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SMART EDUCATIONAL APP SELECTION THROUGH INTELLIGENT RECOMMENDATIONS

Marya Abdul Mannan[1], Dr. Mohammad Pasha[2], Ruqiya Fatima[3]
[1]PG Scholar, Department of CSE, Shadan Women's College of Engineering and Technology, Hyderabad,
maryamannan22@gmail.com
[2]Professor, Department of CSE, Shadan Women's College of Engineering and Technology
Muhammed.pasha@gmail.com
[3]Assot Professor, Department of CSE, Shadan Women's College of Engineering and Technology
ruqiyafatima2716@gmail.com

ABSTRACT
Personalised recommendations are essential for improving students' educational experiences in the quickly changing digital age. The growing use of mobile devices has made it simpler to gather app usage data, which may be used to offer customised recommendations for educational apps. The goal of this study is to recommend appropriate apps for college students based on their app usage habits, with an emphasis on Undergraduate (UG), Postgraduate (PG), and Graduate levels. In order to extract pertinent characteristics from app descriptions and student interaction data, the dataset is pre-processed using Natural Language Processing (NLP) techniques such as text cleaning, tokenisation, and feature extraction. Students' tastes are precisely categorised by the algorithm, which then suggests apps that meet their academic demands.

1. INTRODUCTION
Personalised recommendations are now a crucial part of enhancing students' educational experiences in the contemporary digital learning environment. Students are using mobile applications more and more for learning, research, and skill development as smartphones and tablets become more widely available. These educational apps serve a variety of functions, including collaborative learning, productivity boosting, academic planning, and subject learning. However, students frequently find it difficult to choose the apps that best suit their learning tastes and academic level due to the enormous amount of options. Intelligent recommendation systems can be crucial in pointing students in the direction of pertinent and useful apps in order to solve this problem.But because there are so many apps accessible, students frequently find it difficult to decide which ones best suit their learning style and academic level. Intelligent recommendation systems can be crucial in pointing students in the direction of pertinent and useful apps in order to solve this problem. The goal of this research is to create an educational app recommendation system specifically for undergraduate (UG), graduate, and postgraduate (PG) university students. The algorithm predicts appropriate app recommendations by utilising user interaction patterns and app usage data. App descriptions and user-related textual data are pre-processed and analysed using Natural Language Processing (NLP) techniques such tokenisation, feature extraction, and text cleaning.
These methods aid in gathering insightful data regarding the requirements of students and the features of the app. Because of its outstanding predictive accuracy and capacity to handle big, high-dimensional datasets, the Random Forest Classifier is used as the main model. It provides precise and context-aware recommendations by efficiently categorising user profiles and learning preferences. Because of its ensemble nature, which improves stability and minimises overfitting, the model is perfect for analysing real-world educational data. The suggested strategy performs better than conventional recommendation techniques in terms of accuracy and interpretability, according to experimental evaluation. Additionally, the system offers user-friendly, scalable, and customised recommendations that support students' academic objectives. In the end, our research advances more intelligent educational environments by encouraging digital learning effectiveness and raising student engagement through flexible, tech-driven solutions.

2. EXISTING SYSTEM OF PROJECT
A kind of recurrent neural network (RNN) architecture called the Gated Recurrent Unit (GRU) was created to effectively handle sequential input by recording dependencies across time. In order to deliver individualised app suggestions, GRU is essential to this project's analysis of user engagement patterns with mobile applications. It is ideal for managing time-sensitive and sparse educational data collected through crowdsourcing because of its capacity to recall pertinent historical data and adjust to shifts in user behaviour. The recommendation system may produce more precise and timely recommendations by utilising

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GRU, which enhances the user experience for college students looking for educational apps.

