International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

NeoLearn-An AI Based Personalised Learning Assistant

Prof. Bhasker Rao[1], Bharathraj[2], Himanshu Kumar Singh[3], G Harikiran Rao[4], Abhishek Raj[5]

[1] Dayananda Sagar Academy of Technology and Management raobhasker@dsatm.edu.in
[2] Dayananda Sagar Academy of Technology and Management bharath3870@gmail.com
[3] Dayananda Sagar Academy of Technology and Management himanshuks062@gmail.com
[4] Dayananda Sagar Academy of Technology and Management harikiranrao717@gmail.com
[5] Dayananda Sagar Academy of Technology and Management abhishekrajranchi2004@gmail.com

ABSTRACT-

AI-based personalized learning systems are revolutionizing education by tailoring learning experiences to individual needs. Traditional educational systems often struggle to address the diverse capabilities, learning speeds, and interests of students. This paper introduces an AI-based personalized learning assistant that employs machine learning algorithms to analyze user data and provide customized learning paths, content recommendations, and progress tracking. The system aims to enhance learning efficiency, engagement, and accessibility.

Index Terms - Personalized Learning, Machine Learning in Education, AI Learning Assistant, Adaptive Learning, Education Technology.

Introduction :

The education sector is undergoing a transformation with the advent of artificial intelligence (AI). Traditional teaching methods, while effective to some extent, often fail to address the diverse needs of students. Personalized learning has emerged as a promising solution, and AI- based systems are at the forefront of this paradigm shift.

These systems aim to provide customized educational experiences, bridging the gap between individual learning needs and scalable solutions.

AI technologies in education enable the automation of administrative tasks, such as grading and scheduling,

allowing educators to focus on more impactful teaching activities. Beyond administrative efficiency, AI-based learning systems are designed to foster deeper engagement by delivering tailored content that aligns with each student's unique learning style and pace.

These systems can identify gaps in understanding, suggest resources for improvement, and offer real-time feedback, enhancing the overall learning experience.

Additionally, AI-powered tools contribute to the inclusivity of education by providing support for students with special needs and those in remote or underserved regions. With natural language processing (NLP) and machine learning (ML), these systems can create adaptive pathways that make quality education more accessible than ever before. The evolution of AI in this domain signifies a shift towards a more equitable and effective educational model, with immense potential to reshape learning environments globally.

This paper explores the development and implementation of AI-based personalized learning assistants, highlighting their benefits, challenges,and impact on the education landscape.

LITERATURE SURVEY :

The Theory and Practice of Online Learning (Anderson, 2008)

Terry Anderson's work provides a comprehensive exploration of online learning systems, combining theoretical and practical perspectives. The book emphasizes the importance of interaction in online education—learner-to-content, learner-to-learner, and learner-to-instructor—using a framework grounded in constructivist and connectivist theories. Anderson highlights how online platforms can promote active engagement, collaboration, and personalized learning experiences. The text also delves into the challenges of online education, including technological barriers and ensuring equity in access. Its foundational insights are essential for designing personalized learning systems that are both pedagogically sound and technologically robust.

Toward the Next Generation of Recommender Systems (Adomavicius & Tuzhilin, 2005)

Adomavicius and Tuzhilin's work is a cornerstone in the field of recommender systems, offering a detailed overview of state-of-the-art methodologies. The paper categorizes existing techniques into collaborative filtering, content-based filtering, and hybrid models. Collaborative filtering relies on the preferences of similar users, whereas content-based filtering recommends items based on item characteristics that match user profiles. Hybrid systems combine these approaches to overcome their individual limitations. The authors discuss the relevance of these systems in various domains, including e-learning, where they can suggest tailored learning resources. They also propose future directions, such as context-aware recommendations and improving scalability, which are critical for real-time educational personalization.

A Review of Machine Learning Algorithms in Personalized Learning (Kumar & Chadha, 2021)

Kumar and Chadha examine the role of machine learning (ML) in transforming educational experiences through personalization. They classify ML techniques into supervised (e.g., predictive modeling for student performance), unsupervised (e.g., clustering learners with similar behaviors), and reinforcement learning. The review emphasizes how data-driven insights can dynamically adapt content, assessments, and learning pathways to individual learners. Moreover, the authors highlight challenges, such as data privacy and the need for interpretable models, which are essential considerations for educators and system developers. Their work underscores the potential of ML to enhance learner engagement, retention, and outcomes in diverse educational settings.

