© March 2024| IJIRT | Volume 10 Issue 10 | ISSN: 2349-6002

Skillspire: A Personalised AI Mentor for Lifelong Learning

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Abstract —In an era characterized by an ever-increasing need for upskilling and continuous learning, recent advancements in pre-trained language models, nurtured by the wealth of data harnessed by tech giants, have emerged as beacons of transformative potential. This project sets out to harness the profound capabilities of these advanced models, offering a dynamic platform that empowers learners to navigate the complex landscape of self and lifelong education. Amidst the cacophony of information and the constant evolution of knowledge, this initiative aims to provide learners with a guiding light. It promises not only personalized guidance but also adaptive content curation, ensuring that learners receive precisely what they need when they need it. Gamification elements infuse a sense of excitement and motivation into the learning journey, fostering consistency and a genuine love for learning. In this age of rapid technological evolution, where adaptability and knowledge are paramount, this project envisions a future where learning is more accessible, engaging, and effective than ever before. It seeks to empower individuals to take charge of their own educational destinies, transcending barriers and illuminating the path to success in the ever-evolving landscape of the knowledge economy.

Index Terms —Transformers, LLM, Fine-tuning, EdTech, Self-Learning

I. INTRODUCTION

This template is designed to help you in preparing your manuscript in expected format. The guidelines include complete descriptions of the fonts, spacing and related information for creating your proceedings manuscripts. Please follow them properly. The digital age has brought an overwhelming influx of information, making self-directed learning challenging amidst distractions and lack of structured guidance. However, Large Language Models (LLMs) offer a solution. This text explores the fusion of cutting-edge technology and personalized learning strategies to revolutionize education.

It introduces an AI-driven self-learning app acting as a virtual tutor. Unlike traditional chatbots, this intelligent agent actively engages learners, analyzing educational data to tailor questions and recommendations, creating a customized curriculum aligned with individual proficiency levels. Through dynamic interactions, users receive instant feedback and supplementary materials, enhancing understanding. Utilizing educational data, the app refines recommendations, offering personalized activities and simulations to foster active engagement and skill development. By integrating LLMs, this approach transforms the digital learning landscape into a structured, distraction-free experience. The intelligent agent bridges the gap between information and knowledge, making raw data meaningful. This innovation represents a paradigm shift, empowering self-learners globally by providing personalized guidance, turning information into expertise, one tailored learning experience at a time.

Our problem statement can be stated as – Develop an innovative AI-driven self-learning app that aims to revolutionize the learning experience by providing an intelligent agent capable of enhancing learning efficiency, accelerating skillset development, and offering a fully immersive human-like educational journey. Harness user educational data to generate personalized questions and recommendations, guiding users on their learning path, suggesting supplementary learning activities such as problem-solving exercises, and ultimately empowering users to achieve their educational goals with optimal effectiveness and engagement.

Large language models have notable shortcomings and issues, including bias and fairness concerns, ethical dilemmas like disinformation generation, significant environmental impact due to energy consumption, data privacy risks, a lack of interpretability, resource inequality, over-reliance in critical domains, performance variability, susceptibility to adversarial attacks, language limitations, data dependence, resource-intensive use, lengthy training times, and limited accessibility. Additionally, issues like ownership, access, copyright concerns, and the potential concentration of power among a few organizations further complicate the landscape of large language model deployment and usage.

The proposed self-learning app will employ advanced machine learning algorithms and Large Language Models (LLMs) to analyze user educational data comprehensively. By understanding individual learning patterns, proficiency levels, and areas of difficulty, the app will generate personalized questions and recommendations. This intelligent agent will actively guide users on their learning journey, tailoring the curriculum to their specific needs. Real-time feedback and adaptive learning pathways will ensure that users receive customized support, enhancing their efficiency and engagement. The app will offer a structured, distraction-free environment, transforming raw data into meaningful educational experiences. The app will create an interactive learning ecosystem by integrating gamified problem-solving exercises, interactive simulations, and supplementary activities. These exercises will be dynamically generated based on user performance and learning objectives. By gamifying the learning process, the app will enhance user engagement and motivation. The interactive simulations will provide practical, hands-on experiences, reinforcing theoretical knowledge. Additionally, the app will offer social learning features, enabling users to collaborate, discuss topics, and solve problems collectively. This collaborative environment will foster a sense of community, encouraging peer-to-peer learning and knowledge exchange. Through this immersive, human-like educational journey, users will accelerate their skillset development, achieve their educational goals, and experience a transformative learning experience.

