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AI-Powered Personalized Course Recommender

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***Abstract*—This paper presents an AI-powered Course Recommender System designed to help learners find relevant online courses based on their interests. The system utilizes machine learning algorithms, including TF-IDF with Cosine Similarity and K-Nearest Neighbors (KNN), to recommend courses by analyzing course titles, categories, and user input. A Flask-based web application was developed to offer a user-friendly interface for course search and recommendations. The proposed model ensures improved accuracy in recommendations by integrating both content-based filtering and user similarity approaches. This project aims to assist students, professionals, and lifelong learners in identifying valuable learning resources efficiently.**

***Index Terms*—Course Recommendation, Cosine Similarity, K-Nearest Neighbors, Machine Learning, Natural Language Processing, TF-IDF.**

I. INTRODUCTION

The rise of online learning platforms like Coursera and Udemy has made education widely accessible, but finding relevant courses remains challenging. Recommender systems powered by machine learning offer a solution by providing personalized course suggestions.

Background:
Conventional filtering methods often return irrelevant results. To address this, machine learning techniques like TF-IDF and KNN can analyze course content and user preferences for smarter recommendations.

Goal.and.Research.Question:
This project aims to develop a hybrid recommender using TF-IDF and KNN.
Research Question: How can these techniques enhance course recommendation accuracy?

Importance.of.the.Study:
This system improves course discovery, user satisfaction, and engagement. Its integration with a Flask-based UI ensures usability and real-world application.

II. LITERATURE REVIEW

Recent advancements in content-based recommendation systems have significantly improved user experience across various domains. Reswara et al. [1] designed a book recommendation system using TF-IDF and cosine similarity, enabling efficient matching of book titles. Similarly, Khadka and Lamichhane [2] applied the same techniques in the context of video streaming, helping platforms recommend relevant videos based on user interests.
El-Dosuky et al. [3] enhanced food recommendation accuracy by integrating ontological heuristics with TF-IDF and cosine similarity. Ongko [4] emphasized the practical deployment of machine learning models through Flask, offering efficient ways to create web-based recommender interfaces. The foundational vector space model proposed by Salton, Wong, and Yang [5] laid the groundwork for modern information retrieval, using cosine similarity to measure textual relevance.

III. OBJECTIVE

The primary aim of this study is to develop an AI-powered course recommender system that suggests relevant courses based on user interests, ensuring a personalized learning experience. To achieve this, the research explores different recommendation techniques, specifically comparing Term Frequency-Inverse Document Frequency (TF-IDF) with Cosine Similarity and the K-Nearest Neighbors (KNN) algorithm. These methods are analyzed for their effectiveness in generating meaningful recommendations. Additionally, real-world course datasets from popular platforms such as Coursera and Udemy are processed and examined to enhance the system's ability to match users with the most suitable courses. This ensures that recommendations remain practical and aligned with diverse learning needs.
Furthermore, a user-friendly web interface will be designed using Flask, allowing seamless access to personalized recommendations. This interface is intended to simplify user interaction and improve accessibility. To validate the recommender system,

its performance will be rigorously evaluated based on accuracy and relevance, ensuring that users receive high-quality suggestions. The study ultimately aims to refine and optimize recommendation algorithms, enhancing the overall efficiency of AI-driven course selection.

IV. METHODOLOGY

This study follows a structured approach to build and evaluate an AI-powered course recommendation system. The methodology consists of five major steps:

1. Data Collection

The dataset used in this project was collected from online learning platforms such as Coursera and Udemy. It includes course titles, categories, ratings, number of subscribers, difficulty levels, duration, and course URLs. These features form the foundation for building the recommendation system.

2. Data Preprocessing

To improve the performance and accuracy of the model, the following preprocessing steps were applied:

- Cleaning: Removed duplicate and null values from the dataset.
- Text Normalization: Converted all text to lowercase, removed special characters, and applied tokenization.
- Feature Engineering: Added new columns like clean_title and clean_category for more efficient text matching.
- Label Encoding: Converted categorical variables into numerical format where necessary.

3. Model Development

Two different models were developed and compared:

- TF-IDF + Cosine Similarity: A content-based filtering method that transforms course titles and categories into vectors and calculates similarity between them to recommend relevant courses based on user input.
- K-Nearest Neighbors (KNN): A collaborative filtering approach that recommends courses based on the preferences of users with similar interests.

4. Model Evaluation

The models were evaluated using metrics such as relevance of recommendations and user feedback. Test cases were created to assess how accurately the system suggests courses for various interest keywords.

5. Predictions

Once the models were trained and tested, they were integrated into a Flask-based web interface. Users can input their interests (e.g., “Python, Data Science”), and the system predicts and displays the most relevant courses, linking directly to the original course platforms.

