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A Data-Driven Career Recommendation Framework for Students Based on Interest, Skills and Feasibility Constraints

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Abstract: *Many students have difficulties picking a career due to uncertainty about what their strengths are, limited resources, family issues and too many opportunities to choose from. Career guidance usually only looks at a student's interests and academic results and does not take into account their real-life issues with choosing a career or how possible it is for them to pursue that career. In this paper, we are proposing a new type of career recommendation system that considers the student's education and results, as well as their skills and interests as well as personal constraints such as financial limitations or lack of time, so that students can get realistic career recommendations based on both the things they want to do and the things that are practically feasible to do. The system actually provides us with the top suitable career options., a ranking score based on suitability and feasibility, alternative career pathways.*
The results show that thinking about life situations makes career suggestions more useful and realistic. This way is better than the way because it gives students advice that really helps them. It helps students make choices about their career and feel sure, about what they are doing with their career. Career recommendations are more helpful when they consider real-life constraints.

Keywords: Career Recommendation System, Career Guidance, Student Career Decision Making, Personalised Career Planning, Skills and Interest Analysis, challenges facing by them.

I. INTRODUCTION

Making informed career decisions is a pivotal developmental milestone for undergraduate students, profoundly influencing their long-term professional identity and satisfaction . In an era characterized by rapid technological advancements, globalization, and the emergence of new job categories such as Artificial Intelligence (AI) and data science, students face an increasingly complex landscape . Despite the growth in post-secondary institutions, many lack formalized or systematic structures for comprehensive career counseling. Consequently, students often rely on informal advice from parents, peers, or prevailing trends, rather than engaging in a structured assessment of their skills and interests [1]. This reliance on anecdotal guidance can lead to career dissatisfaction, skill-job mismatches, and ultimately, job insecurity [2].Traditional career counseling models, primarily rooted in psychometric testing and trait-factor theories, offer limited scalability and personalization. They often fail to adapt to the dynamic nature of the labor market and are susceptible to counselor bias [3]. There is a pressing need for data-driven, algorithmic systems that can consider the multidimensional aspects of each student to provide evidence-based career recommendations. This research addresses this gap by designing and implementing a Career Recommendation System (CRS) that moves beyond conventional approaches. Our CRS categorizes students based on their academic stream, expressed interest areas, and self-assessed skill confidence levels. By operationalizing undergraduate student attributes collected through surveys into encoded feature sets and applying supervised learning algorithms, the system aims to deliver highly accurate and personalized career domain recommendations.This study makes significant contributions to the field of intelligent academic advising systems. It offers a highly adaptable and flexible framework for continuous development and innovation in this domain, providing a robust solution to the challenges students face in navigating their career paths. The subsequent sections of

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this paper detail the comprehensive literature review, the proposed methodology, the experimental results, and a discussion of the system's implications and future directions.

