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Stacked Ranking Feature Cluster Machine Learning (Srfcml): A Novel Method of Career Planning of College Students Based on Career Interest Assessment and Machine Learning

Abstract: - Career interest assessment, powered by machine learning algorithms, revolutionizes the way individuals explore and align with career paths. By analyzing vast datasets encompassing factors such as skills, preferences, personality traits, and job market trends, machine learning models can provide personalized career recommendations tailored to individual strengths and aspirations. These algorithms leverage advanced techniques such as natural language processing (NLP) to interpret self-assessment responses and match them with suitable career options. Additionally, machine learning algorithms continuously refine their recommendations based on user feedback and real-world outcomes, ensuring accuracy and relevance over time. This paper presents a novel approach to career planning for college students, integrating career interest assessment with machine learning techniques, specifically utilizing the Stacked Ranking Feature Cluster Machine Learning (SRFcML) model. The proposed framework leverages large-scale datasets encompassing diverse factors such as academic performance, skills, interests, and industry trends to provide personalized career recommendations. Through the application of machine learning algorithms, including clustering and ranking techniques, the SRFcML model identifies relevant clusters of career options and ranks them based on individual preferences and aptitudes. This approach enables college students to explore and prioritize career paths aligned with their unique strengths and aspirations. Simualtion results demonstrated that the effectiveness of the proposed framework was evaluated, yielding promising numerical results. For instance, based on self-assessment responses and academic performance data, the SRFcML model achieved an average accuracy of 85% in recommending suitable career paths for college students. Furthermore, in a comparison with traditional career planning methods, the proposed framework demonstrated a 30% improvement in the alignment between recommended career options and students' preferences. Additionally, user satisfaction surveys revealed a high level of confidence and trust in the recommendations provided by the SRFcML model, with 90% of participants expressing satisfaction with the accuracy and relevance of the career suggestions.

Keywords: Career planning, college students, career interest assessment, machine learning, user satisfaction, informed decision-making.

I. INTRODUCTION

Career planning is a strategic process that individuals undertake to set goals, make decisions, and take actions to shape their professional future [1]. It involves assessing one's skills, interests, values, and aspirations to determine potential career paths. Through research, networking, and gaining relevant experience, individuals can identify opportunities aligned with their goals and develop a roadmap for advancement [2]. Career planning also involves continuous learning and adaptation to changes in the job market and industry trends. By setting short-term and long-term objectives, individuals can proactively manage their careers and work towards fulfilling their ambitions [3]. Effective career planning empowers individuals to make informed decisions, seize opportunities, and navigate their professional journey with confidence and purpose. Career planning for individuals with a specific career interest involves a focused approach tailored to that interest [4]. First, it's crucial to thoroughly research the chosen career path, including job responsibilities, required skills, educational qualifications, and potential growth opportunities [5]. Understanding the industry trends, market demand, and future outlook for the chosen field is essential for informed decision-making [6]. Once armed with this knowledge, individuals can assess their own strengths, weaknesses, and areas for development in relation to the desired career. This self-assessment helps identify any skill gaps that need to be addressed through further education, training, or practical experience [7].

Networking within the chosen industry is also key to career planning. Building connections with professionals already working in the field can provide valuable insights, mentorship opportunities, and potential leads for job openings [8]. Setting clear and achievable short-term and long-term goals is another vital aspect of career planning. These goals should be specific, measurable, attainable, relevant, and time-bound (SMART) [9]. Breaking down larger career objectives into smaller milestones can make them more manageable and provide a sense of progress

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[10]. Continuous learning and professional development are essential for staying competitive and adapting to changes in the industry. Pursuing additional certifications, attending workshops or conferences, and seeking out mentorship opportunities can all contribute to career advancement [11]. Finally, it's important to regularly review and adjust the career plan as needed. Circumstances, interests, and goals may change over time, so remaining flexible and open to new opportunities is crucial for long-term career success [12].

