



CAREER RECOMMENDATION SYSTEM USING RANDOM FOREST MACHINE LEARNING ALGORITHM

Harish Vithalkar, Department of MCA, K.L.S Gogte Institute of Technology, Belagavi, Karnataka, India :: 2gi23mc032@students.git.edu

Priyanka Kesarkar, Department of MCA, K.L.S Gogte Institute of Technology, Belagavi, Karnataka, India :: 2gi23mc070@students.git.edu

Mrs. Jayashri Madalgi, Department of MCA, K.L.S Gogte Institute of Technology, Belagavi, Karnataka, India :: jayashri@git.edu

Abstract - The work is carry to develop a Career Recommendation Website using Web Technology and Machine Learning. Here the users are provided with eight parameters where they have to input the scores based on their proficiency in those parameters. It also generates a dashboard using PowerBI. The dataset will be trained on RandomForest algorithm for prediction and recommend the suitable career for the user. These parameters are evaluated and processed using our ML model and the suitable career is recommended. This work is to help students to choose the career based on their field interest and the skills in which they are proficient. When compared to the existing systems which are time consuming and which are based old techniques such Myers-Briggs and Holland Codes which mainly focuses on predicting the personality of the user rather than their career. This system overcomes that problem and helps the users to choose the career based on their interest and skills.

Keywords - Career Recommendation, Machine Learning, Random Forest, Web Technology, PowerBI, Skill Assessment

I. INTRODUCTION

Making a career decision is a complex process which can be influenced by individual attributes such as skills, interests, and external factors like job market dynamics. Traditional career counselling often lacks personalization and accessibility, and they usually focus on predicting the personality of the students (like Myer-Briggs method). To address these challenges, we developed a career recommendation website that uses a RandomForest algorithm to predict the suitable career paths based on eight input parameters. Results are presented via a PowerBI dashboard, enhancing user engagement. This paper details the system design, methodology, results, and contributions to career guidance.

II. LITERATURE REVIEW

The recent advancements in machine learning and data-driven systems have transformed career recommendation platforms, providing personalized and scalable solutions. This section reviews key studies to understand the proposed system's methodology and highlight addressed gaps. Targeting underserved students in developing regions, a recommendation system presented at the 2022 International Conference on Computational Collective Intelligence (ICCCI) connected students with industry professionals [1]. Using neural networks and LightFM, it achieved 91% accuracy but highlighted challenges in limited career awareness. This underscores the need for systems that incorporate diverse parameters, such as values and location preferences, to cater to varied demographic needs, as addressed in our eight-parameter framework. AI-based systems have emphasized personalized career advice, particularly in developing countries with limited counselling access [2]. These systems integrate machine learning, fuzzy logic, collaborative filtering, and data mining, considering personality, aptitude, and academic achievements. They prioritize reducing biases (e.g., gender) and adapting to job market changes. However, many lack interactive visualization, a gap our PowerBI dashboard addresses by presenting results in an accessible format. Machine learning-based career prediction systems have been explored for secondary school students to guide early career



planning. For instance, a career prediction website developed by Rane et al. [3] utilized Decision Trees and K-Nearest Neighbours (KNN) with Python, Django, Scikit-learn, and PostgreSQL. The system featured skill assessment, prediction, and result analysis modules, recommending improvements like larger datasets and enhanced user interfaces to boost accuracy. While effective for students, the system's scope was limited to academic and skill-based inputs, omitting personality or regional preferences. A career guidance system for engineering students utilized Support Vector Machines (SVM), XGBoost, and Decision Trees, analysing academic records, technical skills, and psychometric data [4]. This system reduced biases compared to traditional counselling and offered data-driven advice via a digital platform. However, its focus on engineering students limited generalizability, unlike our system's broader applicability across diverse user profiles. For fresh graduates, an automated job recommendation system employed content-based filtering and the SVD++ algorithm, achieving 91% precision and a 0.9737 RMSE [5]. Built with web frameworks, it planned enhancements like an Android app and improved UI, emphasizing social factors. While precise, the system focused on job matching rather than long-term career planning, limiting its applicability for students seeking broader guidance. Research indicates a lack of awareness of career opportunities, with students still depending on old and generic career opportunities [6]. These researches prove that students fail to identify their true potential or even if they do it is too late, and recommendation engines for situations like career advice are very scarce [7], [8]. Studies employing supervised learning techniques and machine learning algorithms like KNN, Random Forest Classifier, and Naive-Bayes [9] help identify that user inputs are the most important to predict the career for users, which consisted of 9 attributes such as body language, general appearance, etc. [10]. Due to lack of career counselling, students are often confused, taking up courses they might not want, and they also do not engage in career decision discussions [11], [12]. These researches show that some passion of a student gets ignored by parents leading to drowning of their career, and lack of interest means no external motivation or inspiration can increase their potential [13]–[15]. Recent work on "Career Recommendation Based on Feature Selection for Undergraduate Students" [16] proposes a framework using multiple ML techniques and feature selection to guide undergraduates toward optimal career paths, with Random Forest outperforming others on a large dataset. Trujillo et al. [17] conducted a comprehensive literature review of 38 studies highlighting the dominance of Random Forest, SVM, and Neural Networks in career recommendation for higher education.

