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Volume 14, Issue 4, April 2025 |DOI: 10.15680/IJIRSET.2025.1404191| Smart Career Advisor

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ABSTRACT: Choosing the right career path can be challenging, especially with the vast number of options available today this can be solved using the smart career advisor system. The Smart Career Advisor System is a web-based platform designed to assist individuals in making informed career decisions using a React frontend and a Django backend. The system operates through four key steps: user registration and questionnaire, where users provide information on their interests and skills; machine learning prediction, which analyses user inputs to suggest suitable career paths; sentiment analysis (NLP), which evaluates user responses for better recommendation accuracy; and an AI-powered chatbot and voice assistant, which offer interactive career guidance. By integrating machine learning and natural language processing, the system delivers personalized, data driven career recommendations, enhancing users decision-making processes.

I. INTRODUCTION

In today's rapidly evolving job market, effective career guidance is critical for individuals aiming to make informed professional decisions. Traditional career counselling methods often rely on generic advice and standardized assessments that may not adequately address the unique needs and aspirations of modern job seekers. To bridge this gap, we propose a comprehensive Career Path Recommendation System that combines state-of-the-art machine learning, natural language processing, and conversational interfaces to deliver personalized career recommendations. The system initiates with a user registration process and a structured quiz designed to capture a wide range of inputs, including numerical ratings (e.g., logical quotient, hackathons, coding skills, public speaking, memory capability) and categorical data (e.g., self-learning capability, extra courses, certifications, workshops, reading and writing skills, interests in subjects and career areas). These responses are pre-processed through data cleaning, encoding, and feature extraction to create a robust input dataset for predictive modelling.

At the core of the recommendation engine, several machine learning models—including Decision Trees, Support Vector Machines (SVM), and Random Forests—analyse the pre-processed data to predict the most suitable job role for each user. In cases where the initial recommendation is unsatisfactory, a sentiment analysis component utilizing natural language processing techniques (inspired by methodologies such as those outlined in [3]) evaluates user feedback, enabling dynamic refinement of the recommendation.

Enhancing the user experience, the system integrates an interactive chatbot assistant—leveraging APIs like Google Gemini and frameworks such as LangChain—and a voice assistant built with React Speech Recognition. These conversational agents facilitate natural, real-time interactions, providing users with immediate support and clarification on career-related queries.

The project is implemented using a modern technology stack, with a React-based frontend and a Django backend that employs Django Rest Framework for efficient API development. This architecture supports scalability and seamless integration with additional services such as FAISS for vector-based storage and SQL databases for persistent data management. Building on foundational recommender system research [1], [2] and advances in deep learning for interactive applications [4], [5], our Career Path Recommendation System aims to offer a robust, personalized career guidance solution that adapts to the evolving needs of today's workforce.





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II. RELATED WORK

Career recommendation systems have evolved from early rule-based methods to sophisticated, data-driven models that integrate machine learning and natural language processing techniques. A seminal work by Adomavicius and Tuzhilin (2005) laid the foundation for personalized recommender systems by surveying both collaborative and content-based filtering approaches. Their study highlighted key challenges in tailoring recommendations to individual users—a challenge that remains central in the design of modern career recommendation systems.

Building on these principles, Koren, Bell, and Volinsky (2009) introduced matrix factorization techniques that have become a cornerstone in recommender system research. These techniques are particularly effective in uncovering latent patterns in user-item interactions, which can be applied to predict career preferences based on past performance and interests.

In addition to quantitative methods, the integration of textual data through sentiment analysis is crucial for interpreting qualitative user feedback. Pang and Lee (2008) provide comprehensive methods for opinion mining and sentiment analysis that can be leveraged to understand user reviews and self-assessment responses. Such approaches are essential when the system must evaluate the subtleties in a user's expression of skills and interests.

Recent advances in deep learning have further refined recommendation strategies. Covington, Adams, and Sargin (2016) demonstrated the power of deep neural networks in a large-scale recommender system for YouTube, highlighting how deep learning models can capture complex user behaviours. These models facilitate the extraction of intricate patterns from multidimensional data, which is highly relevant when aligning diverse career factors with appropriate job roles.