The input consists of subject-specific data provided by the user. This data typically comes in a textual format. This could be a user's query, a document, or any textual information related to the chosen subject.

The output is generated based on the user's request and typically takes the form of a specific feature or functionality related to an app, which the user has selected. This output can be structured in various formats to best convey the information, including:

a. Bullet Point Format: The information is presented as a list of concise, bullet-pointed items, providing key details or highlights.
b. Short Notes: The output can include brief and informative notes summarizing the relevant aspects of the subject.
c. Tables: Tabular representations may be used to organize data in a structured manner, making it easier to read and compare different elements.
d. Tree Structure: Information can be structured hierarchically, similar to a tree diagram, to illustrate relationships and dependencies between different components.

The output format is chosen based on the user's preference and the nature of the subject-specific data. It aims to present information in a clear, organized, and easily understandable manner, catering to the user's specific needs and ensuring that the user can access the desired information efficiently.

II. RELATED WORK

Looking into existing platforms that offer personalised learning experiences based on user data. Exploring these has enabled us to understand how these platforms adapt content and learning paths to individual user needs and preferences. Sushant Singh, Aasif Mahmood [1] survey various text representation and word embedding techniques used in Natural Language Processing. Early NLP approaches relied on rule-based and pattern matching techniques using context-free grammars and regular expressions. While simple to implement, they lacked the ability to capture context and meaning. Statistical approaches like Bag-of-Words and TF-IDF emerged to address this, but suffered from high dimensionality and sparsity. Dimensionality reduction techniques like LSI and PLSI were then applied to project text into lower dimensions. Rajvardhan Patil, Sorio Boit, Venkat Gudivada, Jagadeesh Nandigam [2] discuss sophisticated word embeddings that capture intricate word relationships by using dense floating-point values. These context-sensitive embeddings identify synonyms, antonyms, and analogies, enabling accurate predictions of neighboring words. Techniques like Normalized Term Frequency and TF-IDF embedding consider contextual importance, while dynamic embeddings adapt word meanings based on context, addressing polysemy challenges. Peng Xu, Xiatian Zhu, David A. [3] address advancements in neural network based embeddings like Word2Vec, GloVe and FastText that were introduced to capture semantic and syntactic word relationships. These produced static embeddings that did not change with context. Contextual embeddings like ELMo, BERT and XLNet that use language modeling objectives were then proposed to generate dynamic embeddings based on context. The research of Bernardo Breve, Gaetano Cimino, Vincenzo Deufemia[4] investigates the use of natural language processing (NLP) methods for identifying automation rules that are created in Internet of Things (IoT) trigger-action platforms and that might put users' security or privacy at risk. With trigger-action platforms, users may employ event-condition-action rules to customise the behaviour of Internet of Things devices and services. These guidelines, meanwhile, may inadvertently infringe upon users' privacy or put their surroundings in danger. Using the well-known trigger-action platform If This Then That (IFTTT), the researchers assessed their NLP-based models. Approximately 76,000 IFTTT rules were tagged by them according to the kind of harm they may possibly do. Semi-supervised learning approaches were used with manual labelling and automatic labelling to assign the labels. Then, using various combinations of the characteristics in the rules, several classification models were trained. including title, description, trigger, and action. The study by Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova Daniela Onita[5] focuses on Active Learning strategies in combination with heuristics for optimizing performance across different datasets. It emphasizes the Active Transfer (AT) criterion, showcasing its effectiveness, particularly in IMDB and Spam datasets. The text also highlights the careful preprocessing steps, such as handling null values and feature extraction from text files, crucial for accurate analysis in the experiments. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, Illia Polosukhin[6] revolutionized natural language processing (NLP) by introducing the Transformer model. Unlike previous models relying on recurrent or convolutional neural networks, the Transformer utilized a self-attention mechanism, enabling it to weigh the significance of different parts of the input sequence efficiently. This innovation addressed the limitations of sequential computation, allowing for parallelization and significantly speeding up training processes. By eliminating the need for sequential processing, the Transformer model not only achieved state-of-the-art results in various NLP tasks such as machine translation, text generation, and language understanding but also paved the way for the development of larger and more sophisticated deep learning architectures, profoundly impacting the field of artificial intelligence. Renrui Zhang, Jiaming Han , Chris Liu , Peng Gao, Aojun Zhou, Xiangfei Hu , Shilin Yan, Lu Pan, Hongsheng Li , Yu Qiao[7] discusses LLaMA-Adapter, an efficient fine-tuning method for language models, specifically LLaMA, to improve instruction-following capabilities. It introduces learnable adaption prompts and zero-initialized attention techniques to provide fresh learning signals into LLaMA while retaining its prior knowledge acquisition.. This approach achieves high-quality responses comparable to fully fine-tuned models with fewer parameters and training time. The document also mentions the potential impact and ethical implications of language models, as well as other related works in the field. Additionally, it highlights the comparison of LLaMA-Adapter with other instruction-following models and its extension to multi-modal reasoning. We also studied that [8] text is grouped using the syntactic, lexical, and semantic axes by LinguisticLens. It enables users to swiftly browse for an overview and examine specific samples by supporting hierarchical visualization of a text collection to make [9]a comprehensive survey of text classification using transformer models, exploring the dimensions of model width, size, sequence length, accuracy, computational cost, and safety considerations. [10] It examines the impact of these factors on the performance and efficiency of transformer-based text classification models leading to the exploration of risks and drawbacks associated with utilizing synthetic data for grammatical error correction, shedding light on potential limitations and challenges in the effectiveness of such data in this context.