3. RELATED WORK

There are several comprehensive assessments of recommendation systems accessible, such as significant works by Tuzhilin and Adomavicius [6], [7] that categorised CF methods as existing content-based, collaborative, or hybrid and discussed possible extensions. Su and Khoshgoftaar [7] concentrated on CF techniques, encompassing hybrid, model-based, and memory-based methods. This analysis includes the Netflix reward competition as well as the most advanced algorithms available in 2009. A recent thorough analysis of federated recommender systems explores new issues like privacy problems while presenting conventional ideas [8]. Additionally, the first study in [9] uses three different datasets to compare two popular memory-based methods (Pearson correlation and vector similarity) with two traditional model-based methods (clustering and Bayesian network).With a focus on e-commerce applications, a more recent experimental comparison of CF algorithms compares item-based CF, user-based CF, SVM, and numerous other model-based approaches. [11] and [10]. It uses rank scores, recall, precision, F1-measure, and comments on computing complexity as evaluation measures. However, several common evaluation metrics, such as RMSE and MAE, are disregarded by approaches. The most widely used Collaborative Filtering (CF) techniques—memory-based and model-based CF algorithms—are covered in this study in order to forecast the apps that students would use based on their usage patterns [12]. Deep learning algorithms [15], clustering techniques [14], and matrix factorisation [13] are at the center of the new recommendation techniques.

4. PROPOSED SYSTEM

By examining the app usage habits and textual data of Undergraduate (UG), Postgraduate (PG), and Graduate students, the suggested system seeks to suggest appropriate educational applications. NLP techniques including text cleaning, tokenisation, stop-word removal, and vectorisation are used to accomplish this through data pretreatment. The contextual and semantic significance of the applications are represented by structured numerical features that are created from app descriptions and usage information. The method generates a comprehensive dataset that successfully captures the varied preferences and needs of students across academic levels by combining both behavioural patterns and textual features. After that, a Random Forest Classifier is used as the main prediction model to suggest apps according to student categories.

5. MODULES

1. Data Collection

This module gathers information from undergraduate (UG), graduate, and postgraduate (PG) students' use of a variety of educational applications. Textual app descriptions, user interactions, demographic information, and app usage logs are all included in the data. Accurate and pertinent data is gathered using app analytics and structured surveys. The recommendation system is built using the data that has been gathered. In order to uphold ethical standards, appropriate permission and privacy protections are guaranteed during collecting. The module guarantees the availability of adequate and varied data for the model's training and testing.

2. Dataet Features

from student app usage patterns and app metadata—such as app names, categories, descriptions, ratings, and engagement metrics—make up the dataset. A user's interaction with an application and related textual and numerical characteristics are represented in each record. To ensure quality for machine learning, the dataset is cleaned to eliminate inconsistent and superfluous entries. After then, it is set up to enable supervised learning, with labels that indicate the academic levels or preferences of the students. All future preprocessing and modelling operations rely on this module as their primary input.

3. Data Preparation

Data preparation involves preprocessing textual and numerical features to make them suitable for machine learning. NLP techniques such as text cleaning, tokenization, stopword removal, and feature extraction are applied to app descriptions. Categorical features like app categories and user levels are encoded appropriately. The dataset is normalized to ensure balanced feature contribution during model training. Finally, the data is split into training and testing sets, enabling evaluation of the model’s predictive capability.

4. Model Selection

In this module, the Random Forest Classifier is chosen as the core model due to its robustness, interpretability, and ability to handle high-dimensional, mixed-type data. Random Forest can manage missing values, avoid overfitting, and provide feature importance insights,

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making it ideal for educational app recommendations. Hyperparameters such as the number of trees, maximum depth, and splitting criteria are tuned to optimize performance. This module ensures that the model selected is both accurate and scalable for real-world deployment.

5. Analyze and Prediction

After training, the model is used to assess student interaction data and predict suitable instructional applications. The system evaluates behavioural metrics in addition to features extracted from NLP preprocessing to categorise students' preferences. Among the expected outcomes are suggested applications depending on the user's academic standing and preferred method of learning. By identifying the characteristics that have the greatest impact on recommendation judgements, this module also aids in model interpretability and actionable insights.

6. Accuracy on test set

The prediction performance of the trained Random Forest model is assessed using the test dataset. To guarantee trustworthy and consistent recommendations, metrics including accuracy, precision, recall, and F1-score are computed. The superiority of Random Forest in this application is confirmed by comparison with baseline models (e.g., Decision Tree or Logistic Regression). This module verifies the system's ability to effectively generalise to fresh, untested student data.