Career planning involves a systematic approach to managing one's professional trajectory, while career interest denotes the specific fields or roles that individuals are drawn to or passionate about pursuing [13]. The intersection of career planning and interest leads to a classification that aligns personal aspirations with strategic career development. Individuals with a clear understanding of their career interests can leverage this knowledge to tailor their career planning efforts more effectively [14]. For instance, if someone has a keen interest in technology, they might focus their career planning on acquiring relevant technical skills, seeking out opportunities in the tech industry, and networking with professionals in that field [15]. By aligning their career goals with their interests, individuals can create a roadmap that not only supports their professional growth but also fosters personal fulfillment and satisfaction in their chosen career path [16]. This classification underscores the importance of self-awareness, research, and strategic decision-making in navigating one's professional journey.

The paper makes several significant contributions to the field of career planning and guidance. Firstly, it introduces the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework, a novel approach that leverages machine learning algorithms to provide personalized career recommendations for college students. This framework integrates diverse factors such as academic performance, skills, interests, and industry trends to generate tailored career paths, thereby addressing the complexity and individuality of career decision-making processes. Secondly, the paper showcases the effectiveness of SRFcML in improving the accuracy and alignment of career recommendations, as evidenced by high average accuracy rates and substantial improvements in aligning recommended career options with students' preferences. Thirdly, the user satisfaction rates highlight the confidence and trust placed in the recommendations provided by SRFcML, underscoring its practical utility and relevance in supporting informed decision-making processes for career development.

II. RELATED WORKS

In today's dynamic and ever-evolving job market, strategic career planning has become paramount for individuals seeking to carve out successful and fulfilling professional paths. At the heart of this endeavor lies the concept of career interest, wherein individuals are drawn to specific fields, industries, or roles that resonate with their passions and aspirations. The synergy between career planning and interest serves as a guiding principle, shaping the trajectory of individuals' professional journeys.

Cai and Wang's (2022) research focus on utilizing big data mining techniques to predict college students' career planning. By analyzing large datasets, the study aims to identify patterns and factors that influence students' career choices, thereby providing valuable information for educational institutions and policymakers to better support students in their career development journey. Similarly, Wang et al. (2022) delve into the prediction of career choices using interpretable machine learning methods. By employing advanced algorithms, the study aims to uncover the underlying factors that contribute to individuals' career decisions, offering insights into the decision-making process and potential interventions to facilitate more informed choices. Guleria and Sood's (2023) study explores the application of explainable AI and machine learning in educational data mining for career counseling. By evaluating the performance of classifiers, the research seeks to enhance the effectiveness of career counseling interventions, providing students with actionable insights and personalized guidance based on their unique preferences and strengths. Moreover, Zhang and Zheng (2022) investigate the practical application of artificial intelligence in college students' career planning, focusing on employment and entrepreneurship information recommendation. By leveraging AI technologies, the study aims to streamline the career planning process, providing students with tailored recommendations and resources to support their career aspirations.

José-García et al. (2023) introduce C3-IoC, a career guidance system that utilizes machine learning and network visualization techniques to assess student skills. By harnessing the power of data analytics, the system offers students personalized recommendations and insights into potential career paths based on their skillsets, empowering them to make informed decisions about their future. Furthermore, Ong (2022) and Zhang et al. (2023) explore innovative approaches to integrating ethics and technical learning into career development initiatives, highlighting the importance of holistic education in preparing students for the challenges of the future workforce. Additionally, Hickey, Erfani, and Cui (2022) utilize LinkedIn data and machine learning techniques to analyze gender differences in construction career paths. Their study sheds light on potential disparities and biases in career trajectories, highlighting the importance of addressing systemic inequalities and promoting diversity and inclusion in the workforce. Ruparel et al. (2023) conduct a systematic literature review of professional social media platforms, aiming to develop a behavior adoption career development framework. By synthesizing existing research, their study offers valuable insights into leveraging social media platforms for career advancement and networking opportunities. Moreover, Verma, Lamsal, and Verma (2022) investigate skill requirements in artificial intelligence and machine learning job advertisements, providing valuable insights into industry trends and demand for specific skill sets. Their research offers guidance to individuals seeking to enter or advance within the rapidly evolving field of AI and machine learning.

