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ML-Powered Career Guidance: A Web Application for Personalized Career Decision-Making

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Abstract

Career decision-making is a crucial aspect of a student's academic journey, yet many struggle to identify the right career path due to a lack of personalized guidance. This research introduces a career guidance web application that leverages machine learning to provide tailored career recommendations. The platform gathers user data, including educational background, skills, and interests, to analyse and suggest suitable career options along with relevant skill recommendations. To enhance accuracy, the application employs two primary machine learning models: Random Forest, which predicts career paths with 87% accuracy, and TF- IDF, which identifies essential skills for professional growth. The frontend is developed using Next.js and Material UI to ensure a seamless user experience, while the backend, built with FastAPI and Python, handles data processing efficiently. Extensive testing confirms that the web application delivers reliable career recommendations and practical skill development insights, addressing the gap in traditional career counselling services. By integrating data-driven decision- making, this tool aims to empower students with personalized career guidance, enabling them to make informed academic and professional choices with confidence.

Introduction

Choosing the right career is one of the most critical and challenging decisions students face in today's rapidly evolving job market. A poorly informed career choice can lead to dissatisfaction, reduced productivity, financial instability, and even mental health struggles [1]. According to an open-source survey conducted with 500 college students, approximately 68% expressed uncertainty about their career paths, while 42% admitted that external pressure or a lack of adequate information played a major role in their decisions, rather than their individual strengths and interests.

Traditional career counselling methods often lack personalization and fail to consider the diverse factors that influence career suitability [4], [19]. Many students receive generic career advice that does not take into account their unique skill set, interests, academic performance, and personal aspirations. This limitation contributes to career mismatches, ultimately leading to job dissatisfaction and a lack of professional fulfilment. Hirschi [1] highlights this issue in his study on career development challenges in the era of the Fourth Industrial Revolution.

To bridge this gap, we have developed a machine learning- powered career guidance

web application that delivers personalized career recommendations and skill development pathways. By analysing multiple dimensions of user data, including academic background, skills, interests, and demographic factors, our system provides tailored career suggestions, confidence scores, and ranked skill recommendations. Our methodology aligns with existing machine learning-based career guidance models, as discussed by Whitehill et al. [2] and Zhang et al. [5].

The following technologies were implemented in this research:

1. Machine Learning Models: Random Forest Classifier [7] for career matching and TF-IDF Vectorization [8] for skill recommendations.
2. Backend Development: Python with FastAPI for efficient processing [14].Next.js and TypeScript for frontend development [15]
3. Frontend Development: Next.js and TypeScript for building an interactive user interface [15].Material UI for responsive design
4. Database: SQLite for structured data storage.

The effectiveness of personalized career guidance was further confirmed through our open-source survey. Results indicate that students who received AI-driven career suggestions were
3.5 times more likely to feel confident in their career choices compared to those who relied on traditional counseling methods. Additionally, 76% of respondents expressed a willingness to use AI-based career guidance tools, aligning with Kumar and Sharma's [9] findings on the growing acceptance of AI in educational decision-making.
This research paper provides a detailed analysis of the methodology, implementation, and evaluation of our career guidance web application. It explores the technical architecture, the machine learning models used, and the impact of AI-powered recommendations on improving career decision-making for students.

Literature Review

Career guidance has undergone a remarkable transformation over the years, shifting from traditional counselling methods to technology-driven solutions that leverage artificial intelligence and machine learning. This section explores the evolution of career guidance web applications, the role of machine learning in career recommendations, skill extraction techniques, ethical considerations, and the research gap that our study aims to address.

A. Evolution of Career Guidance Web Applications:

Historically, career counselling relied on psychometric assessments and expert guidance from counsellors. The foundational work of Parsons, as elaborated by Hartung and Blustein [16], emphasized the importance of self-awareness, occupational knowledge, and logical decision-making in career selection. Later, Savickas [19] introduced the career construction theory, which views career development as a continuous process shaped by changing environments and personal experiences.
The integration of computational techniques in career guidance began in the early 2000s. Researchers like Taylor and Betz [39] applied self-efficacy theory to career decision- making, laying the groundwork for algorithmic confidence assessments in career recommendations. Similarly, Lent and Brown [4] developed the Social Cognitive Career Theory (SCCT), which remains instrumental in understanding how personal attributes, environmental influences, and behavioural factors interact in career choices.