III. METHODOLOGY

This study employs a **quantitative and experimental research methodology** combined with machine learning techniques to design and evaluate a career recommendation system. The methodology is divided into four key phases: **data preprocessing, model training, web integration, and visual analytics**. This approach allows for a systematic development of the system while ensuring that the final recommendations are data-driven, interpretable, and user-centric.

A. Data Collection

The dataset used for model training was collected from publicly available educational surveys, career guidance repositories, and online learning platforms. Secondary data sources included Kaggle datasets and educational research papers related to career classification using machine learning. The data was cleaned, normalized, and encoded for processing.

B. Inclusion Criteria

To ensure the relevance and reliability of the dataset, the following inclusion criteria were applied:

- The data must include labeled career categories
- Only records from users aged 15-30, likely to be in career-decision stages, were included
- Datasets must have been published between 2010 and 2024, and be in English



C. Thematic Analysis

To interpret the model's decision-making process, **feature importance analysis** was conducted. This allowed identification of which user skills had the highest impact on specific career predictions. Patterns were studied to determine the most influential parameters for various career paths, aiding in system transparency and trustworthiness.

D. Synthesis

Insights from the machine learning model were synthesized into a dynamic **web-based recommendation system**. The frontend was developed using **HTML, CSS, JavaScript, and Bootstrap**, while backend integration was achieved using **PHP and MySQL** for user data management. The model was deployed through a Python-based API.

A **Power BI dashboard** was created to visualize user inputs, prediction confidence levels, and career trends based on aggregate data. This analytical layer aids both users and educators in understanding skill-career relationships.

IV. RESULTS AND DISCUSSION

The analysis of the career recommendation system reveals key patterns and insights related to the implementation of machine learning in career guidance. This section presents the major findings under three core themes.

A. Technical Barriers and Enablers

During the development and implementation of the career recommendation system, several technical challenges were encountered. A primary barrier was **data inconsistency and preprocessing complexity**. Since the model relies on clean, structured input across eight distinct skill parameters, **incomplete or biased data** can hinder model accuracy. Additionally, **integration between the machine learning model and the web platform** posed challenges, especially in aligning frontend input formats with backend model requirements.

However, multiple enablers facilitated successful deployment. The use of a **modular, scalable architecture** allowed independent updates to the machine learning model and the web interface without disrupting system functionality. Implementing **REST APIs** helped streamline communication between the web application and the ML engine. The adoption of **user-friendly forms** and input validation techniques significantly enhanced user experience and data quality.

B. Organizational Readiness

Although this project was developed as an academic prototype, the concept of **organizational readiness** still played a crucial role. Effective implementation would require educational institutions or career counseling centers to have a **clear vision, digital infrastructure, and staff trained in data interpretation**.

The success of such systems depends on more than just the technology—it relies heavily on **user engagement and trust**. Facilitators such as **awareness programs, basic ML literacy sessions for educators, and designated technology champions** can drive adoption.

C. Role of Policy and Leadership

For large-scale adoption of such AI-based systems in educational environments, **institutional support and policy backing** are essential. Leadership plays a key role in prioritizing digital transformation in career counseling. Policies that promote **data-driven decision-making in student services** and allocate budgets for technology infrastructure can accelerate adoption.