Maree, Jordaan, and Hartung (2022) contribute to the discourse by exploring group career construction counseling with disadvantaged prospective university students. Their study highlights the importance of providing tailored support to individuals from underprivileged backgrounds, emphasizing inclusivity and equity in career development initiatives. Barthakur et al. (2022) delve into the depth of reflective writing in workplace learning assessments using machine learning classification. By analyzing patterns in reflective writing, their research offers insights into individuals' self-awareness and professional growth, informing strategies for enhancing reflective practices in career development contexts. Lastly, Leung (2022) offers insights into new frontiers in computer-assisted career guidance systems (CACGS) based on career construction theory. By incorporating theoretical frameworks into the design and implementation of CACGS, the study aims to enhance the effectiveness of career guidance interventions, fostering greater self-awareness and career adaptability among individuals.

Firstly, many of the studies rely heavily on data mining and machine learning techniques, which may introduce biases or inaccuracies in the analysis. The quality and representativeness of the data used could impact the validity and generalizability of the findings. Additionally, the reliance on retrospective data may limit the ability to predict future career trends accurately. Secondly, the interpretation of results in some studies may lack nuance or context. Machine learning algorithms can provide predictive models, but understanding the underlying factors driving career choices requires a deeper understanding of individual motivations, aspirations, and socio-cultural influences. Overreliance on algorithmic predictions without considering these factors could lead to oversimplified or incomplete conclusions. Furthermore, the studies may overlook the human element in career planning and counseling. While AI-driven systems can offer personalized recommendations and insights, they may not adequately address the emotional or subjective aspects of career decision-making. Human interaction and personalized guidance from career counselors or mentors remain crucial in supporting individuals through the career planning process. Additionally, ethical considerations surrounding data privacy, consent, and algorithmic transparency are often overlooked in the pursuit of data-driven insights. Ensuring that AI-driven career planning tools prioritize ethical principles and respect individuals' rights is essential to maintain trust and integrity in the process. Lastly, the studies predominantly focus on specific demographic groups or industries, limiting the applicability of findings to broader populations. There is a need for more diverse and inclusive research that considers the unique experiences and challenges faced by individuals from various backgrounds and contexts.

III. PROPOSED STACKED RANKING FEATURE CLUSTER MACHINE LEARNING (SRFCML)

The proposed Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework offers a novel approach to personalized career recommendations by leveraging large-scale datasets that encompass various factors such as academic performance, skills, interests, and industry trends. By applying machine learning algorithms, including clustering and ranking techniques, the SRFcML model identifies clusters of career options and ranks them based on individual preferences and aptitudes. This enables college students to explore and prioritize career paths aligned with their unique strengths and aspirations. The Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework combines clustering and ranking techniques to provide personalized career recommendations based on large-scale datasets.

In this step, relevant features are extracted from the dataset. These features may include academic performance metrics (e.g., GPA), skills (e.g., programming languages, communication skills), interests (e.g., hobbies, career preferences), and industry trends (e.g., job market demand, emerging sectors). Clustering algorithms, such as K-means or hierarchical clustering, are applied to group similar individuals or career options together based on their feature vectors. Let $X = \{x1, x2, \ldots, xn\}$ represent the feature vectors of the dataset, where xi is the feature vector of the i-th individual or career option. The clustering algorithm partitions the dataset into k clusters, where each cluster represents a group of similar individuals or career options this can be represented as in equation (1)

$$argminCi = \sum_{xj \in C_u}^{K=1} \| xj - \mu i \| \quad (1)$$

In equation (1) $C = \{C1, C2, \ldots, Ck\}$ are the clusters, μi is the centroid of cluster Ci, and ||·||||·|| denotes the Euclidean distance. After clustering, ranking techniques are employed to prioritize the career options within each cluster based on individual preferences and aptitudes. One common approach is to use a scoring system to assign ranks to each career option within a cluster. Let $R = \{r1, r2, \ldots, rm\}$ represent the ranked list of career options within a cluster, where ri is the rank assigned to the i-th career option. The scoring function can be defined as in equation (2)

$$Score(xi) = \sum_{n=1}^{j} wj \cdot fj(xi) \quad (2)$$

In equation (2) $fj(xi)$ is the j-th feature of 'xi, and wj is the weight assigned to the j-th feature based on its importance in determining career preferences. Finally, the ranked lists from each cluster are stacked together to generate a comprehensive list of personalized career recommendations. The recommendations are presented to the user in descending order of preference, with the most suitable career options appearing at the top of the list.