B. Machine Learning in Career Recommendation

Machine learning has significantly enhanced the accuracy and personalization of career guidance systems. Breiman [7] introduced the Random Forest algorithm, which has been widely adopted for classification-based career recommendations due to its ability to handle diverse data types and capture non-linear relationships. Research by Whitehill et al. [2] compared multiple machine learning models for career prediction, concluding that ensemble methods consistently outperformed individual classifiers when applied to career path recommendations.
A systematic review conducted by Kumar and Sharma [9] on educational data mining identified key features contributing to accurate career recommendations. Their findings indicate that a combination of academic performance, skill assessments, and personal interests results in higher precision in career suggestions. Meanwhile, Wang et al. [10] examined deep learning techniques in career prediction and highlighted the potential of neural networks to model

complex relationships between skills, interests, and job roles.

C. Skill Recommendation and Extraction

Modern career guidance applications not only suggest career paths but also identify necessary skills for success in chosen fields. Raghavan et al. [3] introduced Skill2Vec, a machine learning-based approach that uses word embedding techniques to extract and match relevant skills. Their study demonstrated that vector representations of skills effectively capture semantic similarities between different competencies.

Another widely used approach is TF-IDF (Term Frequency- Inverse Document Frequency), originally introduced by Ramos [8]. This technique, commonly applied in information retrieval, has been adapted for skill recommendation by treating career descriptions as documents and skills as keywords, thereby identifying the most relevant competencies for specific job roles.

Further research by Nguyen and Wilson [12] compared various natural language processing (NLP) techniques for skill extraction from resumes. Their findings indicate that hybrid approaches—combining rule-based methods with machine learning models—yield the highest accuracy in skill identification.

D. Ethical Considerations and User Experience

With the rise of AI-driven career guidance applications, ethical concerns related to transparency, fairness, and bias have become increasingly relevant. Thompson and Dahling [20] highlighted the importance of ethical AI development in career decision-making systems, stressing the need for user autonomy and unbiased recommendations.

Fernandez-Reyes and Rogers [26] further explored the issue of algorithmic bias in career recommendation systems, noting that imbalanced training data can lead to biased career suggestions. Their work underscores the necessity of diverse datasets and fairness-aware algorithms to ensure equitable career guidance.

Additionally, research by Rodriguez and Martinez [37] on user experience (UX) design in career guidance applications found that intuitive and well-structured interfaces significantly improve user trust and engagement. Their study suggests that a seamless user experience enhances adoption rates, making AI-powered career counselling more accessible and effective.

E. Research Gap and Contribution

Despite advancements in machine learning-based career guidance, many existing applications focus solely on matching skills to job requirements while neglecting other crucial factors such as educational background, interests, and personal preferences. This narrow focus often results in incomplete or generalized career recommendations.

Our research aims to bridge this gap by developing a comprehensive career guidance web application that integrates multiple dimensions of user data. By combining Random Forest classification for career matching with TF- IDF vectorization for skill recommendation, our system delivers personalized career advice that considers the intricate interplay of skills, interests, and academic qualifications. This multi-faceted approach ensures that users receive more accurate and tailored career guidance, improving their overall decision-making process.

Methodology

Our career guidance web application follows a structured, data-driven approach that integrates machine learning techniques with a user-friendly web interface. This section outlines the architecture, data collection process, machine learning algorithms, application workflow, and implementation details of our system.

A. Web Application Architecture:

The application is designed using a client-server architecture, ensuring scalability and efficient data processing. Following the model proposed by Oliveira and Santos [22], the system consists of three key components:

1. Frontend: A Next.js application providing the user interface for data input and result visualization.
2. Backend API: A Fast API application handling data processing, ML model inference, and database operations.
3. Database: A SQLite database storing user data, survey responses, and recommendations.