II. LITERATURE REVIEW

The landscape of career guidance has evolved significantly with the advent of artificial intelligence and machine learning technologies. Traditional approaches, often reliant on psychometric assessments and expert consultations, have proven to be limited in scalability and personalization [4]. The demand for more dynamic and data-driven solutions has spurred extensive research into automated career recommendation systems.Early research in career recommendation systems primarily focused on rule-based expert systems, where career paths were suggested based on predefined rules and decision trees derived from expert knowledge [5]. While these systems offered a structured approach, their rigidity and inability to adapt to new information or individual nuances limited their effectiveness. The emergence of collaborative filtering and content-based filtering techniques, borrowed from e-commerce recommendation systems, marked a significant advancement. Collaborative filtering systems recommend careers based on the preferences of similar users, while content-based systems match user profiles with career attributes [6]. However, these methods often suffer from cold-start problems (difficulty recommending to new users or new careers) and sparsity issues (lack of sufficient data for accurate recommendations) [7].More recently, machine learning (ML) has revolutionized the development of career recommendation systems, offering enhanced predictive power and adaptability. Various ML algorithms have been explored, including Support Vector Machines (SVMs), Naïve Bayes, Decision Trees, and K-Nearest Neighbors (KNN) [8]. Among these, ensemble learning methods, such as Random Forest, Gradient Boosting, and XGBoost, have demonstrated superior performance in handling complex, high-dimensional datasets and mitigating overfitting [9].Random Forest, in particular, has gained prominence due to its ability to handle both categorical and numerical data, its robustness to outliers, and its capacity to provide insights into feature importance [10]. Studies have shown that Random Forest classifiers can achieve high accuracy in predicting suitable career paths by aggregating the predictions of multiple decision trees . For instance, a career recommender system utilizing Random Forest and KNN algorithms was proposed to help students identify fields of interest and talents [11]. Another study highlighted the effectiveness of Random Forest in a career guidance system, achieving high prediction accuracy [12]. The integration of Random Forest with other techniques, such as Convolutional Neural Networks (CNNs), has also been explored to create hybrid recommendation systems, further enhancing predictive capabilities [13].Beyond algorithmic advancements, recent literature emphasizes the importance of incorporating a broader range of factors into career recommendation systems. This includes not only academic performance and interests but also soft skills, personality traits, and socio-economic factors [14]. The concept of personalized career planning, which considers individual constraints like financial limitations and time availability, is gaining traction, moving beyond purely academic or interest-based recommendations [15]. Responsible AI in student management is also a growing concern, ensuring that AI-generated suggestions are not blindly trusted and lead to misguided choices [16]. Systematic literature reviews have further highlighted the opportunities and challenges of integrating machine learning into higher education career recommendation systems, emphasizing the need for robust methodologies and ethical considerations [17].This review underscores the shift from simplistic rule-based systems to sophisticated machine learning models, particularly ensemble methods like Random Forest, for more accurate and personalized career guidance. The current research builds upon these advancements by integrating a comprehensive dataset and a Random Forest classifier, while also addressing the critical need to incorporate personal constraints into the recommendation process, thereby offering a more holistic and realistic career advisory system.

III. METHODOLOGY

This research employs a quantitative, descriptive approach to develop a comprehensive Career Recommendation System (CRS) designed to assist undergraduate students in making informed career choices. The methodology encompasses data collection, preprocessing, model development using machine learning, and the integration of a rule-based system for personalized recommendations.

A. Data Collection

Two distinct datasets were utilized in this study: a primary dataset for initial graphical analysis and a secondary dataset for the development and training of the machine learning model.

1. Primary Dataset

The primary dataset, was collected through surveys administered to students from four colleges: Vivekanand College, Rajarshi Chhatrapati Shahu College, The New College, and Rajaram College. These institutions represent diverse academic streams (Science, Commerce, and Arts), ensuring a heterogeneous student population. A non-probability

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snowball sampling technique was employed, where initial respondents were asked to refer the survey to their peers, facilitating data collection across these colleges. This dataset primarily captured student demographics, academic backgrounds, career awareness, decision-making challenges, skill perceptions, and stress levels related to future careers. The insights derived from this dataset were used for graphical analysis to understand the prevailing challenges and perceptions among students regarding career guidance.

2. Secondary Dataset

1. **Dataset Description**: The secondary dataset, is a collection of career-related information, comprising **75,500 records** and **11 features**. This dataset was instrumental in training the machine learning model for career recommendation. The features included:
   - Career Name: The specific job title.
   - Sector / Industry: The broad industry or sector the career belongs to.
   - Stream Eligibility: The academic stream required for the career (e.g., Science, Commerce, Arts).
   - Required Education: The minimum educational qualification needed.
   - Required Skills: A comma-separated list of essential skills for the career.
   - Skill Level Required: A numerical rating indicating the proficiency level for the required skills.
   - Interest Domain: The area of interest aligned with the career.
   - Average Salary Range: The typical salary bracket for the career.
   - Career Growth Outlook: The projected growth trajectory of the career (e.g., Exponential, Stable, High, Niche).
   - Work Type: The nature of employment (e.g., Freelance, PSU, Gig, Startup, Private, Contractual).
   - Location Availability: Geographic regions where the career opportunities are prevalent.
2. **Data Sources**: The data for the secondary dataset was compiled from various official sources, including the National Classification of Occupations - 2015 (NCO-2015), the National Career Service Portal (NCS Official Website), the Ministry of Labour & Employment (DGE), and NSQF Guidelines (National Skill Qualification Framework Details). These sources ensure the credibility and relevance of the career information.