V. SYSTEM REQUIREMENTS

1. Hardware: Intel Core i5+, 8 GB RAM (16 GB recommended), 1 GB free disk space, Windows 10/11 or Ubuntu 20.04+.
2. Programming Language: Python 3.8+.
3. Tools: VS Code, Jupyter Notebook, or Google Colab; Flask 2.0+/Streamlit for UI.
4. Database: SQLite for user authentication.
5. Libraries: pandas, scikit-learn, nltk/re, flask-login, flask-bcrypt, matplotlib/seaborn.

VI. FLOWCHART

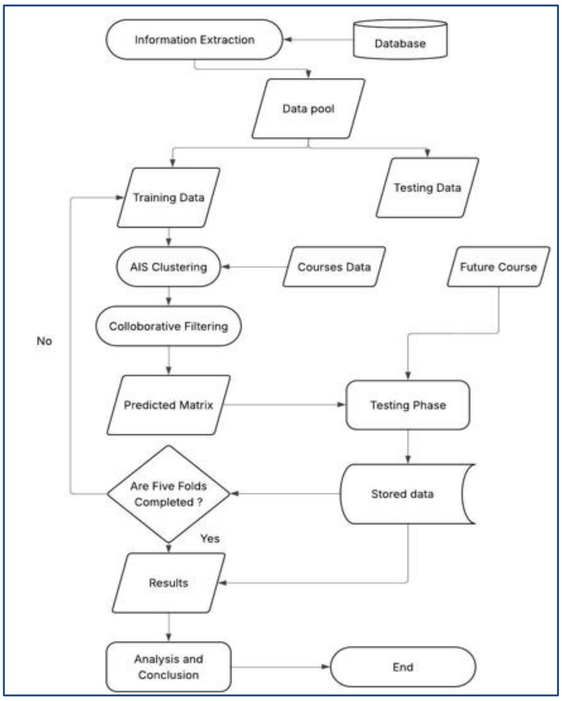

Figure 1. SystemFlowchart

VII. BENEFITS

- Personalized Learning: The system provides course recommendations tailored to individual interests and preferences.

- Efficient Search: Reduces time spent searching for relevant courses by automatically filtering based on keywords and user similarity.
- Improved Accuracy: Combining TF-IDF with KNN improves recommendation precision by considering both content relevance and user behavior.
- Scalability: The model can be extended to various platforms and updated with new course data dynamically.
- Ease of Use: A user-friendly web interface allows users to interact with the recommendation engine without any technical background.

VIII. APPLICATIONS

- E-Learning Platforms: Integrate into platforms like Coursera, Udemy, or edX to enhance user engagement.
- University Portals: Assist students in selecting elective or certification courses based on their area of interest.
- Corporate Training: Recommend upskilling and reskilling courses to employees based on job roles and learning paths.
- Career Counseling Tools: Serve as a backend tool in guidance platforms to recommend educational resources to students.
- Online Education Marketplaces: Boost visibility of niche or high-quality courses by matching them with relevant learners.

IX. CONCLUSION

This research presents an efficient AI-powered course recommendation system utilizing TF-IDF with Cosine Similarity and KNN algorithms. By analyzing course titles, categories, and user inputs, the system accurately suggests relevant courses that match the user's interests. The model leverages content-based filtering and instance-based learning to improve personalization and user engagement.

Through data preprocessing, feature extraction, and integration with a web-based interface, the system ensures both scalability and ease of use. The combination of intelligent filtering and a user-friendly design makes it a practical solution for deployment in real-world educational platforms, helping learners discover meaningful content more effectively.

X.RESULTS

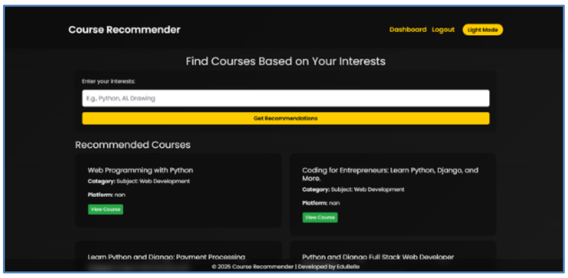

Figure 2. Login Interface

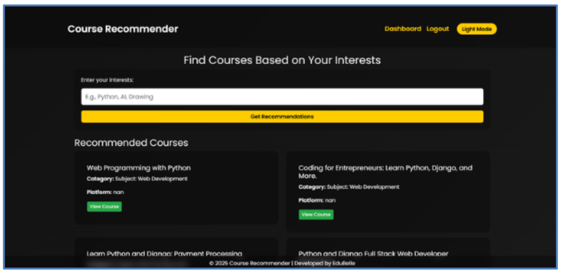

Figure 3. Course Recommendation Interface

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