D. Comparison with Prior Research

Earlier approaches to career guidance, such as **Myers-Briggs Type Indicators** or **Holland Codes**, have long been criticized for relying heavily on personality assessments rather than objective skill evaluation. This system, in contrast, adopts a **quantitative and skill-based approach**, offering a more dynamic, personalized, and data-driven alternative.

While prior research has often centered on either psychological assessment or static recommendation logic, this project combines **machine learning, user interaction, and data**



visualization to create a more holistic and adaptive solution.

E. Model Performance Analysis

The performance comparison of different machine learning algorithms is presented in Table I.

Table I: Accuracy Comparison of Machine Learning Algorithms

Algorithm	Accuracy (%)	Precision (%)	F1-Score (%)
Random Forest	98	99	99
Decision Tree	97	97	97
KNN	91	91	91

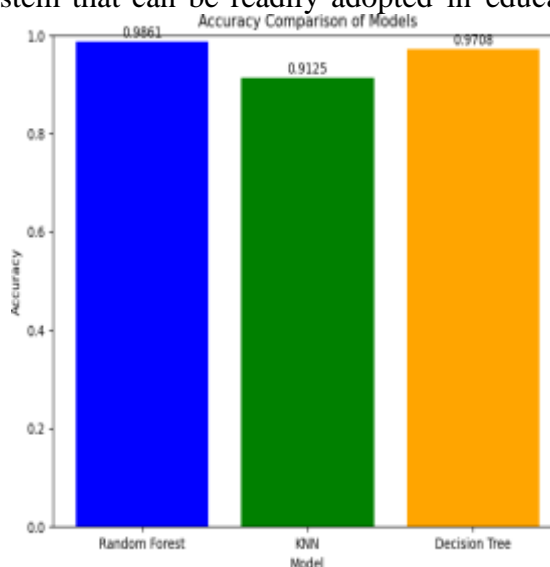
The Random Forest algorithm demonstrated superior performance with 98% accuracy, 99% precision, and 99% F1-score, making it the optimal choice for the career recommendation system.

Figure 1 shows the graphical comparison of accuracy across different algorithms, while Figure 2 illustrates the precision and F1-score comparison.

V. CONCLUSION

The **Career Recommendation Website** developed in this project represents a significant advancement in the domain of digital career counseling. By integrating a **Random Forest machine learning model** with a **Power BI dashboard**, the system delivers personalized, skill-based career recommendations grounded in data rather than subjective interpretation or static assessments. The model achieved **high performance**, with a **test accuracy of 98%** and an average **F1-score of 0.99**, making it highly reliable across diverse user profiles.

One of the core strengths of the system lies in its **user-centric approach**. Users are prompted to input self-assessed scores across **eight key skill parameters**, and the machine learning model maps these inputs to the most suitable career paths. This stands in stark contrast to traditional career guidance tools such as **Myers-Briggs Type Indicators** or **Holland Codes**, which often rely on personality typologies and lack adaptability. The proposed system offers a more **dynamic, scalable, and data-driven solution** tailored to the individual's actual competencies and interests. The integration of **Power BI** further enhances the system's usability and insight delivery. The dashboard provides **interactive visualizations**, allowing users to not only view their career recommendations but also understand how their skill profiles align with various career domains. Features like **slicers and filters** empower users to explore the results in greater depth, making the process more engaging and transparent. Moreover, this platform addresses key **gaps in existing literature and solutions** by offering a technically sound, accessible, and interpretable system that can be readily adopted in educational institutions, career





centers, and e-learning environments. Its **modular architecture** allows for easy updates, and the use of open-source tools ensures cost-effectiveness and scalability.