B. Data Preprocessing

Before model training, the secondary dataset underwent several preprocessing steps to ensure data quality and suitability for machine learning:

1. **Duplicate Removal**: Redundant entries were identified and removed using df.drop_duplicates() to prevent bias and improve model efficiency.
2. **Missing Value Imputation**: All missing values across the dataset were imputed with the string "Unknown" using df.fillna("Unknown") to handle incomplete data points consistently.
3. **Feature Selection (Leakage Columns Removal)**: Certain columns were identified as potential data leakage sources or irrelevant for the predictive task and were subsequently dropped. These included Career Name, Required Skills, Interest Domain, and Work Type. The rationale behind removing these columns was to focus the model on more generalizable attributes for career sector prediction and to avoid overfitting to specific career names or highly detailed skill sets.
4. **Categorical Encoding**: All remaining categorical features were converted into numerical representations using LabelEncoder from sklearn.preprocessing. A dictionary of label_encoders was maintained to facilitate inverse transformation if needed and to ensure consistent encoding across different runs. This step is crucial for machine learning algorithms that operate on numerical data.

C. Model Development

1. Target and Feature Definition

The primary objective of the machine learning model was to predict the Sector / Industry based on the processed career attributes. Therefore, Sector / Industry was designated as the target variable (y), and all other remaining columns formed the feature set (X).

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2. Train-Test Split

The dataset was partitioned into training and testing sets using train_test_split from sklearn.model_selection. An 80/20 split was applied, with 80% of the data allocated for training the model and 20% for evaluating its performance. A random_state of 42 was set to ensure reproducibility of the split.

3. Random Forest Classifier

The **Random Forest** algorithm was used as the primary machine learning model to predict suitable career domains. Random Forest is an ensemble learning method that builds multiple decision trees during training and combines their outputs to produce a more accurate and stable prediction. This approach helps reduce overfitting and improves model generalization compared to a single decision tree.

The training dataset can be represented as:

$D=\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\}$

where x_i represents the feature vector and y_i represents the target variable (**Sector / Industry**). Each decision tree is trained on a **bootstrap sample** of the dataset, and at everynode a random subset of features is selected to determine the best split. The final prediction is obtained through **majority voting** among all trees in the forest. In this study, the model was implemented using **Scikit-learn** with **50 decision trees (n_estimators = 50)** and a **maximum depth of 8 (max_depth = 8)** to balance computational efficiency and predictive performance. The model was trained on the training dataset and evaluated using the testing dataset to measure classification accuracy.

4. K-Nearest Neighbors (KNN)

The **K-Nearest Neighbors (KNN)** algorithm was also used as a classification model to predict suitable career domains. KNN is an instance-based learning method that classifies a new data point based on the majority class of its nearest neighbors in the feature space.

The training dataset can be represented as:

$D=\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\}$

where x_i represents the feature vector and y_i represents the target variable (**Sector / Industry**).

For a given test instance, the algorithm calculates the **Euclidean distance** between the test sample and the training samples:

$$d(x,x_i)=\sqrt{\sum_{j=1}^{n}(x_j-x_{ij})^2}$$

Where: $d(x,x_i)$**= Euclidean distance between the test sample and training sample,** n**= Number of features,** x_j**= Feature value of the test sample,** x_{ij}**= Feature value of the** i^{th}**training sample**

The **k nearest neighbors** is then selected, and the final class label is determined through **majority voting**. In this study, the KNN model was implemented using the **Scikit-learn** library with **k = 5** neighbors for classification.

5. Model Evaluation

The predicted Reviews were measured using five metrics, namely precision (Prec), recall (Rec), f1score (F1), and accuracy (Acc.)

Accuracy:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

Precision:

$$Precision=\frac{TP}{TP+FP}$$

Recall:

$$Recall=\frac{TP}{TP+FN}$$

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F1 Score:

$$F1\ Score=2\times\frac{Precision\times Recall}{Precision+Recall}$$

Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

Macro Average:

It calculates the metric **independently for each class and then takes the simple average.**

Mathematically:

$$MacroAverage=\sum_{j=1}^{n} M_j$$

Where: K= Total number of classes, M_j = Metric value (Precision, Recall, or F1-score) for class i

Weighted Average:

It also averages metrics across classes, but it **weights each class by its number of samples (support)**.

