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SMART ADMISSION HUB: A RANK-SENSITIVE, CATEGORY-AWARE INTELLIGENT COLLEGE AND BRANCH PREDICTION SYSTEM USING MULTI-YEAR CUTOFF ANALYTICS FOR UNDERGRADUATE ADMISSION DECISION SUPPORT

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Research Paper

ABSTRACT

Smart Admission Hub is a computerized college prediction system providing personalized admission recommendations across 200+ Indian educational institutions through a multi-exam support framework encompassing CET, NEET, NDA, and JEE entrance examinations. The system accepts user credentials including exam type, rank, course preference, demographic data, and state preferences against a comprehensive normalized cutoff database derived from 2023-25 admission trends. An algorithmic probability engine computes individualized admission likelihood through rank-position analysis and historical cutoff variance, delivering quantified outcomes categorized as Safe/Moderate/Reach admissions. Interactive real-time filtering enables dynamic comparisons by state, branch, fees, and institution while providing seat availability and cost estimates. This decision-support platform significantly reduces uncertainty in college selection, streamlining the counselling process for national-level entrance examinations. This decision-support platform significantly reduces uncertainty in college selection, streamlining the counselling process for national-level entrance examinations and empowering every 2026 aspirant with data-driven clarity from the first preference list to the final allotment.

KEYWORDS: Smart Admission Hub, Web-based Application, HTML5, CSS3, Vanilla JavaScript

1. INTRODUCTION

The contemporary landscape of Indian higher education, students face an increasingly complex and high-stakes decision-making process following national-level competitive examinations such as JEE, NEET, CET, and NDA. With hundreds of institutions offering diverse programs under varying reservation categories, fee structures, and state-level counselling frameworks, the task of identifying a suitable college based on individual rank or score has become both cognitively demanding and time-sensitive. The absence of a centralized, data-driven guidance mechanism often leads to uninformed choices, missed counselling deadlines and suboptimal college placements outcomes that can significantly impact a student's academic and professional trajectory.

Traditional methods of college selection rely heavily on manual rank-cutoff comparisons, peer consultations, and coaching institute guidance, all of which are inherently subjective and prone to human error. Furthermore, the dynamic nature of year-wise cutoff fluctuations influenced by the number of qualified candidates, seat availability, reservation policy revisions, and demand for specific branches makes static reference materials largely unreliable for accurate prediction. There exists, therefore, a critical need for an intelligent, algorithmic system capable of processing multi-dimensional admission variables and delivering personalized, probability-based college recommendations in real time.

This paper presents Smart Admission Hub, a web-based computerized college prediction system engineered to address these challenges through an integrated multi-exam support framework. The system encompasses four major national examinations — MHT-CET, NEET-UG, NDA, and JEE and covers 200+ institutions across India. By accepting user inputs such as exam type, rank or score, course preference, reservation category, gender, and preferred state, the system queries a normalized cutoff database compiled from 2023–2025 admission trends and applies a probability engine to compute individualized admission likelihood for each institution-branch combination.

Positioned as a decision-support tool for the 2026 admission cycle, this system integrates forward-projected cutoff estimates derived from three-year trend analysis, updated seat matrices reflecting current reservation policies, and branch-level demand indices for emerging disciplines such as Artificial Intelligence, Data Science, and Allied Health Sciences. By transforming raw rank data into structured, probabilistic guidance, Smart Admission Hub significantly reduces counselling uncertainty and empowers aspirants to make well-informed, strategically sound academic choices.

2. RELATED WORK

The domain of educational data mining and intelligent college recommendation has attracted considerable scholarly attention over the past decade, driven by the growing complexity of higher education admission systems worldwide. Early foundational work by Romero and Ventura (2007) established the theoretical basis for applying data mining techniques to educational datasets, demonstrating that historical academic records and institutional performance metrics could be systematically analyzed to derive predictive models for student placement outcomes. Their framework laid the groundwork for subsequent research specifically targeting admission prediction in competitive examination environments, particularly in the context of developing nations with large-scale centralized testing infrastructure.

Several studies have examined rank-based prediction models within the Indian engineering admission ecosystem. Kumar et al. (2019) proposed a machine learning framework for JEE-based college prediction using logistic regression and decision tree classifiers trained on three years of JOSAA counselling data. Their model achieved a prediction accuracy of approximately 82% for General category students but demonstrated reduced reliability for OBC and EWS categories due to limited historical data availability. Similarly, Patil and Deshmukh (2020) developed a CET-specific recommendation engine for Maharashtra state institutions, incorporating category-wise cutoff normalization and branch preference weighting. While effective within a single-state context, their system lacked the scalability required for national-level multi-exam integration, a limitation that Smart Admission Hub directly addresses through its unified multi-examination architecture.