7. Saving the Trained Model

Following evaluation, the trained model is saved for further use using Python libraries like pickle or joblib. This eliminates the need for retraining when deploying the recommendation system in online or mobile applications. Based on their app usage habits, the saved model can produce predictions for new students in real time. Reproducibility and scalability are guaranteed by appropriate version control and documentation. This component guarantees the system's continued effectiveness, usability, and ease of integration with online learning environments.

6. TECHNIQUES USED IN PROJECT

EXISTING TECHNIQUE:

The Gated Recurrent Unit (GRU) is a sort of recurrent neural network (RNN) architecture that uses gating methods to regulate the flow of information in order to efficiently capture and model sequential data. By merging the forget and input gates into a single update gate, it streamlines the conventional RNN and preserves long-term dependencies while lowering computational complexity. Because GRUs are more effective than normal RNNs at handling vanishing gradient problems, they are frequently utilised for jobs involving time-series data, natural language processing, and recommendation systems.

PROPOSED TECHNIQUE:

The Random Forest Classifier is an ensemble learning algorithm that constructs multiple decision trees during training and combines their outputs to achieve more accurate and stable predictions. In this system, Natural Language Processing (NLP) techniques are applied to preprocess app-related text data, including descriptions, reviews, and usage patterns, by performing cleaning, tokenization, and feature extraction. These processed textual features are then converted into numerical vectors and used as inputs for the Random Forest model. Each decision tree in the forest makes a classification decision regarding the suitability of an app for Undergraduate, Postgraduate, or Graduate students, and the final prediction is determined by majority voting across all trees. This approach reduces overfitting, handles high-dimensional text data efficiently, and ensures robust and interpretable recommendations tailored to academic needs.

7. RESULT

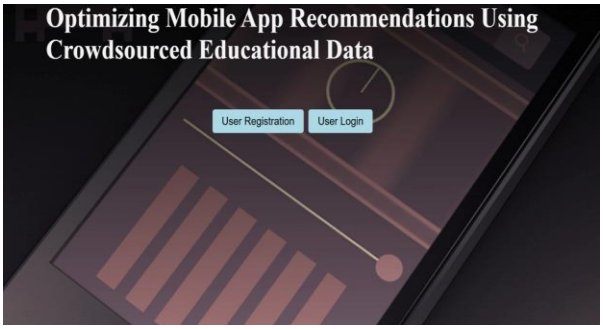


Fig 7.1: Home Page

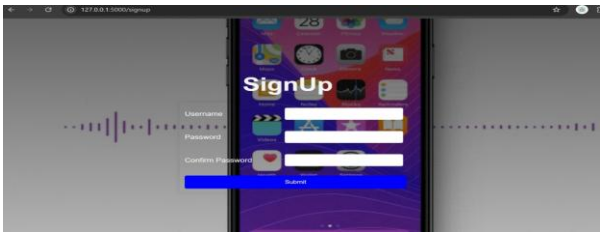


Fig 7.2: Student Registration/ Signup

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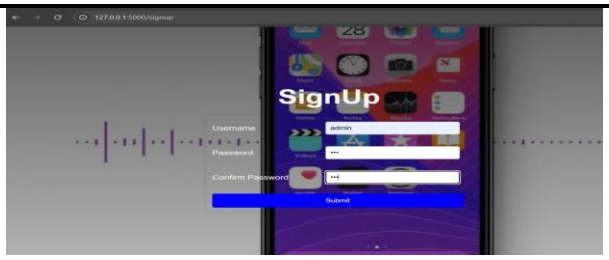