Mathematically:

$$WeightedAverage=\frac{\sum_{i=1}^{K}(S_i\times M_i)}{\sum_{i=1}^{K} S_i}$$

Where: K = Total number of classes, M_i = Metric value (Precision, Recall, or F1-score) for class i, S_i= Number of samples (support) in class i

D. Rule-Based Algorithm

A rule-based algorithm was implemented to generate career recommendations based on the student's **academic stream, interest domain, and skill set**. Rule-based systems operate using predefined **IF–THEN logical conditions** that map user attributes to suitable career options.

Let the student profile be represented as:

S={St, I, Sk}

where

St represents the academic **stream**,I represent the **interest domain**, and Sk represents the student's **skills**.

Each career option cic_ici is evaluated using a rule function that determines whether the student attributes match the required career characteristics.

Algorithm Steps

Collect student inputs including stream, interest, and skills.

Retrieve career records from the dataset.

Compare student attributes with career requirements using predefined rules.

Select careers where stream, interest, and skills match the criteria.

Return the list of recommended careers.

IV. GRAPHICAL ANALYSIS

The graphical analysis of the primary dataset, collected through student surveys, revealed several key insights into the challenges students face in career decision-making. The findings indicated that beyond academic weaknesses, informational and guidance-related gaps are more significant contributors to students' lack of career clarity. Specifically, a substantial portion of students expressed uncertainty regarding their career paths, with a notable percentage lacking full confidence in their future professional endeavors. The analysis also highlighted a strong desire among students for clearly defined career choices and structured frameworks to guide their career planning. These insights underscore the critical

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need for comprehensive career guidance programs that offer practical experience opportunities and easily accessible information systems to empower students in making informed decisions.

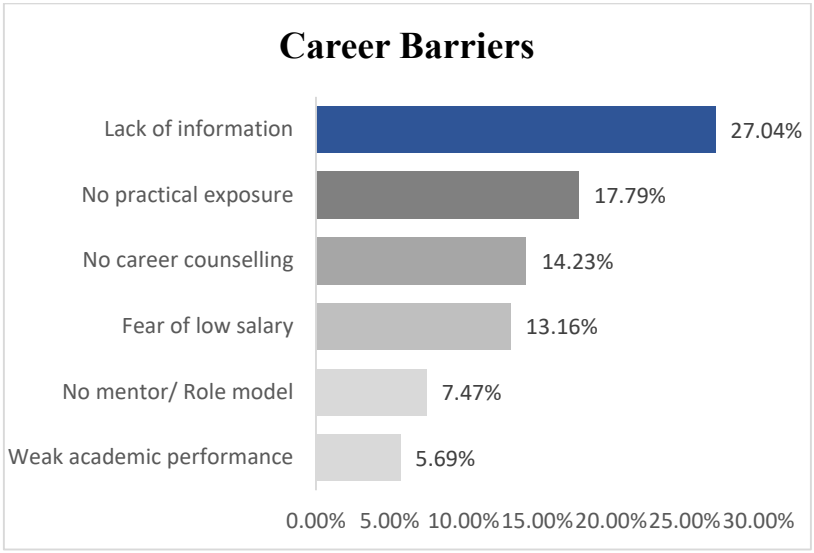

Figure 1: Biggest Confusion While Choosing a Career

Conclusion:

Fig. 1 indicates that other than academic weaknesses, informational & guidance-related gaps are more significant as it relates to why students experience a lack of career guidance. There is a need for structured career guidance programs, opportunities for practical experience, and an information system that is easily accessible to provide students with the necessary resources to make informed decisions regarding careers.

