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# **Campus Bazaar: College Recommendation System**

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**ABSTRACT:** The project titled "COLLEGE RECOMMENDATION SYSTEM- CAMPUS BAZAAR" focuses on addressing the challenges faced by students and institutions during the engineering admission process. With the increasing number of applicants and diverse preferences, it becomes crucial to provide a personalized and efficient recommendation system that matches students' interests, academic performance, and geographical constraints with suitable engineering colleges. This recommendation engine leverages advanced machine learning and data analysis techniques to analyse student data, including academic scores, location preferences, and branch interests. By integrating this information with a comprehensive dataset of engineering colleges, the system provides tailored suggestions to help students make informed decisions. The proposed system employs algorithms like collaborative filtering. The engine is designed to enhance accessibility through a user-friendly web-based interface, ensuring a smooth experience for both students and educational institutions. Additionally, it incorporates scalability and flexibility, making it adaptable to future requirements and datasets. The implementation of this recommendation engine aims to optimize the admission process, reduce the decision-making time, and ensure better alignment of student aspirations with institutional offerings. This project highlights the potential of data-driven solutions in transforming traditional admission systems into intelligent, efficient, and student-centric processes

**KEYWORDS**: - 1.Machine learning 2.Recommendation system 3.Data analysis 4.collaborative filtering 5.Webbased interface development

#### I. INTRODUCTION

In moment's data- driven digital period, the engineering admission process is witnessing a abecedarian metamorphosis, driven by the adding need for intelligent decision- making tools. The complexity of assessing multitudinous sodalities, understanding admission criteria, and aligning particular preferences has made the process inviting for scholars. contemporaneously, institutions face difficulties in attracting campaigners that stylish align with their academic immolations and structure. This exploration explores the design and perpetration of a substantiated College Recommendation Engine for First Year Engineering Admission, aiming to address these critical challenges. The result leverages advancements in machine literacy, stoner data analysis, and recommendation system methodologies to deliver acclimatized council suggestions grounded on each pupil's academic performance, preferences, and eligibility. The system employs intelligent filtering ways to simplify the council selection process, reducing decision- making time and adding the delicacy of matches. cooperative and happy- grounded filtering approaches are used in combination to assay both pupil behaviours and institutional attributes. Clustering algorithms, similar as K- Means, member sodalities into meaningful groups grounded on features like position, arrestment species, and placement history, farther refining recommendations. A stoner-friendly web interface enables flawless commerce, allowing druggies to input preferences and incontinently admit substantiated suggestions. With real- time rigidity and scalable armature, the machine can integrate with sanctioned admission doors and career comforting tools. This enhances its impact and availability across the broader educational ecosystem. By presenting perceptivity through rich illustrations and detailed analytics, the result supports informed decision- making for scholars and institutions likewise, eventually streamlining the entire admission trip.





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#### **PROBLEM STATEMENT:**

#### A. Data Ingestion and Preprocessing

Students provide input data including MHT-CET scores, academic history, preferences (such as location, budget, and placements), and personal requirements (e.g., hostel, caste reservations). This data is collected through a web-based interface and preprocessed to ensure consistency—handling missing values, normalizing features, and preparing it for analysis.

#### B. Profile Chunking and Feature Embedding

To capture the complexity of student profiles and institutional data, inputs are broken down into key categorical and numerical components. Advanced feature engineering is applied, including profile weighting, text embedding (for unstructured inputs), and categorization. These transformed features are embedded into vector space representations suitable for similarity comparison and clustering.

#### C. Recommendation Query Handling

Upon receiving a query explicit or implicit the system filters and compares profile embeddings against institutional data. Machine learning models then identify top matches based on factors such as cutoffs, rank compatibility, and user-defined preferences.

#### D. Recommendation Generation

Recommendations are generated using predictive models like Random Forest or XGBoost, combined with collaborative and content-based filtering. The top-ranked institutions are dynamically selected based on matching scores and user priorities. If no match meets the criteria, fallback suggestions or feedback are provided.

#### E. Frontend Display and Interaction

The results are presented through an interactive Flask-based web interface. Students receive college suggestions in structured lists, detailed views, and graphical formats. Session-based chat history or dashboards allow users to revisit, compare, and refine their choices over time.

## **II. LITERATURE SURVEY**

Choosing the right college is a significant decision that shapes both the academic and professional trajectory of a student. Given the wide range of available institutions, students often struggle to find options that align with their academic profiles and personal preferences. To tackle this challenge, numerous research efforts have proposed smart recommendation systems powered by machine learning and data-centric techniques.

Ambole et al. [1] proposed a system driven by machine learning to suggest engineering colleges based on a student's academic performance and preferences. Their model utilizes decision trees along with semi-supervised learning algorithms to estimate admission chances, with the goal of minimizing the time students spend searching for relevant institutions manually.