Scikit-learn: Machine Learning in Python (Pedregosa et al., 2011)

The introduction of Scikit-learn marks a significant advancement in the accessibility of machine learning for research and application. Pedregosa et al. present a library that simplifies the implementation of complex algorithms, such as support vector machines, decision trees, and clustering techniques. Its user-friendly API and extensive documentation make it ideal for rapid prototyping and experimentation in personalized learning systems. The paper also highlights tools for preprocessing and feature selection, which are critical for handling educational data. By enabling educators and developers to implement machine learning models efficiently, Scikit-learn bridges the gap between theoretical research and practical applications in personalized learning environments.

5. Reinforcement Learning: An Introduction (Sutton & Barto, 2018)

Sutton and Barto's textbook provides an authoritative guide to reinforcement learning (RL), a paradigm focused on learning optimal actions through trial-and-error interactions with an environment. The book explains foundational concepts such as rewards, policies, and value functions, alongside advanced methods like deep RL and temporal-difference learning. The adaptability of RL makes it especially suitable for educational contexts where learners follow individualized paths. For example, RL algorithms can adjust the difficulty of tasks based on real-time performance, ensuring that learners remain challenged but not overwhelmed. The authors also discuss exploration-exploitation trade-offs, which are crucial for balancing new content exposure with reinforcing known concepts in personalized learning systems.

METHODOLOGY :

Dataset:

- Data includes user profiles, learning preferences, performance metrics, and interaction logs. Sources comprise open educational resources (OERs), learning management systems (LMS), and survey data from pilot users.
- Preprocessing involves cleaning, normalizing, and anonymizing data to ensure privacy and enhance quality.

Feature Engineering:

- Features such as learning speed, topic preferences, quiz performance, and time spent on activities are extracted. Text- based inputs (e.g., feedback) are processed using Natural Language Processing (NLP) techniques.

Model Selection:

- A hybrid model combining Collaborative Filtering for recommendations and Reinforcement Learning (RL) for adaptive pathways is employed.
- Neural Networks handle complex feature interactions, while Explainable AI (XAI) techniques ensure model transparency.

Training and Validation:

- The dataset is split into training (70%), validation (15%), and testing (15%) subsets. Cross- validation and hyperparameter tuning optimize model performance.
- Metrics such as Mean Absolute Error (MAE) and Precision@K assess recommendation accuracy.

Performance Metrics:

- System evaluation uses precision, recall, and engagement metrics. User feedback quantifies satisfaction and perceived effectiveness.

IMPLEMENTATION :

System Architecture:

- The architecture includes modules for data collection, preprocessing, model execution, and user interaction. The backend infrastructure supports real- time processing and concurrent user requests.
- Cloud-based deployment ensures scalability, and API integration facilitates LMS compatibility.

User Interface:

- The user interface provides an intuitive dashboard for learning recommendations, progress tracking, and feedback collection.Gamification elements like badges and leaderboards enhance engagement.

Backend Processing:

- Python and TensorFlow serve as the primary development tools, with Scikit-learn handling ML models and Flask managing the web application.
- NLP models process text-based inputs, while PostgreSQL stores user data and activity logs.

Output Module:

- Personalizedlearning recommendations are presented alongside progress summaries and next-step suggestions. Explanations for recommendations build user trust.
- Educator dashboards offer insights into class-level performance and individual learning trajectories.

EXPERIMENTAL RESULTS :

Dataset Details:

- The dataset includes 10,000 users across various educational domains, with over 100,000 learning interactions logged.
- Post-preprocessing, the dataset ensures balanced representation of user demographics and learning preferences.