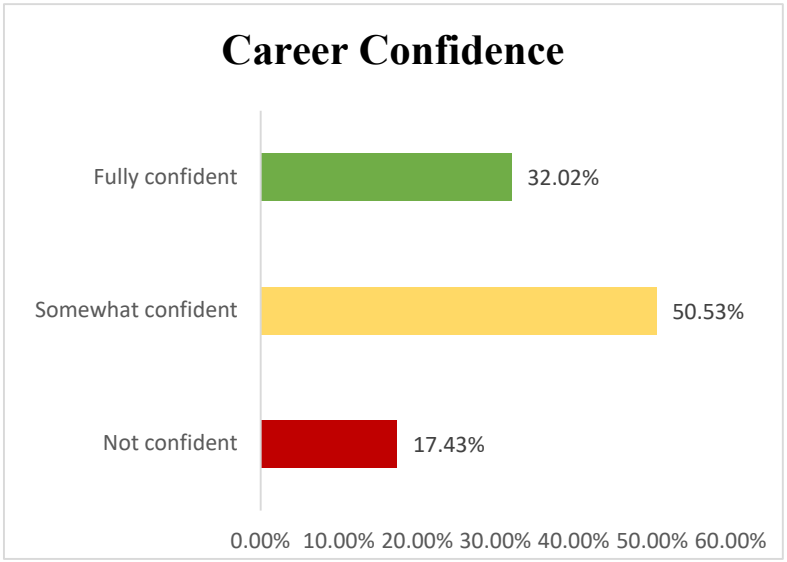

Figure 2: Student Career Decision-Making

Conclusion: Fig.2 indicates that even though many students are somewhat confident, some students doubt themselves with regard to where they are headed. It provides support for continuing the motivational support, mentoring, and structured planning provided to increase students' confidence and decision-making skills.

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Conclusion: Fig.3indicates that students mainly look to find their way in determining what type of career will be suited for them. Providing clearly defined career choices combined with a structured framework to guide the student could greatly enhance their readiness for a given job and the overall outcome of planning a successful career.

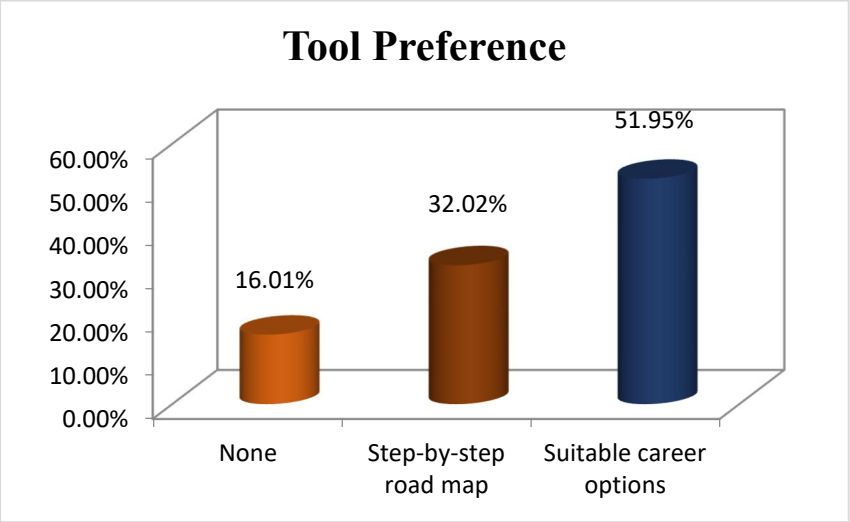

Figure 3: Student Confidence in Future Career Building

V. Statistical Analysis

Random Forest Classification:

Random Forest classification was applied to predict suitable career sectors based on the selected input features. The model was trained using the training dataset and evaluated on the testing dataset. Performance was assessed using statistical metrics including **accuracy, precision, recall, and F1-score** to measure the model's classification effectiveness. The overall results indicate that the Random Forest model achieved strong predictive performance across multiple career categories.

TABLE I

Metric	Precision	Recall	F1-Score
Macro Average	0.88	0.88	0.87
Weighted Average	o.87	0.87	0.87
Accuracy	0.88	-	-

From **Table I**, the overall model accuracy was **87%**, indicating strong predictive capability of the Random Forest classifier. The macro average precision and recall values of **0.88** suggest balanced classification performance across the multiple career categories. Similarly, the weighted average F1-score of **0.87** demonstrates that the model performs consistently while considering the distribution of samples across different classes.