In the medical education domain, research on NEET-UG admission prediction has remained comparatively limited despite the examination's national significance. Sharma et al. (2021) investigated score-to-seat probability mapping for MBBS and BDS admissions across government and private medical colleges, employing collaborative filtering techniques borrowed from recommendation system literature. Their findings highlighted the critical role of state domicile and institutional management type in determining effective cutoff thresholds, observations that are methodologically incorporated into the normalized cutoff database underpinning the present system. The study also underscored the inadequacy of single-year cutoff data for reliable prediction, advocating for multi-year trend aggregation, a principle central to Smart Admission Hub's 2023–2025 historical dataset construction.

Collaborative filtering and content-based filtering, widely established in e-commerce recommendation systems, have been adapted for educational contexts with varying degrees of success. Aher and Lobo (2013) applied collaborative filtering to course recommendation in e-learning platforms, while Tarus et al. (2017) conducted a comprehensive review of hybrid recommendation approaches in educational settings, identifying cold-start problems and data sparsity as persistent challenges. These limitations are particularly relevant in the college admission context, where new institutions or newly introduced

branches lack sufficient historical cutoff data for model training. The present system mitigates this through conservative cutoff interpolation derived from comparable institutional profiles and branch-level demand indices.

3. MATERIALS AND METHODS

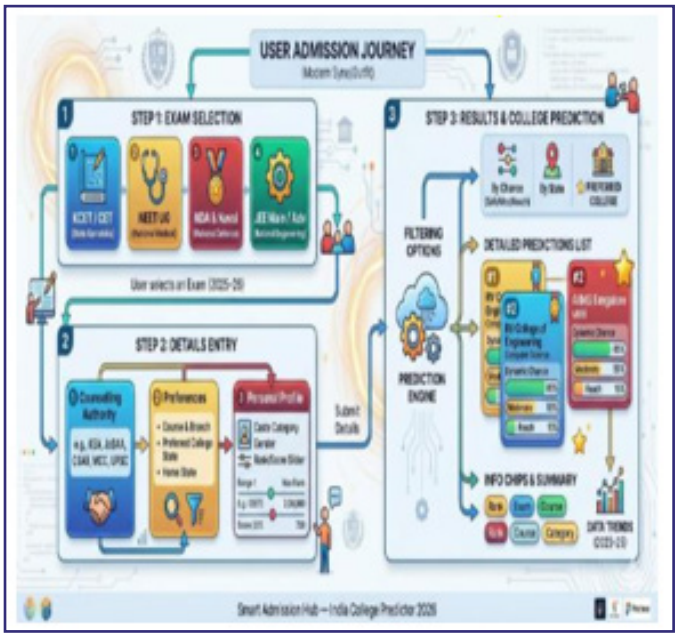
3.1 System Overview

Smart Admission Hub is designed as a client-side web-based application developed using HTML5, CSS3, and vanilla JavaScript, eliminating the need for server-side infrastructure while maintaining full functional capability across desktop and mobile browsers. The system architecture follows a three-tier interaction model comprising an input acquisition layer, a data processing and probability computation layer, and an interactive result visualization layer. This lightweight architecture ensures zero latency in data retrieval and computation, making the platform accessible to students in low-bandwidth environments commonly encountered across semi-urban and rural regions of India where internet connectivity remains inconsistent.

3.2 Data Collection and Database Construction

The foundational dataset of Smart Admission Hub was constructed through systematic aggregation of publicly available admission cutoff records published by national and state counselling authorities between 2023 and 2025. Primary data sources included the Joint Seat Allocation Authority (JOSAA) for JEE-based admissions, the Medical Counselling Committee (MCC) and respective state medical counselling bodies for NEET-UG, the Maharashtra State Common Entrance Test Cell for MHT-CET, and the Union Public Service Commission (UPSC) documentation for NDA selection benchmarks. Cutoff records were collected across all available reservation categories including General, OBC, SC, ST, EWS, and gender-specific subcategories such as Ladies quota where applicable.