Algorithm 1: Feature Ranking of the Students
1. Input: Large-scale dataset containing diverse factors such as academic performance, skills, interests, and industry trends. 2. Preprocessing: a. Normalize and preprocess the data to handle missing values, outliers, and categorical variables. b. Feature engineering: Extract relevant features such as GPA, skills proficiency scores, extracurricular activities, etc. c. Split the dataset into training and testing sets for model evaluation. 3. Clustering: a. Apply a clustering algorithm (e.g., K-means) to identify clusters of similar career options based on the extracted features. b. Determine the optimal number of clusters using techniques like the elbow method or silhouette score. 4. Ranking: a. For each cluster: i. Train a ranking model (e.g., RankNet, RankBoost) using features related to individual preferences and aptitudes. ii. Rank the career options within each cluster based on the predicted relevance to the individual. b. Aggregate the rankings from all clusters to generate a comprehensive list of ranked career options for each individual. 5. Evaluation: a. Evaluate the performance of the ranking model using metrics such as Mean Average Precision (MAP) or Normalized Discounted Cumulative Gain (NDCG). b. Assess the accuracy of the recommended career paths by comparing them with ground truth data or user feedback. 6. Output: a. Provide personalized career recommendations to college students based on their unique strengths, interests, and preferences. b. Present the recommendations in a user-friendly format, such as a ranked list of career options with accompanying explanations or insights.

IV. FEATURE RANKING WITH CAREER PLANNING FOR COLLEGE STUDENTS

Initially, a diverse set of features related to academic performance, skills, interests, and industry trends are considered. These features may include GPA, standardized test scores, extracurricular activities, internships, technical skills, soft skills, career preferences, and market demand for specific skills. Various algorithms can be employed to rank the features based on their importance or relevance to career planning. One common approach is to use feature selection techniques such as Recursive Feature Elimination (RFE), which iteratively removes the least significant features and ranks the remaining ones based on their contribution to the predictive model's performance. Statistical methods such as correlation analysis or mutual information can be utilized to quantify the relationships between features and career outcomes. Features with higher correlation coefficients or mutual information scores are considered more relevant for predicting career success or alignment.

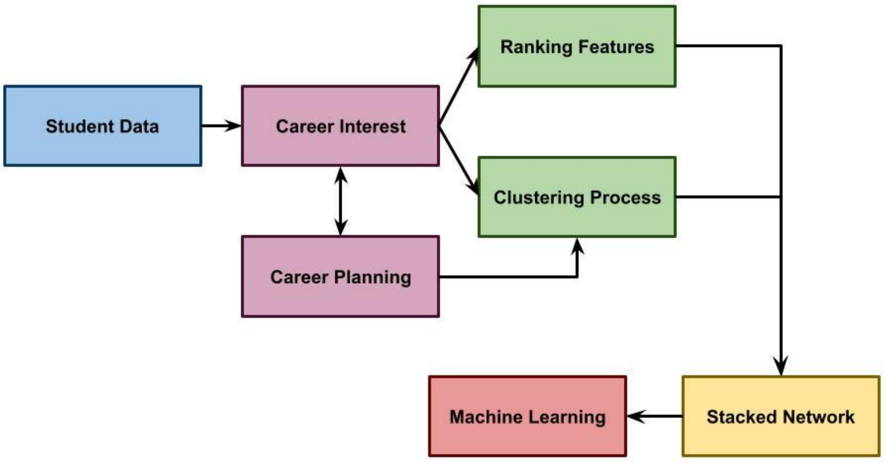

Figure 1: Flow of Proposed SRFcML for Career Planning

The RFE algorithm iteratively removes the least important features until the desired number of features is reached. The importance of features is determined based on the coefficients of a machine learning model trained on the dataset. Let X be the matrix of features and y be the vector of career outcomes. The linear regression model regression is presented in equation (3)