Fig 7.3: Admin Signup Details

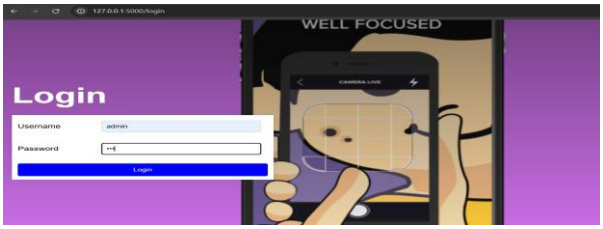


Fig 7.4: Login Page



Fig 7.5: Recommendation Page

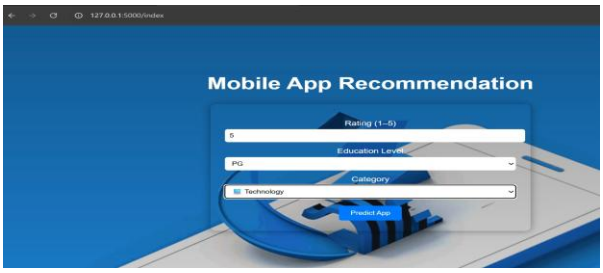


Fig 7.6: Student's Inputs

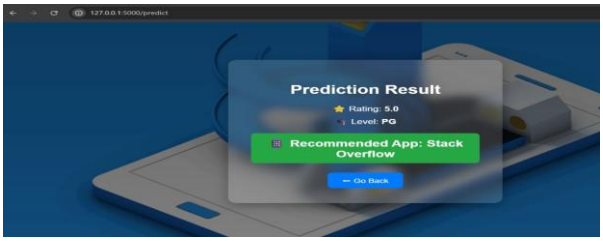


Fig 7.7: Predicted App

8. CONCLUSION

This project offers a customised educational app suggestion system intended to improve undergraduate, graduate, and postgraduate students' educational experiences. Thesystem uses Natural Language Processing techniques to extract significant elements that reflect students' academic demands and preferences from textual app descriptions and app usage statistics. Because of its durability, interpretability, and capacity to handle high-dimensional data, the Random Forest Classifier functions as the fundamental prediction model. The model achieves good accuracy, precision, and recall, generating dependable and pertinent recommendations, according to experimental evaluation. The system offers scalable, context-aware recommendations that are customised to each student's learning style while successfully mitigating data sparsity issues.The methodology guarantees that recommendations are in line with academic objectives and improve student engagement with educational apps by combining behavioural and content-based elements.The methodology makes sure that suggestions are in line with academic objectives and improve students' use of educational applications. Real-time predictions are made possible by the saved trained model, which makes it appropriate for use on mobile or web platforms. This method helps create more intelligent, AI-powered learning environments that help students choose the best learning resources. The project also emphasises how crucial data-driven personalisation is to digital education, encouraging effectiveness and better use of the resources at hand. Future improvements, such as language support, deep learning integration, and hybrid recommendation approaches, can boost system performance even further. All things considered, this research shows how merging machine learning and natural language processing (NLP) can enhance educational outcomes and produce a more customised, engaging, and productive digital learning environment. which makes it appropriate for use on mobile or web platforms. This method helps create more intelligent, AI-powered learning environments that help students choose the best learning resources. The project also emphasises how crucial data-driven personalisation is to digital education, encouraging effectiveness and better use of the resources at hand. Future improvements, such as language support, deep learning integration, and hybrid recommendation approaches, can boost system performance even further. All things considered, this research shows how merging machine learning and natural language processing (NLP) can enhance learning outcomes and produce a more individualised, engaging, and productive digital learning environment.

9. FUTURE ENHANCEMENT

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Future research could improve the system by using more sophisticated deep learning models, like BERT, RoBERTa, or LSTM, to better extract contextual meaning from app descriptions. Continuous monitoring and dynamic recommendation changes can be made possible by integrating real-time student engagement data from mobile apps. Personalisation can be enhanced by additional behavioural variables including learning results, click habits, and the amount of time spent on each app. Students who utilise apps in regional languages could benefit from multilingual help. Cold-start and data sparsity problems can be solved by hybrid recommendation techniques that combine content-based and collaborative filtering. Recommendation decisions can be made more transparent and understandable for educators and students by using explainable AI algorithms.

Recommendations that are smoothly in line with course curriculum can be obtained by integration with university learning management systems (LMS). It is possible to create a mobile or web-based interface that gives students fast access to customised app recommendations. To improve motivation and engagement, gamification components might be used. Lastly, long-term research can be done to gauge how the system affects academic results and student learning performance.

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