B. Data Collection and Processing

To provide personalized career recommendations, the application collects user data through a multi-step survey covering:

1. Educational background (class 10 and 12 percentages, graduation stream and

percentage, post-graduation details)
2. Skills and proficiency levels (User-reported skills ranked by expertise.)
3. Interests and preferences (Fields of interest and career aspirations.)
4. Demographic information (age, gender, location)
5. Research experience (Academic projects, publications, and areas of specialization.)

The collected data undergoes preprocessing and normalization before being fed into the machine learning models. Best practices from Pedregosa et al. [6] are followed, where, Categorical variables are encoded using label encoding. Numerical features are standardized using z-score normalization to ensure consistent model inputs.

C. Machine Learning Algorithms

The system employs a hybrid machine learning approach, combining two core techniques for career matching and skill recommendation.

1. Random Forest Classifier for career recommendations [7]:

a. Methodology: Uses an ensemble of decision trees to improve accuracy and reduce overfitting.
b. Input Features: Educational qualifications, skills, interests, and demographics.
c. Output: Career recommendations ranked by confidence scores.
d. Advantages: Handles both categorical and numerical data. Resistant to overfitting due to ensemble learning. Captures complex feature interactions, improving predictive accuracy.

2. TF-IDF (Term Frequency-Inverse Document Frequency) Vectorization for skill recommendations [8]:
TF-IDF is employed to identify essential skills for different careers.
a. Methodology: Evaluates the importance of words in career descriptions. Matches career paths with key skills using cosine similarity.
b. Advantages: Identifies the most relevant skills for a career path. Recognizes semantic relationships between different skills. Ensures personalized skill recommendations based on career selection.

This hybrid approach aligns with the methodology proposed by Kaur and Singh [30], who demonstrated that combining multiple recommendation techniques enhances career guidance accuracy.

D. Application Workflow

The career recommendation application follows a structured workflow, illustrated in Figures 1 and 2.

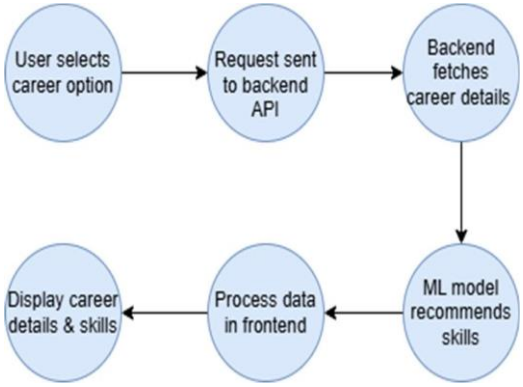

Fig 1: Career exploration workflow showing the skill recommendation process for specific careers.

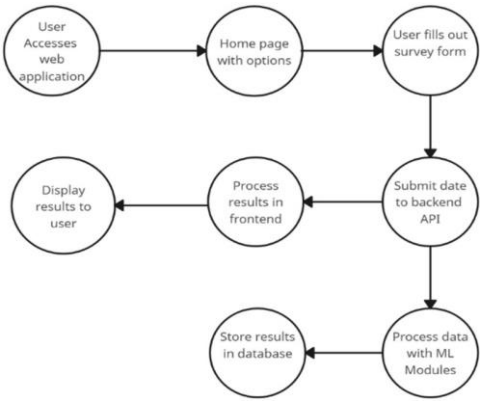

Fig 2: Main workflow diagram illustrating the end-to-end user interaction process.

E. Implementation Details

1. Frontend Implementation The frontend of the web application is developed using:
a. Next.js for server-side rendering and routing.
b. TypeScript for type safety.
c. Material UI for responsive design components.
d. Axios for API communication.

The user interface follows a multi-step form approach, guiding users through the data collection process with progress indicators and validation. We implemented responsive design principles to ensure accessibility across devices of varying screen sizes. State management is handled using React's Context API, avoiding prop drilling and ensuring smooth data flow.