III. METHODOLOGY OF PROPOSED SYSTEM

We’ll start building the frontend of the app. This is where users interact with our platform. We’ll implement essential features like user registration, data upload, model selection, and results display.

i. Here the users will have an option to interact with previous models and also have an option of starting a new model instance. Of course they will be bombarded with a highly interactive UI that will keep them engaged with the previous trained models. Our backend will be the powerhouse. It’ll handle data processing, model training, and user management. We’ll set up databases to store user data, datasets, and training histories. This will be the core part of the app that will include the entire backend functionality starting from model training to accessing various features that are available for learning. We’ll develop machine learning models for code suggestions, academic summarization, and problem-solving insights. Then, we’ll fine-tune and integrate these models into our app.

ii. Coming right to the engine or the heart of the app is the kind of models that would be used for training. The more versatile the models, better they can handle user demands. These will be pretrained models by algorithms which will be the brain of our app. We'll create algorithms for personalized learning roadmaps and gamification elements for the daily learning rewards system to keep users motivated.

iii. Algorithms will be devised according to technical requirements. To ensure the frontend and backend communicate seamlessly, we'll develop APIs (like pathways for data to flow). These APIs will help different parts of our app work together smoothly.

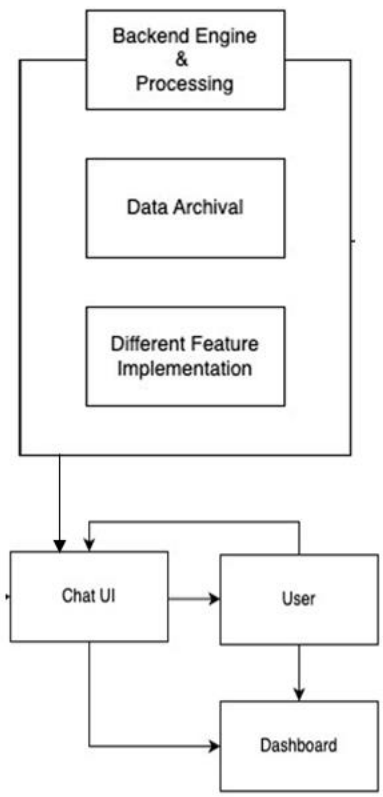

Figure 1: Block Diagram

iv. Here we deploy SOTA retrieval techniques for faster extraction of information from our database.

v. We are going to incorporate various APIs in this app to ensure smooth working. We'll test everything, from parts (unit testing) to how everything works together (integration testing). We'll squash any bugs we find and make sure the app meets all requirements. Logging and monitoring of the app will be performed after deploying the app.

vi. Lastly, this app will be highly customizable and, in the future, will also come with functionality specifically for developers to edit features and design them according to their needs.