Sonawane et al. [2] focused on the limited access to proper guidance, particularly in rural regions. Their recommendation engine evaluates not only academic data but also factors such as faculty quality, hostel facilities, and placement statistics. By incorporating assessments of student interests along with rich datasets, the system improves recommendation precision and reliability.

Dhande et al. [3] introduced a filter-based recommendation approach that allows users to input entrance exam scores and preferences. Their framework is designed to reduce the need for manual research by leveraging intelligent data filtering, aiding students in making informed decisions that align with their educational aspirations.

Sharma et al. [4] concentrated on using data mining techniques to guide the college selection process. They integrated accreditation information from agencies like NAAC and NBA to support students and their guardians. Their platform includes customized interfaces for different user roles and structured modules to ensure accessibility and ease of use, especially in preventing overlooked opportunities due to a lack of accessible information.





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Together, these studies emphasize the growing relevance of personalized recommendation systems in the education sector. By utilizing students' academic history, interests, and preferences, such systems offer targeted and meaningful suggestions. The increasing application of machine learning, collaborative filtering, and data mining has significantly enhanced the capability and accuracy of these systems.

Building on this existing research, the proposed Campus Bazaar platform introduces a scalable and user-friendly webbased interface. This system integrates user preferences, geographic limitations, and academic performance using collaborative filtering techniques to deliver a dynamic, responsive, and student-centered college recommendation experience.

## **III. PROPOSED METHODOLOGY**

#### 1. Strategy for Dividing the Dataset

To fairly assess a model's capability, the dataset is separated into three main components: training, validation, and testing. The training data is used to expose the model to patterns and associations within the input features. The validation set is leveraged during the tuning phase to optimize model settings and avoid overfitting by checking how well the model generalizes. The test set is held back until final evaluation and is used to examine how the model performs on previously unseen data.

#### 2. Application of K-Fold Cross-Validation

When working with a large enough dataset, k-fold cross-validation is implemented to produce more trustworthy evaluation results. This approach splits the data into k equal sections. For each iteration, the model is trained using k - 1 of those sections and tested on the remaining one. The process repeats until each section has been used once as the validation set. The final performance score is computed by averaging the results across all folds, reducing dependency on any single data split and ensuring a well-rounded evaluation.

#### 3. Performance Comparison Using Baseline Methods

To validate the model's effectiveness, its outputs are compared to those from basic recommendation systems, such as random choice or simple rule-based filters. These baseline methods serve as control benchmarks, making it easier to quantify how much improvement the machine learning model delivers. Through this comparison, the added value of using intelligent algorithms for generating relevant and personalized suggestions becomes clear



#### System architecture:





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The dataset may exhibit inherent imbalances due to variations in college cutoffs, placement percentages, and preferences across branches and castes.

**Imbalance Impact:** Features such as highly selective cutoffs for specific branches or limited data for less-preferred locations may skew the model's learning.

**Mitigation:** Techniques such as oversampling underrepresented categories or using weighted loss functions during training can address this imbalance to ensure fair recommendations across diverse inputs.

#### **IV. RESULTS AND ANALYSIS**

#### A. Evaluation Metrics

1. Accuracy and Precision

Accuracy reflects the proportion of correct college recommendations made by the system, while precision gauges how closely those suggestions align with the individual's academic qualifications and preferences. These two metrics are crucial for assessing the dependability and relevance of the system's recommendations.

#### 2. Recall and F1-Score

Recall indicates how effectively the system identifies all potential college options suited to the user, ensuring that valuable choices are not missed. The F1-score, which blends precision and recall into a single metric, provides a comprehensive view of the system's ability to make useful and inclusive recommendations.

#### 3. User Feedback

Feedback from actual users—particularly students—plays a key role in evaluating how well the recommendation system performs in real-world contexts. This practical insight helps identify strengths and areas for improvement, ultimately guiding enhancements to usability and accuracy.

#### **B.** Methodology

#### 1. Data Splitting

To enable thorough training and evaluation, the dataset is divided into three parts: training, validation, and testing. The model is trained on one subset, tuned using another, and finally tested on new data to evaluate its real-world performance.

#### 2. Cross-Validation Approach

The model's robustness is tested through k-fold cross-validation, where the data is split into k groups. The model is trained on k-1 of these and validated on the remaining part, cycling through all combinations. This helps ensure that the results are consistent across various data configurations and prevents overfitting.

#### 3. Baseline Evaluation

To understand the value added by the machine learning model, it is compared with simpler strategies such as random selection or rigid filtering methods. This comparison makes it easier to highlight the improvements achieved through advanced algorithmic approaches.

#### C. Model Optimization

#### Hyperparameter Fine-Tuning

The model's performance is enhanced by carefully adjusting key settings such as the learning rate, tree depth, and dropout rate. These parameters are tuned through repeated experimentation to ensure the model delivers accurate results without excessive computational cost, even when handling complex and diverse datasets.