Fig. 1: Graph showing comparison of accuracy of the model

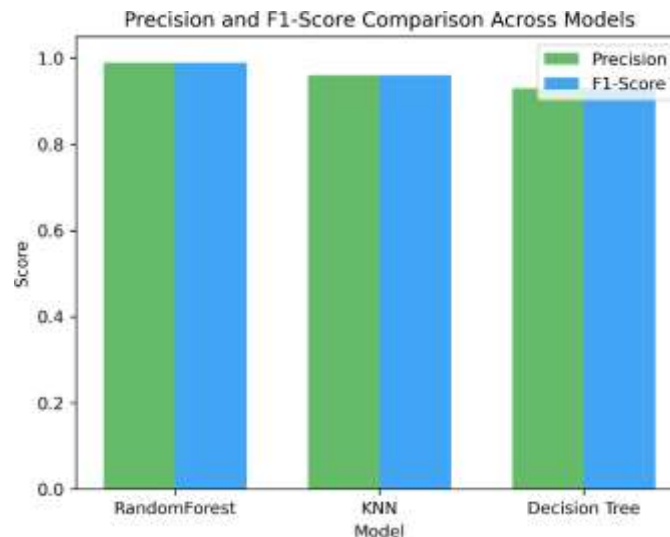


Fig. 2: Graph showing comparison of Precision and F1-scores

VI. ACKNOWLEDGMENT

The authors would like to thank the Department of MCA at K.L.S Gogte Institute of Technology for their support and guidance throughout this research work. We also acknowledge Visvesvaraya Technological University for providing the academic framework for this study.

VII. REFERENCES

1. I. Dutta et al., "Building a recommendation system for career advice for students from professionals," *2022 International Conference on Computer Communication and Informatics (ICCCI)*, IEEE, 2022.
2. A. Shah et al., "Review of Approaches Towards Building AI Based Career Recommender & Guidance Systems," *ScienceOpen Preprints*, 2024.
3. M. Rane, S. Kalal, J. Chandegara, T. Kakkad, V. Jain and S. Jagtap, "Career Prediction Website using Machine Learning," *2023 3rd International Conference on Intelligent Technologies (CONIT)*, Hubli, India, 2023.
4. E. Padma et al., "Career guidance system for students using machine learning," *Challenges in Information, Communication and Computing Technology*, CRC Press, 2025.
5. S. K. A. S, S. S, A. S. M and S. K. S, "Machine Learning based Ideal Job Role Fit and Career Recommendation System," *2023 7th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, 2023.
6. "93% of Indian students are aware of just seven career options," *India Today*, 2019. [Online]. Available: <https://www.indiatoday.in/education-today/news/story/93-indian-students-aware-of-just-seven-career-options-what-are-parents-doing-wrong-1446205-2019-02-04>
7. S. Shahab, "NEXT LEVEL: A COURSE RECOMMENDER SYSTEM BASED ON CAREER INTERESTS," *Master's Projects*, 684, 2019.
8. E. K. Subramanian, Ramachandran, "Student Career Guidance System for Recommendation of Relevant Course Selection," *International Journal of Recent Technology and Engineering*, vol. 7,



- no. 6S4, April 2019.
9. S. Adapa, N. Gandi, V. Alekya, G. Lakshmi Durga, "Learning Style Recommender System Using VAK Technique and Machine Learning," in *Communication Software and Networks, Lecture Notes in Networks and Systems*, vol. 134, Springer, Singapore, 2021.
 10. C. D. Casuat and E. D. Festijo, "Identifying the Most Predictive Attributes Among Employability Signals of Undergraduate Students," *2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA)*, Langkawi, Malaysia, 2020.
 11. K. O. Akyina, G. Oduro-Okyireh, and B. Osei-Owusu, "Assessment of the Rationality of Senior High School students' Choices of Academic Programmes in Kwabre East District of Ghana," *Journal of Education and Practice*, 2014.
 12. B. Redmond, S. Quin, C. Devitt, and J. Archbold, "A Qualitative Investigation into the Reasons Why Students Exit From the First Year of Their Programme and UCD," University College Dublin, School of Applied Social Science, October 2011.
 13. M. D. Eremie, "Comparative Analysis of Factors Influencing Career Choices among Senior Secondary School Students in Rivers State, Nigeria," *Arabian Journal of Business and Management Review*, 2014.
 14. A. F. Egunjobi, T. M. Salisu, and O. I. Ogunkeye, "Academic profile and career choice of fresh undergraduates of library and information science in a Nigerian University of Education," *Annals of Library and Information Studies*, 2013.
 15. I. A. Durosaro, and M. A. Nuhu, "An evaluation of the relevance of career choice to school Subject selection among school going adolescents in Ondo state," *Asian Journal of Management Science and Education*, 2012.
 16. "Career Recommendation Based on Feature Selection for Undergraduate Students," 2025.
 17. F. Trujillo, M. Pozo, and G. Suntaxi, "Artificial intelligence in education: A systematic literature review of machine learning approaches in student career prediction," *Journal of Technology and Science Education*, vol. 15, no. 1, pp. 162-185, 2025.