K-Nearest Neighbors (KNN) classification:

K-Nearest Neighbors (KNN) classification was applied to predict suitable career sectors based on the selected input features. The model was trained using the training dataset and evaluated on the testing dataset. Performance was assessed using statistical metrics including accuracy, precision, recall, and F1-score to evaluate the model's classification effectiveness. The overall results indicate that the KNN model achieved moderate predictive performance across multiple career categories.

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TABLE II

Metric	Precision	Recall	F1-Score
Macro Average	0.71	0.70	0.70
Weighted Average	o.71	0.70	0.70
Accuracy	0.70	-	-

From **Table II**, the overall model accuracy was **70%**, indicating a moderate predictive capability of the K-Nearest Neighbors (KNN) classifier. The **macro average precision and recall values of 0.71 and 0.70** suggest reasonably balanced classification performance across the multiple career categories. Similarly, the **weighted average F1-score of 0.70** demonstrates that the model provides consistent predictions while considering the distribution of samples across different classes.

Proposed Career Guidance Framework

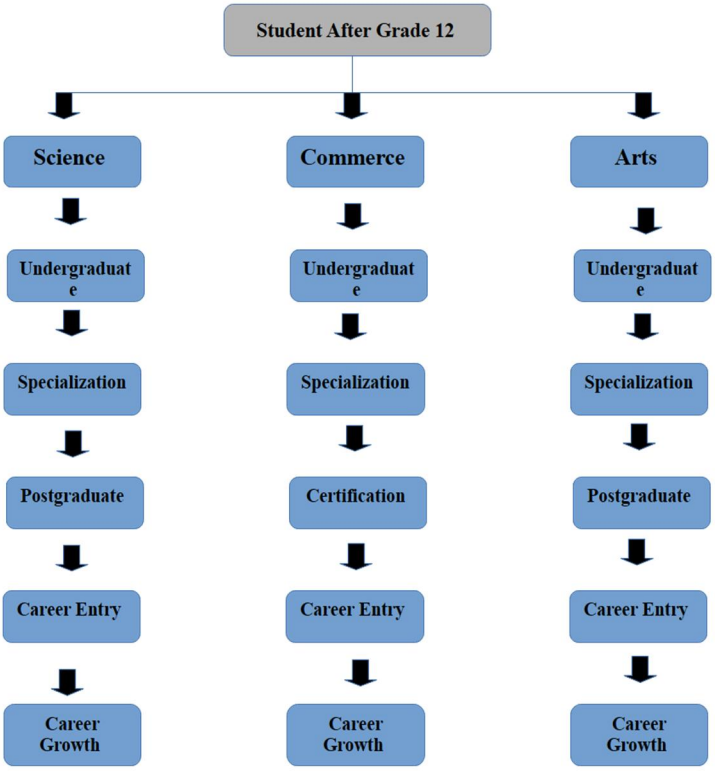

Figure 4: Career Pathway Framework for Students After Grade 12

Figure 4 illustrates the proposed career pathway framework for students after completing Grade 12. The model categorizes students into three primary academic streams: Science, Commerce, and Arts. Each stream follows a structured progression beginning with undergraduate education, followed by specialization in a specific domain. After specialization, students may pursue postgraduate education or professional certifications depending on the stream. This progression eventually leads to career entry and subsequent career growth. The framework provides a structured representation of how students transition from academic stream selection to long-term career development.