Conversational interfaces, as explored by Serban et al. (2016), enhance user engagement by enabling interactive dialogues. These systems can serve as a natural medium for career guidance by interpreting queries and dynamically adjusting recommendations based on user input.

Finally, Jurafsky and Martin's (2020) textbook on Speech and Language Processing provides the theoretical and practical underpinnings for natural language understanding and generation. Their work informs many of the techniques used to analyse user language in career recommendation systems, ensuring that the system not only matches skills quantitatively but also understands qualitative nuances in user responses.

Together, these real contributions from the literature illustrate a clear evolution from traditional recommender systems to integrated, multi-modal approaches. By combining established techniques with recent advancements in deep learning and natural language processing, modern career recommendation systems can provide more accurate, personalized guidance to help individuals navigate complex career choices.

III. METHODOLOGY

The development of the Career Path Recommendation System follows a structured, multi-stage process that encompasses data acquisition, pre-processing, feature engineering, model training, and system integration. The system is designed to generate personalized job role recommendations based on user responses collected via a quiz, where the dataset includes both numerical ratings and categorical responses.

Data Collection and Dataset Overview: User responses are gathered through a structured quiz that evaluates various skills and preferences. The dataset comprises features such as logical quotient rating, hackathons participation, coding skills rating, public speaking points, self-learning capability, completion of extra courses, certifications, workshops attended, reading and writing skills, memory capability score, and details on interests (subjects, career areas, company type preferences, inputs from seniors, preferred book types, management versus technical inclination, team collaboration, and introversion). The final column, "Suggested Job Role," serves as the target variable, providing the ground truth for recommendation outcomes. The dataset sample shows that users may receive recommendations like "Applications Developer" based on their scores and preferences.





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Data Pre-processing and Feature Engineering: Pre-processing is crucial to ensure that the raw quiz responses are in a format suitable for machine learning.

Steps include:

- **Data Cleaning:** Removing any noise or inconsistencies within the dataset. Categorical responses such as "yes/no" are standardized, and numerical values are checked for outliers.
- Encoding and Normalization: Categorical features (e.g., "self-learning capability?" "Extra-courses did," "Management or Technical") are transformed into numerical values using encoding techniques. Numeric features like ratings are normalized to ensure uniformity across different scales.
- **Text Processing:** For free-text inputs, such as "Interested subjects" or "Interested Type of Books," techniques like tokenization and vectorization (e.g., TF-IDF) are applied to convert text into numerical representations that capture semantic meaning.
- Feature Selection: Based on domain knowledge and exploratory analysis, the most relevant features are identified to feed into the machine learning model, ensuring that redundant or less informative variables are minimized.

Model Development and Training: The recommendation engine is built as a multi-class classification model that predicts the "Suggested Job Role" based on the processed features. The approach involves:

- **Training and Validation:** The pre-processed data is divided into training and validation sets. Various machine learning algorithms (such as decision trees, support vector machines, or ensemble methods) are evaluated to determine which best captures the relationships between user attributes and the recommended job role.
- **Hyperparameter Tuning:** Iterative adjustments of model parameters are conducted to enhance prediction accuracy and avoid overfitting. Cross-validation techniques are used to ensure the model generalizes well to unseen data.
- **Performance Evaluation:** Model performance is measured using accuracy, precision, recall, and F1-score. This evaluation ensures that the system consistently provides reliable and personalized career recommendations.

Integration and Deployment: Once the model is trained and evaluated, it is integrated into a Django-based backend. The integration process includes:

- **Django Model Integration:** Custom Django models are used to store user profiles and career data. The machine learning model is embedded within the Django application, allowing real-time processing of new user quiz responses.
- API Development: A RESTful API is developed using Django Rest Framework to expose the recommendation engine. This API receives user inputs from the frontend, processes the data through the trained model, and returns the predicted job role.
- Frontend Interface: A React-based frontend is employed to facilitate user interaction. The interface collects user responses, sends them to the Django backend, and displays the recommended job role along with any additional feedback mechanisms (such as sentiment analysis of user feedback).
- System Testing and Deployment: Comprehensive testing is performed to ensure seamless communication between components. The final system is deployed on a scalable web server, ensuring that it can handle multiple simultaneous users and dynamically update recommendations as new data becomes available.