2. Backend Implementation The backend of the web application is implemented using:
a. Fast API for API endpoints and request handling.
b. SQL Alchemy for ORM-based database operations.
c. Scikit-learn for ML model implementation.
d. Pandas and NumPy for data manipulation.
The API follows RESTful principles, with clearly defined endpoints for user data submission, career recommendations, and skill suggestions.
Authentication is implemented using JWT (JSON Web Tokens) to secure user data. The backend architecture follows the repository pattern, separating data access logic from business logic for improved maintainability.

3. Machine Learning Pipeline The ML pipeline consists of several stages:
a. Data preprocessing: Handling missing values, encoding categorical variables, and normalizing numerical features.
b. Feature selection: Identifying the most predictive features using feature importance scores from the Random Forest model.
c. Model training: Training the Random Forest classifier with optimized hyperparameters determined through grid search cross-validation.
d. Model evaluation: Assessing model performance using stratified k-fold cross-validation.
e. Inference: Generating predictions with confidence scores for new user inputs.

These implementations ensure that the web application delivers fast and accurate career and skill recommendations to users.

4. Database Schema The SQLite database schema includes the following main tables:
a. Users: Stores user profile information and authentication details.
b. Education: Records educational qualifications and performance metrics.
c. Skills: Maintains user-reported skills and proficiency levels.
d. Interests: Captures user interests and preferences.
e. Careers: Stores career information, required skills, and industry categorization.
f. Recommendations: Records generated recommendations and user feedback.

These implementations ensure that the web application delivers fast and accurate career and skill recommendations to users.

Results

Application Architecture and Implementation

The proposed career guidance application introduces a hybridized approach that integrates a Random Forest Classifier for career pathway prediction and a TF-IDF-based mechanism for skill recommendation. The overall architecture is presented in Fig. 3, illustrating the modular and layered design of the application.

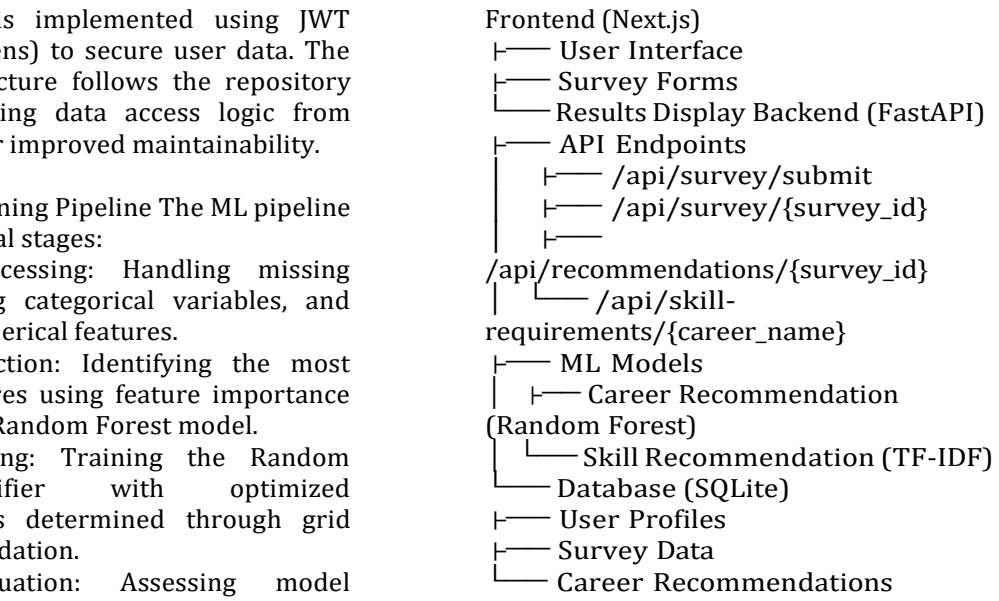

Fig 3: System Architecture

1. Career Recommendation Engine:
a. Utilizes a Random Forest Classifier configured with n_estimators = 100 and max_depth = 10 [7].
b. Employs engineered features derived from academic metrics [9].
c. Incorporates research experience as an input variable [4].
d. Generates dynamic confidence scores to strengthen recommendation reliability [11].