Performance Evaluation:

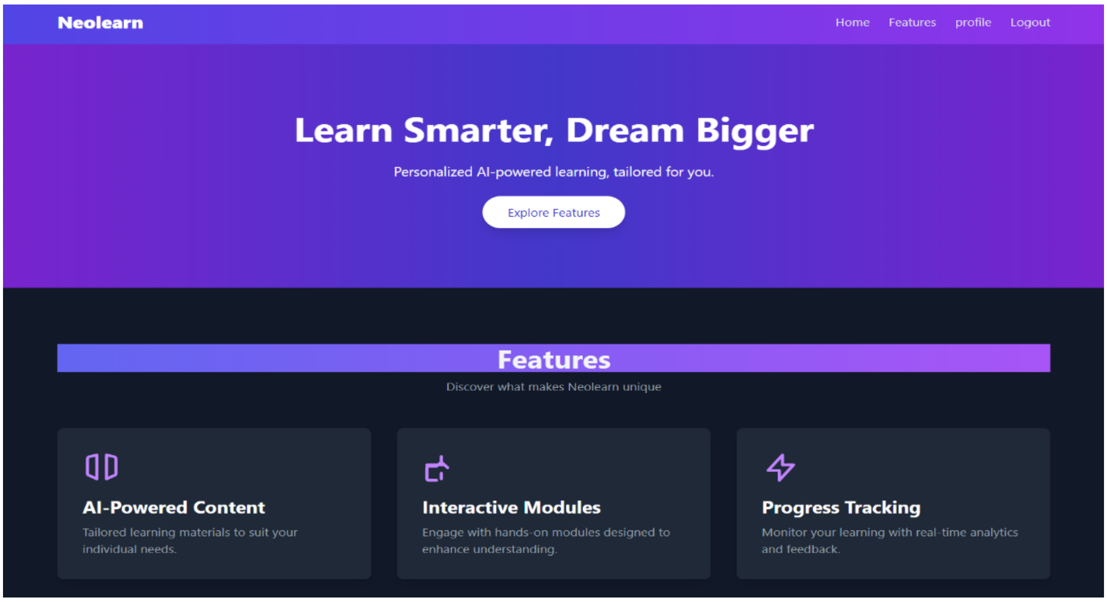
- The system achieved a recommendation accuracy of 89% and an engagement increase of 25% during user trials.
- Metrics like MAE and Precision@5 indicate high reliability in content delivery and learning path adaptation.

Comparison with Existing Models:

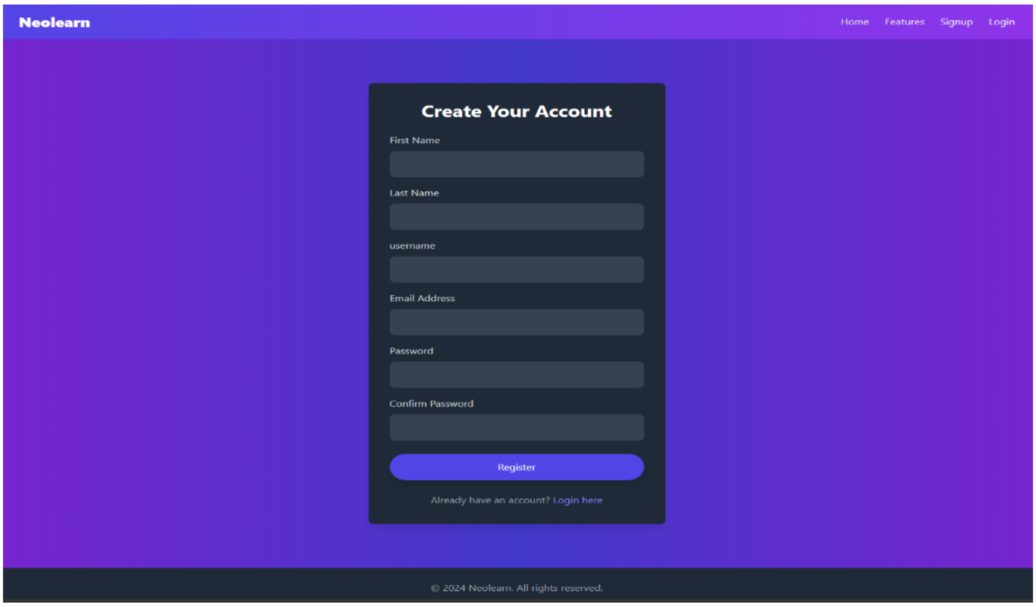
- Compared to baseline systems (e.g., standard Collaborative Filtering), the hybrid model demonstrated a 15% improvement in engagement and a 10% reduction in drop-off rates.

