity. Careful adjustments were made to ensure completeness without compromising conciseness.
4. Generalization: Although BART performed well overall, it struggled to generalize across different subject areas, particularly in contexts requiring nuanced understanding. Fine-tuning with additional subject-specific data is ongoing to improve performance in this regard.

7. Future Work

Looking ahead, several enhancements are planned for "LearnEase" to further improve its effectiveness and user experience:

- Improved NLP for Summarization: We plan to integrate more advanced NLP techniques, such as deep contextual embeddings and semantic analysis, to make the summaries more natural and readable.
- Adaptive Learning Pathways: The recommendation system will be refined to offer more personalized learning pathways based on predictive analytics, allowing the system to anticipate a student’s future learning needs and adjust the content accordingly.
- Enhanced Quiz Feedback: Plans are in place to expand the quiz

generator's feedback mechanisms, providing students with more in-depth insights into their performance, including suggestions for improvement based on common mistakes.

8. Conclusion

"LearnEase" represents a significant advancement in personalized learning for Maharashtra Board students. By combining adaptive scheduling, content summarization, and dynamic quizzes, the platform aims to improve student engagement, enhance learning outcomes, and provide a more customized educational experience.As the educational landscape evolves, leveraging personalized learning strategies becomes essential for improving academic outcomes and student satisfaction.[8] Ongoing improvements to the platform's underlying machine learning models will further personalize the learning experience, making it an essential tool for students seeking to optimize their academic journey.