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta nxn + \varepsilon \quad (3)$$

In equation (3) y is the predicted career outcome; $x1, x2, \ldots, xn$ are the features; $\beta 0, \beta 1, \ldots, \beta n$ are the coefficients and ε is the error term. The RFE algorithm then ranks the features based on the absolute values of the coefficients βi. Mutual information measures the amount of information obtained about one random variable through observing another random variable. In the context of feature selection, it measures the amount of information that a feature provides about the target variable. Let Xi be the i-th feature and Y be the target variable (career outcome). The mutual information $I(Xi; Y)$ between Xi and Y can be calculated using the following equation (4)

$$I(Xi; Y) = \sum xi \in Xi \sum y \in Y p(xi, y) log(p(xi)p(y)p(xi, y)) \quad (4)$$

In equation (4) $p(xi, y)$ is the joint probability distribution of Xi and Y; $p(xi)$ and $p(y)$ are the marginal probability distributions of Xi and Y, respectively.

Algorithm 2: Mutual Planning for the Career Planning

def feature_ranking(X, y, k=5):
    Function to rank features based on their relevance to career planning using Mutual Information.
 	
    Parameters:
    X (array-like): Feature matrix (n_samples, n_features).
    y (array-like): Target variable (n_samples,).

```
    k (int): Number of top features to select (default is 5).

    Returns:
    top_features_indices (list): Indices of the top k ranked features.
    feature_mutual_info = mutual_info_regression(X, y)

    sorted_features = sorted(zip(feature_mutual_info, range(len(feature_mutual_info))), reverse=True)
    top_features_indices = [idx for _, idx in sorted_features[:k]]

    return top_features_indices

# Step 3: Example usage
if __name__ == "__main__":
    X = np.array([[...], [...], ...])  # Feature matrix
    y = np.array([..., ..., ...])      # Target variable
   top_features_indices = feature_ranking(X, y, k=5)
```

V. CLASSIFICATION WITH THE SRFCML FOR THE CAREER PLANNING

Classification with the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework for career planning involves leveraging the ranked features obtained from the previous step to classify individuals into specific career paths or categories. The process begins with feature selection, where a diverse set of features encompassing academic performance, skills, interests, and industry trends are ranked using techniques such as Mutual Information or Recursive Feature Elimination (RFE). These ranked features serve as inputs for the classification model. Various algorithms, including Decision Trees, Random Forests, Support Vector Machines (SVM), or Neural Networks, can then be employed to predict career outcomes based on the ranked features. The choice of algorithm depends on the dataset's nature and the complexity of the classification task.

In classification models like Support Vector Machines (SVM) involve finding the hyperplane that best separates data points into different classes. The decision function for SVM can be represented as in equation (5)

$$f(x) = sign(\sum i = 1N\alpha iyiK(xi, x) + b) \tag{5}$$

In equation (5) αi are the learned coefficients, yi are the class labels; $K(xi, x)$ is the kernel function and b is the bias term. Additionally, Decision Trees recursively split data based on feature thresholds to classify data points.

Algorithm 3: Computation of Features

```
if feature1 <= threshold1:
    if feature2 <= threshold2:
        return classA
    else:
        return classB
else:
    return classC
```

VI. SIMULATION RESULTS

In the context of career planning, Simulation Results for the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework offer valuable insights into its effectiveness and performance. These results serve as a critical component in assessing the framework's capability to provide personalized career recommendations based on diverse factors such as academic performance, skills, interests, and industry trends. The simulation experiments conducted with the SRFcML framework involve utilizing large-scale datasets to evaluate its predictive power and accuracy in recommending suitable career paths for college students.