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Fig 1: Component Diagram

This methodology enables the Career Path Recommendation System to effectively process diverse user inputs, transform them into actionable insights, and deliver personalized career recommendations through an integrated, user-friendly platform.

IV. RESULTS

The prediction phase of the Career Path Recommendation System was evaluated using three machine learning models: Decision Tree, Support Vector Machine (SVM), and Random Forest. The dataset comprised 6,901 entries with 20 features (reduced to 19 after pre-processing), with no missing values detected. The features included a mix of numerical ratings (such as logical quotient, hackathons, coding skills, and public speaking) and categorical variables that were encoded for model input.

Model Performance:

• Decision Tree:

The Decision Tree model achieved an accuracy of approximately 86.17%, with a precision of 0.086 and an F1-score of 0.086. For the test instance, the model predicted the job role "Applications Developer" with a predicted probability of 1.0. The high accuracy, despite low precision and F1 scores, suggests that while the overall correct classification rate was high, the model may be challenged by class imbalance or subtle differences among job roles.

• Support Vector Machine(SVM):

The SVM classifier demonstrated a slightly higher accuracy of around 87.62%, but with a lower precision (0.083) and F1-score (0.072) compared to the Decision Tree. Interestingly, the SVM model predicted a different outcome—"Network Security Engineer"—with a notable probability score (approximately 11.30, likely representing a decision function output rather than a normalized probability). This indicates that SVM's decision boundary may be capturing different aspects of the feature space compared to the tree-based methods.

• Random Forest:

The Random Forest model delivered an accuracy of about 83.27%, with a precision of 0.086 and an F1-score of 0.083. In this case, the predicted job role was "Applications Developer" with a probability of 0.68. Although its overall accuracy was slightly lower than the other models, its performance metrics were in a similar range, reinforcing the consistency in predicting this job role for the evaluated instance.

V.OBSERVATIONS AND DISCUSSION:

Despite all models achieving a high overall accuracy (above 83%), the relatively low precision and F1-scores across the board point to potential issues such as class imbalance or overlapping feature distributions among the job roles. The disparity in predictions—where Decision Tree and Random Forest favoured "Applications Developer" while SVM





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identified "Network Security Engineer"—suggests that each model emphasizes different patterns in the data. The distinct probability scores further imply that the confidence levels vary significantly between models.

Overall, these results highlight both the promise and challenges in modelling career path recommendations. While the models are generally effective in distinguishing among job roles, further refinement through advanced feature engineering, hyperparameter tuning, or ensemble approaches may be necessary to enhance the precision and robustness of the recommendations.



Fig 2: User Interface

Fig 2 shows user interface of the Application which then leads to a registration page.

VI. CONCLUSION

The Career Path Recommendation System represents a comprehensive, multi-faceted solution designed to empower individuals in navigating their professional futures. The system integrates several advanced components to provide personalized career guidance. It begins with a robust user registration process followed by a detailed quiz that captures a diverse range of user inputs—from quantitative ratings (logical quotient, coding skills, hackathons, public speaking, and memory capability) to qualitative preferences (self-learning, extra courses, certifications, workshops, reading and writing skills, and various interests). These responses are pre-processed through cleaning, encoding, and feature extraction to transform raw data into a structured format suitable for analysis.

The prediction engine leverages machine learning models (such as Decision Trees, Support Vector Machines, and Random Forests) to analyse the processed data and generate tailored career recommendations. In cases where users are dissatisfied with the initial prediction, a sentiment analysis component—implemented using NLP techniques and the NLTK library—evaluates their feedback, ensuring that recommendations are continuously refined. Complementing these features, the system also includes an interactive chatbot assistant powered by Google Gemini API and LangChain, as well as a voice assistant enabled through React Speech Recognition. Together, these conversational interfaces create an intuitive and engaging user experience, bridging the gap between complex backend computations and user-friendly front-end interactions.

The architecture is built on a modern tech stack with a React frontend and a Django backend (using Django Rest Framework for API development), ensuring scalability, maintainability, and ease of integration with additional services such as FAISS for vector-based data storage and SQL databases for persistent storage. Overall, the system not only demonstrates the effective application of machine learning and natural language processing techniques in career guidance but also establishes a solid foundation for future enhancements in personalized recommendation systems.





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