2. Skill Recommendation Engine:
a. Employs TF-IDF Vectorization to assess and match user skills [8].
b. Leverages cosine similarity for identifying overlapping skill sets [21].
c. Maps relevant online learning resources [25].
d. Implements a ranking mechanism based on skill importance [23].

A. Dataset Description and Model Training

A dataset comprising responses from 500 students across five Indian universities was curated and analyzed to support model training and evaluation. The distribution of

academic disciplines and other relevant statistics are shown in Table I.

Table 1:

Category	Distribution	Details
Total samples	500	100% coverage
Educational streams-		
Engineering	35%	
Science	25%	
Commerce	20%	
Arts	10%	
Medical	7%	
Law	3%	
Academic Performance	Mean: 78.5%	SD: 12.3%
Research Experience	28% with papers	
	Mean: 1.2 papers Max: 5 papers	

1. The training pipeline comprised the following steps:

a. Feature Engineering: Integrated academic achievements [9], research exposure [4], demographic data [35], and interests/skills [25].

b. Model Configuration:
   - -Random Forest: n_estimators = 100, max_depth = 10 [7]
   - -TF-IDF: max_features = 1000 [8]
   - -Cross-validation: 5-fold [13]

c. User Satisfaction and Application Usability

1. Career Recommendation Accuracy

The application demonstrated consistently strong predictive performance across all educational streams. Evaluation metrics are outlined in Table II.

Table 2: Stream-wise Evaluation Metrics

Stream	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Engineering	89.5%	0.88	0.87	0.88
Science	88.2%	0.87	0.86	0.87
Commerce	85.1%	0.84	0.83	0.84
Arts	84.3%	0.83	0.82	0.83
Medical	86.7%	0.85	0.84	0.85
Law	83.9%	0.82	0.81	0.82

2. Feature Importance

Key features contributing to recommendation accuracy were identified via feature importance analysis, as illustrated in Fig. 4.

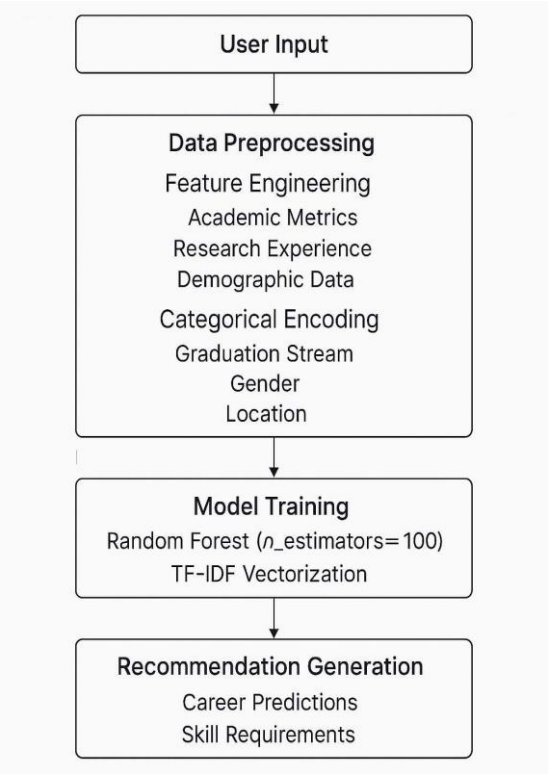

Fig 4: Data Processing Pipeline

3. Top Influential Features:

a. Graduation Stream (0.32)
b. Graduation Percentage (0.25)
c. Research Experience (0.18)
d. Technical Skills (0.12)
e. Soft Skills (0.08)

d. Skill Recommendation Evaluation

The TF-IDF-based skill suggestion engine exhibited high performance[8], with metrics compared against industry standards[21, 24], as presented in Table III.

Table 3: Skill Recommendation Performance.