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Fig 1:Home Page



#### Fig 2:Rigester Page

CAMPUS BAZAAR	HOME REGISTER LOGIN FAQS CONTACT
	Register page
	Register your account
	Name Vour Name
	Email Your Email
	Password
	Confirm your Password
	Confirmation
	Fig 3:Login Page

# Login page

HOME REGISTER LOGIN FAQS CONTACT

Log in to your account	
Name	
Your Name	
Email	
Your Email	
Password	
Password	
Agree to terms and conditions	
Continue	

CAMPUS BAZAAR





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Fig 4:Details Page

CAMPUS BAZAAR	HOME REGISTER LOGIN FAQS CONTACT
	Details page
	Please provide details asked below CET Score 65 JEE Score 50 Location ©Enter some location other than your current location Enter your location here
	Give your current location Choose engineering branches
CAMPUS BAZAAR	Fig 5: Details Page HOME REGISTER LOGIN FAQS CONTACT
	Location • Enter some location other than your current location pune

#### Fig 6:Result

Computer Science and Engineering(Data Science)
Artificial Intelligence and Data Science
Bechanical Engineering
Chemical Engineering
Electronics and Telecommunication Engg
Automobile Engineering

OGive your current location Choose engineering branches Computer Engineering Information Technology

CAMPUS BAZAAR		HOME REGISTER LOGIN FAQS CONTACT		
Cutoff	Institute Name	Branch	Exam	More
47.3984733	5124 Jagadamba Education Soc. Nashiks S.N.D. College of Engineering & Reserch Babulgaon	Computer Engineering	JEE	link
47.0339246	3219 Koti Vidya Charitable Trusts Smt. Alamuri Ratnamala Institute of Engineering and Technology Sapgaon Tal. Shahapur	Information Technology	JEE	link
46.6043774	2129 M.S. Bidve Engineering College Latur	Information Technology	JEE	link
45.7902205	1127 Jagadambha Bahuuddeshiya Gramin Vikas Sansthas Jagdambha College of Engineering and Technology Yavatmal	Computer Engineering	JEE	link
45.7804866	6183 Al Ameen Educational and Medical oundation College of Engineering Koregaon Bhima	Computer Engineering	JEE	link
45.7804866	5184 Amruta Vaishnavi Education & Welfare Trusts Shatabdi Institute of Engineering & Research Agaskhind Tal. Sinnar	Computer Engineering	JEE	link
45.0374181	3147 Saraswati Education Society Yadavrao Tasgaonkar Institute of Engineering & Technology Karjat	Computer Engineering	JEE	link
44.9736417	5382 Ahmednagar Jilha Maratha Vidya Prasarak Samajache Shri. Chhatrapati Shivaji Maharaj College of Engineering Nepti	Computer Engineering	JEE	link
43.1388868	3219 Koti Vidya Charitable Trusts Smt. Alamuri Ratnamala Institute of Engineering and Technology Sapgaon Tal. Shahapur	Computer Engineering	JEE	link
43.1388868	5401 Jawahar Education Societys Institute of Technology Management & Research Nashik.	Computer Engineering	JEE	link
43.1388868	6149 Choudhary Attar Singh Yadav Memorial Trust Siddhant College of Engineering Maval	Information Technology	JEE	link
42.4413035	5399 Sanghavi College of Engineering Varvandi Nashik.	Computer Engineering	JEE	link

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#### **D.** Summary and Insights

Statistical findings.

The device exhibits outstanding results in terms of accuracy, precision, recall, and f1-score. These results show that the recommendation engine consistently delivers users with accurate and comprehensive recommendations.

#### Descriptions of Our Experiments:

Positive user feedback validates the systems functionality in real-world scenarios. There are some areas that can be improved, such as increasing the dataset size, improving preference processing, and including more real-time variables.

#### Suggestions for Further Study:

Other enhancements include dynamic ranking that adapts to shifting cutoff scores, incorporation of student studies and recommendations, and integration with official admission portals to raise relevance and credibility.

#### V. CONCLUSION

The project is a Flask-based web application developed to streamline and optimize various workflows by utilizing Python for robust backend processing and SQLite as a lightweight yet powerful database solution for effective data management. By integrating Flask, a minimal and flexible web framework, the application delivers a smooth and responsive user experience, allowing users to navigate and perform tasks with ease through a clean, intuitive, and user-friendly interface.

This web application exemplifies the practical application of modern web technologies and emphasizes a modular development approach that simplifies maintenance and scalability. The use of Flask facilitates rapid development and efficient handling of HTTP requests, while SQLite ensures quick and reliable data storage without the overhead of more complex database systems. Together, they create a balanced architecture well-suited for small to medium-scale applications.

The project not only demonstrates technical proficiency but also highlights the practicality and efficiency of combining lightweight frameworks with embedded databases to address real-world challenges. Its modular and scalable design allows for easy customization, expansion, and integration with additional features or services in the future. As a result, the application stands as a dependable and adaptable solution, capable of serving users across diverse industries and use cases, with the potential for continued innovation and enhancement.

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