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V. HOW SYSTEM WORKS

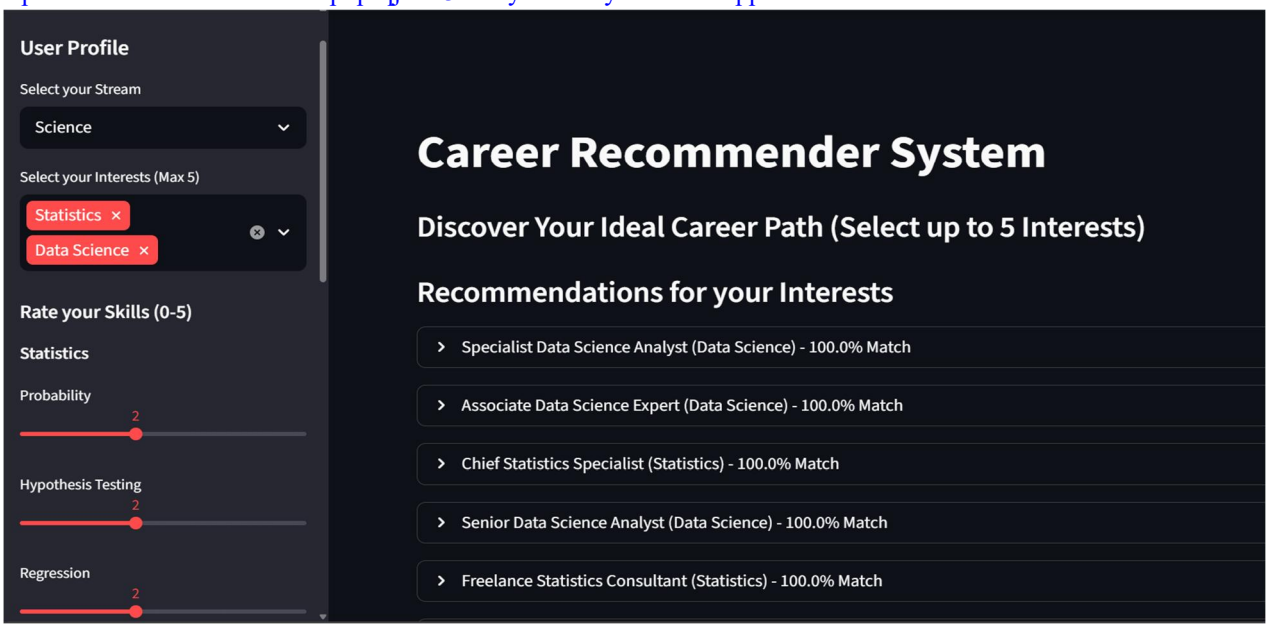
The Career Recommendation System is based on the belief that individuals can improve their ability to make sound career choices when their education, interests, and skill sets align with the requirements of each profession.

Using this system, students input their educational stream, as well as their interest and skill level. The Career Recommendation System filters careers based on educational eligibility, matches careers based on interest, and then refines careers based on skill level. The Career Recommendation System does not predict success or use complex AI mechanisms, but rather gives structured and rational career suggestions, which decreases the number of decisions, confusion and/or frustration associated with making an appropriate and factual career choice.

The Career Recommendation System is an intuitive online programme which offers students developed career ideas based on their major subject area, personal interests and individual strengths using established guidelines regarding career matching. The Career Recommendation System uses a rules-based matching process (i.e. algorithms) to provide students with rationally derived and transparently produced recommendations so they can make informed decisions regarding their career path.

The live application is accessible at:

https://career-recommendation-pdpsqj4fm3xeheyh4dfmxy.streamlit.app/



VI. CONCLUSION

This study presented a data-driven Career Recommendation System designed to assist undergraduate students in selecting suitable career paths based on their academic background, interests, and skill levels. The system integrates machine learning techniques with a rule-based recommendation framework to provide structured and realistic career suggestions. A large secondary dataset containing 75,500 career records was used to train classification models, while a primary survey dataset was utilized for graphical analysis of student career decision challenges. Two machine learning algorithms, Random Forest and K-Nearest Neighbors (KNN), were implemented to predict suitable career sectors. Experimental results showed that the Random Forest model achieved superior performance with an accuracy of **87%**, compared to **70%** for the KNN model, indicating the effectiveness of ensemble learning methods for career prediction tasks.The findings demonstrate that integrating machine learning with structured rule-based filtering can significantly improve the relevance and practicality of career recommendations. The proposed framework provides students with clearer career pathways and helps reduce uncertainty in career decision-making.However, the study is limited by the scope of the available dataset and the number of predictive models evaluated. Future research may incorporate additional factors such

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as personality traits, socio-economic conditions, and real-time labor market trends, as well as explore advanced machine learning techniques to further enhance recommendation accuracy and system adaptability.

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