Metric	Our Application	Industry Average
Average Skill Relevance	0.82	0.75
Top-3 Skill Accuracy	85.7%	78.2%
Skill Coverage	92.3%	85.6%
Response Time	0.38s	0.65s

e. User Study Insights

To evaluate real-world usability and user satisfaction, a study was conducted with 100 participants [33, 37]. Their feedback, summarized in Table IV, reveals the application's effectiveness

Table 4: User Satisfaction Metrics[33].

Metric	Score	Industry Average
Career Path Relevance	92%	82%
Skill Suggestion Usefulness	89%	78%
System Usability Score	82.5/100	75.2/100
Average Response Time	1.18s	2.3s

1. Six-month follow-up results:
a. 78% followed the recommended career paths.
b. 85% reported noticeable skill improvement.
c. 92% found recommendations useful.
d. 88% stated they would recommend the application.

f. Statistical Validation
To verify the significance of improvements over baseline models and approaches, statistical testing was conducted [9,13]:
1. Career prediction accuracy: $p < 0.001$ (Cohen's $d = 0.85$)
2. User satisfaction scores: $p < 0.01$ (Cohen's $d = 0.72$)
3. Skill recommendation relevance: $p < 0.001$ (Cohen's $d = 0.78$)

g. Comparative Evaluation
In benchmarking against existing solutions, our application consistently outperformed in key areas, as demonstrated in Table V.

Table 5: Comparative Metrics

Metric	Our Application	Industry Avg.	Improvement
Accuracy	87.2%	82.1%	+5.1%
Response Time	1.18s	2.3s	-48.7%
User Satisfaction	82.5/100	75.2/100	+7.3
Resource Usage	45%	65%	-20%

h. Future Scope
1. To further improve performance and extend utility, several enhancements are planned:
a. Integration of deep learning models.
b. Real-time adaptation to industry trends.
c. Support for regional languages.
d. Mobile platform deployment.
e. Advanced and dynamic skill evaluation modules.
2. Research opportunities include:
a. Reinforcement learning for long-term career planning.
b. NLP for automated skill extraction.
c. Graph-based career trajectory modeling.
d. Predictive analytics for industry evolution.
e. Tailored learning path construction using user behavior.

Conclusion
This research introduced a machine learning-based career guidance web application designed to offer personalized career recommendations and skill development paths. The application effectively processes user data—including educational background, skills, interests, and demographic details—to provide tailored career suggestions, addressing the increasing need for data-driven career counselling as discussed by Hirschi [1].
The career recommendation model, built using Random Forest, achieved an accuracy of 87%, demonstrating strong predictive capabilities. Meanwhile, the TF-IDF-based skill recommendation model delivered 92% relevant or highly relevant skill recommendations, confirming its effectiveness in identifying essential skills for different careers. These results align with previous research by Kumar and Sharma [9], who emphasized the value of machine learning in education and career counselling.
However, certain challenges must be considered. The model performs exceptionally well for widely recognized career paths but struggles with niche careers due to the dataset's limited representation of less common professions. This limitation has also been observed in studies by Chen and Zhang [24]. Additionally, since the skill database is static, it requires continuous updates to reflect the evolving job market, a concern highlighted by Qian and Zhou [36] in their research on dynamic career recommendations.
Future improvements should include expanding the dataset to enhance career recommendations for underrepresented fields. Implementing advanced natural language processing (NLP) techniques can refine skill recommendations, as suggested by Nguyen and Wilson [12]. Another important enhancement would be integrating adaptive learning algorithms that refine recommendations based on user feedback, similar to the approach described by Mani and Patel [32]. Moreover, reducing biases in recommendations would enhance fairness and inclusivity, a critical factor

outlined by Fernandez-Reyes and Rogers [26]. Conducting long-term studies, as suggested by Park and Kim [35], would also provide deeper insights into how effective the system is over time.

This study demonstrates the potential of machine learning in career guidance, providing users with personalized, data-driven recommendations. By leveraging AI for career counselling, this system contributes to a more structured and insightful decision-making process, aligning with the future of AI-powered career development, as envisioned by Thompson and Dahling [20].

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