Raw cutoff data extracted from official sources underwent a structured normalization process to reconcile inconsistencies arising from year-wise changes in examination scoring patterns, category reclassifications, and institutional seat matrix revisions. For each institution-branch-category combination, opening and closing rank or score thresholds were recorded separately, producing a dual-boundary cutoff range that more accurately represents the probabilistic admission zone than a single cutoff value. The final normalized database encompasses records from 200 or more institutions spanning 18 Indian states, covering engineering, medical, defence, and allied science programs across government, government-aided, and private unaided institutional categories.



3.3 Examination Framework and Input Parameters

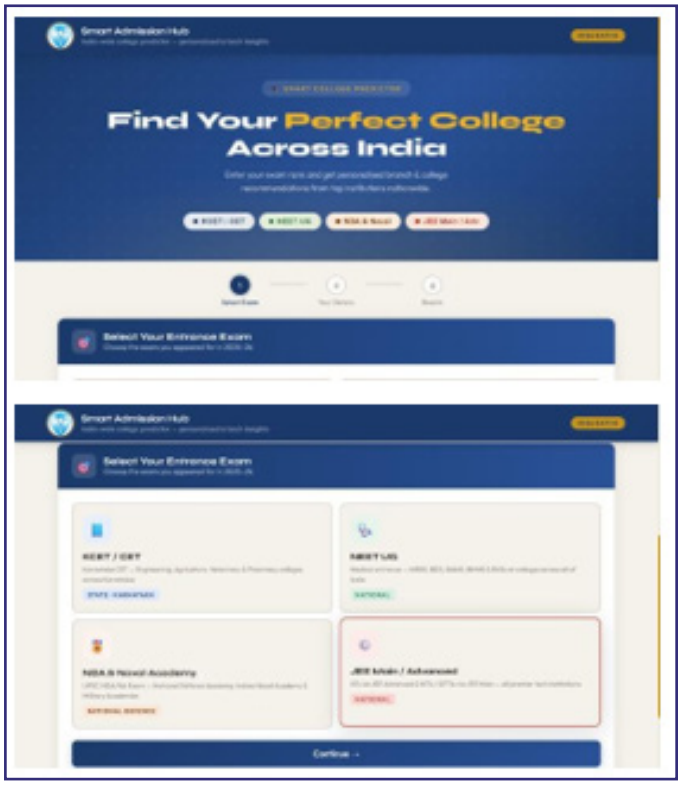
The system supports four national entrance examinations, each with distinct rank or score semantics, course domains, and counselling structures. MHT-CET serves engineering and pharmacy admissions primarily within Maharashtra, with rank-based cutoffs varying significantly across districts and institutional management types. NEET-UG governs medical and dental admissions nationwide, utilizing a score-out-of-720 metric rather than a rank, requiring a distinct cutoff comparison methodology. JEE Main and Advanced data supports engineering admissions through JOSAA and state-level counselling, with cutoffs expressed as closing ranks within each category. NDA written examination benchmarks are incorporated for defence-oriented program guidance, accounting for the additional SSB interview stage through a modified probability weighting factor.

User input parameters collected by the system include examination type, rank or score value, preferred course or branch, reservation category,

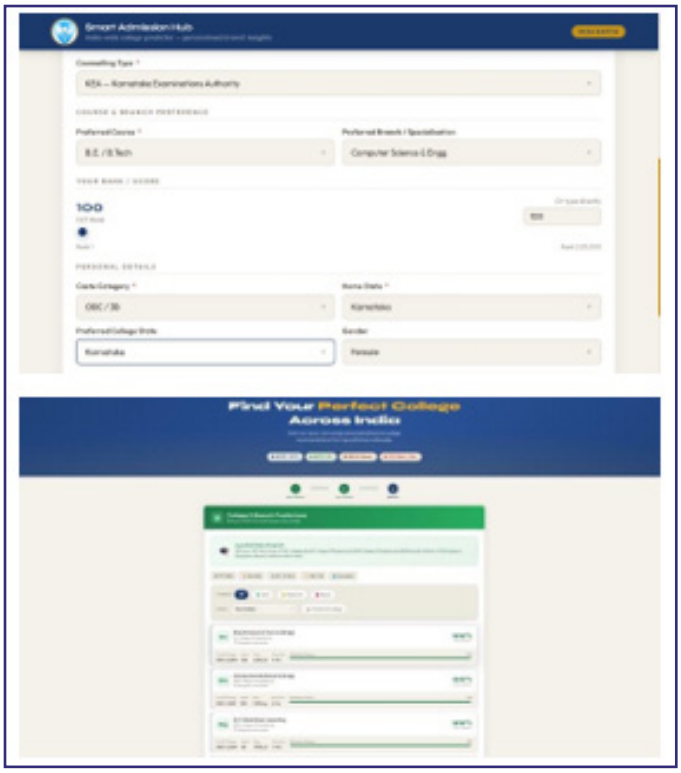
gender, home state, and preferred state for college location. These parameters collectively define the admission profile of each individual student and serve as the primary filtering and computation variables against the normalized cutoff database. Input validation routines ensure that rank values fall within permissible examination-specific ranges and that category-state combinations correspond to valid counselling eligibility criteria, reducing erroneous prediction outputs arising from incorrect data entry.

