Personalized E-Learning Recommendation System with Skill Gap Analysis

VINMUGILAN.E

Department of Computer Science, Rathinam College of Arts and Science (Autonomous), Coimbatore,

Tamil Nadu, India

Corresponding Author : vinmugilan728@gmail.com

Abstract - This paper presents a Personalized E-Learning Recommendation System with Skill Gap Analysis designed to identify learners' skill levels and recommend suitable learning paths. In modern digital education platforms, learners often face challenges in selecting appropriate courses due to the lack of personalized guidance. The proposed system overcomes this limitation by analyzing user data such as experience level, quiz performance, and learning pace. The system uses the Random Forest algorithm to classify users into skill levels such as Basics, Intermediate, and Advanced. Based on the classification, the system provides personalized course recommendations and structured learning paths. This approach enhances learning efficiency, improves user engagement, and supports better decision-making.

Keywords – E-learning, Machine Learning, Recommendation System, Skill Gap Analysis, Random Forest, Personalized Learning

I. INTRODUCTION

The rapid growth of digital technologies has significantly transformed the education sector. E-learning platforms have made education more accessible, flexible, and cost-effective for learners across the globe. However, despite these advancements, most online learning systems still follow a one-size-fits-all approach, where the same content is delivered to all users regardless of their individual skill levels and learning needs.

This lack of personalization often results in confusion among learners while selecting courses. Some learners may choose courses that are too advanced, while others may opt for basic content that does not contribute to their growth. This leads to reduced motivation, poor engagement, and inefficient learning outcomes.

The proposed system introduces a Personalized E-Learning Recommendation System with Skill Gap Analysis, which aims to overcome these challenges. By

analyzing user data and identifying their current skill levels, the system provides customized recommendations tailored to each learner. This ensures a structured learning path and helps users progress from beginner to advanced levels effectively.

A. Need for the System

Traditional systems fail to identify individual learning needs. This creates confusion and reduces motivation among learners.

B. Objective

The objective is to design a system that identifies skill gaps and provides personalized recommendations using machine learning techniques.

II. RELATED WORK

In recent years, several recommendation systems have been developed to improve e-learning experiences. Traditional systems primarily rely on manual methods, expert suggestions, or predefined rules. These approaches lack accuracy and fail to adapt to dynamic user behavior.

With the advancement of machine learning, more intelligent systems have been introduced. These systems analyze user data and provide better recommendations. Algorithms such as Decision Trees, Support Vector Machines, and Random Forest have been widely used in recommendation systems.

Among these, Random Forest is particularly effective due to its ability to handle large datasets, reduce overfitting, and improve prediction accuracy.

A. Existing Systems

Existing e-learning systems mainly:

1.Provide generalized recommendations
2.Do not analyze detailed user performance
3.Lack adaptive learning mechanisms

B. Limitations of Existing Systems

- No proper identification of skill gaps
- Lack of personalized learning paths
- Low accuracy in recommendations
- Poor user engagement
- Static content delivery

III. SYSTEM DESIGN

The proposed system is designed as a multi-module architecture that integrates web technologies with machine learning techniques. The system consists of frontend, backend, and machine learning components that work together to provide accurate recommendations.

A. System Architecture

The architecture includes:

- User Interface (Frontend)
- Data Processing Module
- Machine Learning Model
- Recommendation Engine

The user interacts with the system through a web interface, and the backend processes the data to generate results.

B. Data Collection

The system collects user data through input forms. The inputs include:

- Age
- Experience Level
- Programming Language
- Quiz Scores
- Lessons Completed
- Learning Pace

This data is essential for understanding the learner's performance.

C. Data Preprocessing

Raw data is not suitable for machine learning models. Therefore, preprocessing is required:

Encoding: Converts categorical data into numerical form

Normalization: Scales numerical values

Data Cleaning: Removes inconsistencies

This improves the accuracy of the model.

D. Model Training

The system uses the Random Forest algorithm for classification. It works by:

- Creating multiple decision trees
- Combining their outputs
- Improving prediction accuracy

The model is trained using a dataset and evaluated using metrics like:

- Accuracy
- Confusion Matrix
- Classification Report

E. Skill Gap Analysis

The system identifies the gap between current skills and required skills. It classifies users into:

- Basics
- Intermediate
- Advanced

This helps in understanding learning needs.

F. Recommendation Engine

Based on the predicted skill level, the system suggests:

- Core Programming courses
- Web Development
- AI and Machine Learning

It provides a structured learning path.

IV. RESULT AND DISCUSSION

The system was tested with multiple user inputs to evaluate its performance. The results show that the model accurately predicts the skill levels of users and provides relevant recommendations.

A. Performance Evaluation

The model is evaluated using:

- Accuracy Score
- Confusion Matrix
- Precision and Recall

The Random Forest algorithm shows high accuracy and reliability.

B. Analysis

- The system improves learning efficiency
- Provides personalized recommendations
- Enhances user engagement

The results confirm that the system is effective in real-world scenarios.

V. CONCLUSION

The proposed system successfully addresses the limitations of traditional e-learning platforms by providing personalized recommendations based on user data. It uses machine learning techniques to identify skill gaps and guide learners effectively.

The system enhances:

- Learning experience
- Decision-making
- Skill development

Overall, it provides a smart solution for modern education systems.

VI. FUTURE ENHANCEMENT

The system can be further improved by:

- Integrating deep learning algorithms
- Adding real-time feedback systems
- Developing mobile applications
- Supporting multiple languages
- Including chatbot assistance

These enhancements will make the system more advanced and user-friendly.

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