The findings underscore the need for careful consideration and evaluation when employing synthetic data in grammatical error correction tasks.

IV. CHALLENGES

Explained below are few of the challenges that may be encountered in the development and implementation of a self-learning AI-driven education platform, particularly one utilizing Large Language Models (LLMs) and specialized niche models:

i. Data Privacy and Security:

Developing an AI-driven educational platform involves collecting and analyzing significant amounts of user data to provide personalized learning experiences. Ensuring the privacy and security of this data is a paramount challenge. Striking a balance between personalization and safeguarding sensitive user information is crucial. Implementing robust data encryption, compliance with data protection regulations, and transparent user consent mechanisms are vital aspects of overcoming this challenge.

ii. Ethical AI Use and Bias Mitigation:

AI models, including LLMs, can inadvertently perpetuate biases present in the training data. Addressing bias in AI responses, especially in educational contexts, is essential. Ensuring the AI models provide fair and unbiased information while avoiding sensitive topics or controversial opinions is a complex challenge. It requires ongoing monitoring, bias detection algorithms, and constant fine-tuning to minimize biased responses and ensure a diverse and inclusive learning experience for all users.

iii. Content Relevance and Accuracy:

Curating accurate and relevant educational content is challenging, especially when dealing with a diverse user base and a wide array of subjects. Ensuring the AI-generated content is not only contextually accurate but also up-to-date and aligned with the latest educational standards is crucial. Striving for a balance between generality and specificity in responses is challenging, as overly specific answers might not cater to all users, while overly general responses might lack depth. Continuous validation and feedback loops are necessary to refine the AI models and improve the accuracy and relevance of the content provided.

iv. User Engagement and Motivation:

Sustaining user engagement and motivation over time poses a significant challenge in self-learning platforms. While personalized content and interactive features can enhance engagement, keeping users motivated to consistently learn and progress is a multifaceted challenge. Designing gamified elements, interactive simulations, and social learning features can address this challenge. However, understanding user behavior and preferences to tailor these engagement strategies effectively requires extensive user research and constant adaptation to evolving user needs and learning patterns.

Addressing these challenges demands a comprehensive approach, combining technical expertise, user-centered design principles, and ethical considerations. By tackling these obstacles, developers can create a robust and user-friendly self-learning platform that effectively leverages AI technology to empower learners on their educational journeys.

V. CONCLUSION

In conclusion, our self-learning app harnesses the power of cutting-edge AI technology, including Large Language Models (LLMs), to revolutionize the educational experience. Rooted in personalization, the app's intelligent agent acts as a virtual tutor, tailoring learning paths to individual needs and styles. It simplifies the overwhelming landscape of online information, ensuring a distraction-free, structured learning environment. The platform fosters a sense of community through a collaborative social space, encouraging knowledge exchange and active participation. Committed to ethical AI use, we prioritize user privacy, data security, and transparency. Continuous evaluations and feedback mechanisms drive the app's evolution, refining content and interactions. Ultimately, our app aims to empower self-learners globally, fostering a lifelong passion for learning and enabling them to achieve their educational goals effectively and confidently.

ACKNOWLEDGEMENT

We express deep gratitude to our professors whose guidance inspired and guided us throughout this venture. Their valuable advice and ideas have been instrumental in our work, and we are sincerely thankful to them. Prof. Shreeya Palkar, in particular, has been an exceptional source of direction, support, and assistance during the project, and we are truly appreciative of her help. Furthermore, we extend our thanks to our university for providing us with essential resources crucial for the success of this project. Overall, our heartfelt thanks go out to everyone involved in this assignment and those who contributed their suggestions, enhancing the quality of the project.

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