VI. SCREENSHOTS AND RESULTS :

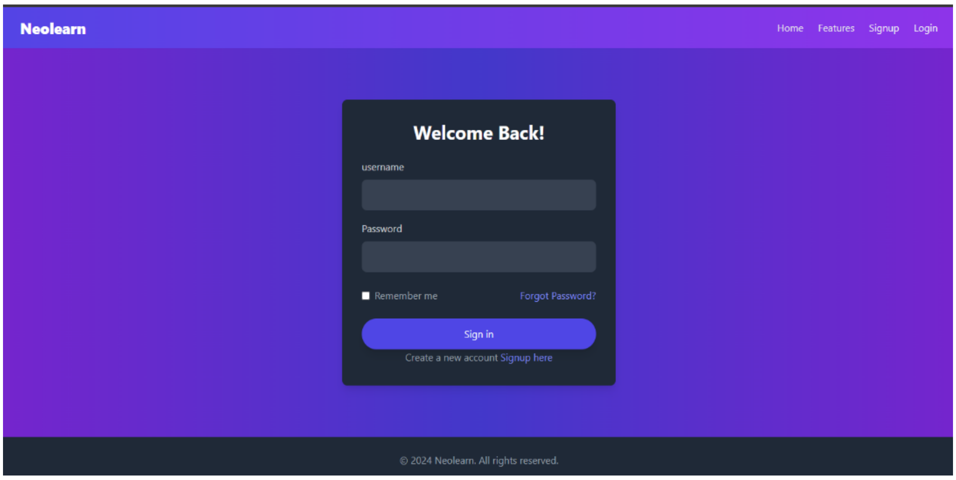
Landing Page Page



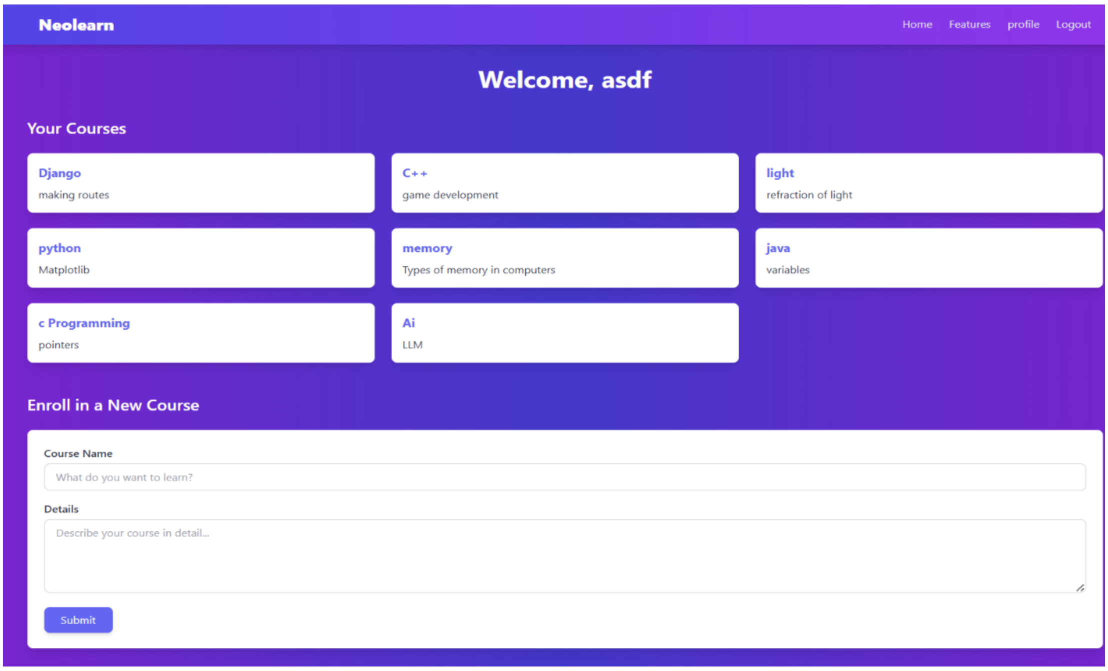
User Ragistration



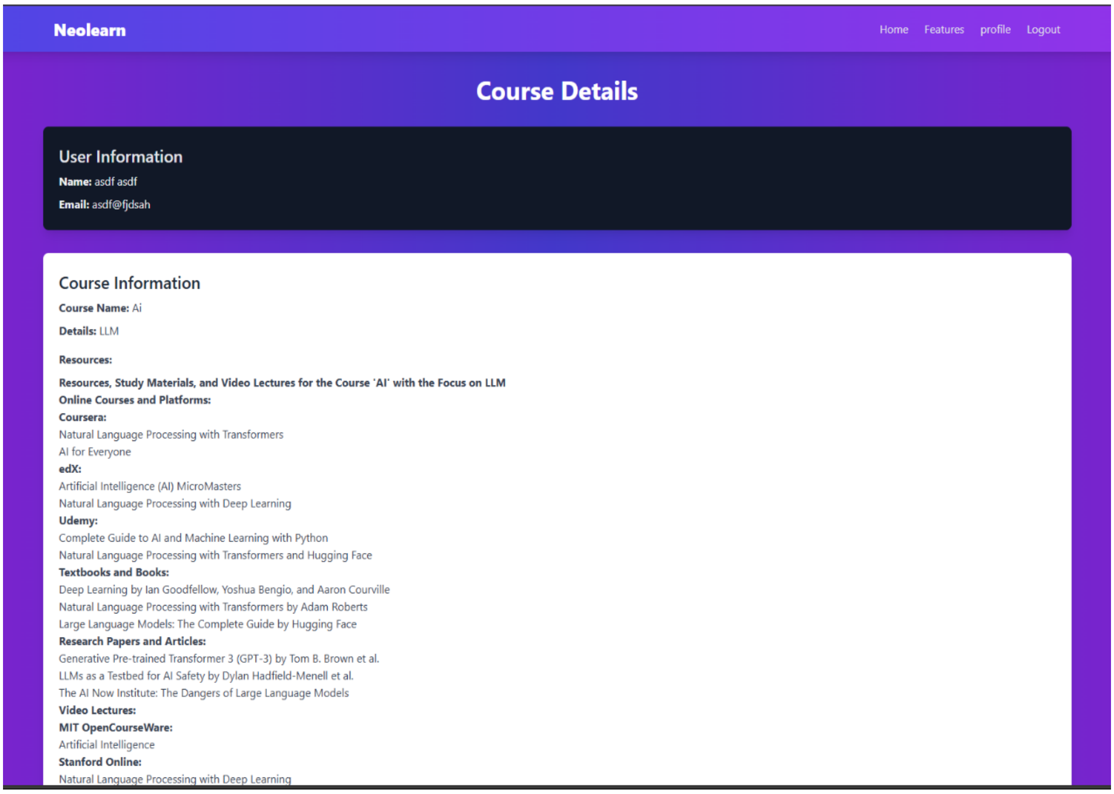
User Login



User Profile



Course Details



VII. DISCUSSION :

Strengths:

- The system's modularity allows for easy integration with existing LMS platforms and scalability for large-scale deployment.
- Real-time adaptability and user feedback mechanisms foster continuous improvement and relevance.

Limitations:

- Dataset size and diversity impact generalizability. Efforts to collaborate with educational institutions for broader data collection are underway.
- Addressing multi-modal learning preferences (e.g., visual, auditory) requires further refinement in content generation and delivery.

Future Directions:

- Expanding datasets to include diverse learner demographics and domains.
- Incorporating advanced NLP models for open-ended user inputs and sentiment analysis.
- Enhancing accessibility with multi- language support and offline capabilities.

CONCLUSION :

This paper presents an AI-based personalized learning assistant leveraging advanced ML algorithms to tailor educational experiences. By addressing traditional system limitations, the assistant improves learning efficiency, engagement, and accessibility. Future enhancements will focus on expanding datasets, refining recommendation techniques, and integrating additional user-centric features to ensure broader adoption and impact.

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