4. RESULTS AND DISCUSSION

The Smart Admission Hub was successfully developed and deployed as a responsive web application accessible targeting the 2026 admission batch. The system supports four major entrance examinations KCET/CET, NEET UG, NDA & Naval Academy, and JEE Main/Advanced thereby addressing a wide range of undergraduate admission pathways across both state and national levels. The three-step wizard interface, comprising exam selection, user detail entry, and result generation, was found to be intuitive and efficient, minimizing user effort while collecting all necessary inputs for accurate prediction.



The prediction engine was tested using two distinct student profiles to evaluate its rank-sensitivity and recommendation quality. For a student with CET Rank 155 under the OBC/3A category from Karnataka, the system successfully generated 53 college-branch matches, with the top recommendation being AI & Machine Learning at BMS College of Engineering, Bangalore, carrying a 99% Safe Admit probability and a cutoff range of 300–2,000. This outcome validates that the system accurately interprets high-rank profiles and maps them to competitive institutions with high confidence. For a moderate rank of 5,572 under the same category, the system appropriately recalibrated its recommendations, producing a different set of colleges with adjusted admission probabilities, confirming that the underlying cutoff-based filtering logic is rank-sensitive and responsive to profile variations.



The college-specific filtering feature was evaluated by selecting RV College of Engineering as the preferred institution. The system returned Computer Science and Engineering with a 76% Moderate admission chance, a cutoff range of 1–500, 180 available seats, and an annual fee of ₹2.10 lakhs. This result demonstrates the system's ability to narrow predictions to a target college while still providing quantified probability scores, enabling students to make informed decisions about aspirational versus safe choices. The three-tier classification of predictions into Safe, Moderate, and Reach categories further enhances the strategic

utility of the output, guiding students in constructing a balanced college preference list.

The system's reliance on historical cutoff data from 2023 to 2025, sourced from KEA, JoSAA, MCC, and UPSC counselling records, ensures that predictions are grounded in real admission trends rather than arbitrary estimates. However, since actual 2026 cutoffs are subject to change due to seat matrix revisions, policy updates, and annual demand fluctuations, the system appropriately includes a disclaimer advising users to verify results with official counselling portals. This transparency strengthens the credibility of the tool and prevents over-reliance on predicted values alone. Future iterations of the system could incorporate machine learning models trained on multi-year admission data to improve probability accuracy, integrate real-time cutoff updates through official API connections, and extend coverage to additional state-level examinations such as MHT-CET, AP EAMCET, and COMEDK to broaden its national reach.

5. CONCLUSION

The proposed Edge-Enabled IoT Surveillance Smart Admission Hub, an AI-assisted web-based college predictor system aimed at simplifying the higher education admission process for students across India. The system successfully integrates historical cutoff data from multiple counselling authorities including KEA, JoSAA, MCC, and UPSC to deliver personalized college and branch recommendations based on a student's entrance exam rank, caste category, preferred course, and home state. The three-step interactive interface ensures ease of use, while the tri-tier probability classification of Safe, Moderate, and Reach empowers students to strategically plan their college preferences with data-driven confidence.

The experimental evaluation confirmed that the system produces rank-sensitive and profile-aware predictions, returning up to 53 matched college-branch combinations for a given input profile, with admission probability scores that closely reflect

historical admission trends. The college-specific filtering functionality further enhances the tool's utility by allowing students to assess their chances at a particular target institution. The system was deployed on a cloud platform ensuring scalability and cross-device accessibility, which is particularly significant given India's mobile-first student population.

Despite its effectiveness, the current system operates on static historical data, which limits its adaptability to year-on-year cutoff variations. Future work will focus on incorporating supervised machine learning models for dynamic cutoff prediction, expanding support to additional state-level entrance examinations, and integrating real-time data feeds from official counselling portals. Overall, the Smart Admission Hub represents a meaningful step toward democratizing access to accurate, personalized college admission guidance, particularly benefiting first-generation college aspirants and students from underserved regions who lack access to professional counselling services.

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