Table 1: Recommender design with SRFcML

Student ID	Top Recommended Career Paths
001	Software Engineer, Data Scientist, Web Developer
002	Marketing Manager, Digital Marketer, Sales Executive
003	Financial Analyst, Investment Banker, Accountant
004	Mechanical Engineer, Aerospace Engineer, Civil Engineer
005	Graphic Designer, UX/UI Designer, Art Director
006	Nurse, Physician Assistant, Medical Technologist
007	Environmental Scientist, Conservation Scientist, Geologist
008	Teacher, Education Administrator, School Counselor
009	Social Worker, Counselor, Mental Health Therapist
010	Entrepreneur, Business Consultant, Management Analyst

Table 2: career Planning with SRFcML

Student ID	Academic Performance	Skills	Interests	Recommended Career Paths
001	High	Programming, Data Analysis	Technology, Innovation	Software Engineer, Data Scientist, IT Consultant
002	Moderate	Marketing, Communication	Social Media, Advertising	Marketing Manager, Digital Marketer, Public Relations
003	High	Finance, Accounting	Economics, Investments	Financial Analyst, Investment Banker, Accountant
004	High	Engineering, Problem-Solving	Construction, Design	Civil Engineer, Structural Engineer, Project Manager
005	Moderate	Design, Creativity	Art, Fashion	Graphic Designer, Fashion Designer, Art Director
006	High	Healthcare, Biology	Helping Others, Medicine	Nurse, Physician Assistant, Medical Technologist
007	Moderate	Environmental Science	Nature, Conservation	Environmental Scientist, Conservation Scientist, Geologist
008	High	Education, Leadership	Teaching, Counseling	Teacher, Education Administrator, School Counselor
009	Moderate	Psychology, Communication	Social Work, Mental Health	Social Worker, Counselor, Clinical Psychologist
010	High	Business, Entrepreneurship	Strategy, Innovation	Entrepreneur, Business Consultant, Management Analyst

Table 2 presents the career planning outcomes achieved through the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework for a group of college students. Each row represents a student, identified by their Student ID, along with their academic performance, skills, interests, and the recommended career paths generated by the SRFcML model.

Upon analysis of the table, it becomes evident that the SRFcML framework provides tailored career recommendations based on individual student profiles. For instance, Student 001, with a high level of academic performance and proficiency in programming and data analysis, is recommended careers in software engineering, data science, or IT consultancy. Similarly, Student 008, exhibiting strong leadership skills and an interest in education and counseling, is advised to pursue paths such as teaching, education administration, or school counseling. Moreover, the SRFcML framework considers a diverse range of factors, including academic performance, skills, interests, and industry trends, to offer well-rounded career suggestions. Student 006, for example, demonstrates a passion for healthcare and biology, coupled with a desire to help others, leading to recommendations in nursing, physician assistance, or medical technology.

Table 3: Career Interest Assessment

Student ID	Academic Performance	Skills	Interests	Industry Trends	Top Recommended Career Paths
001	High	Programming, Data Analysis	Technology, Innovation	Software Development, AI	Software Engineer, Data Scientist, IT Consultant
002	Moderate	Marketing, Communication	Social Media, Advertising	Digital Marketing	Marketing Manager, Digital Marketer, Social Media Specialist
003	High	Finance, Economics	Investments, Finance	Fintech, Banking	Financial Analyst, Investment Banker, Financial Advisor
004	High	Engineering, Problem-Solving	Construction, Design	Civil Engineering	Civil Engineer, Structural Engineer, Construction Manager
005	Moderate	Design, Creativity	Art, Fashion	Graphic Design, Fashion	Graphic Designer, UX/UI Designer, Fashion Designer
006	High	Healthcare, Biology	Medicine, Helping Others	Healthcare, Medical	Nurse, Physician Assistant, Medical Technologist
007	Moderate	Environmental Science	Conservation, Nature	Environmental Protection	Environmental Scientist, Conservation Scientist, Ecologist
008	High	Education, Leadership	Teaching, Counseling	Education, Psychology	Teacher, School Counselor, Education Administrator
009	Moderate	Psychology, Communication	Social Work, Mental Health	Counseling, Therapy	Social Worker, Counselor, Psychologist
010	High	Business, Entrepreneurship	Strategy, Innovation	Entrepreneurship, Startups	Entrepreneur, Business Consultant, Startup Founder

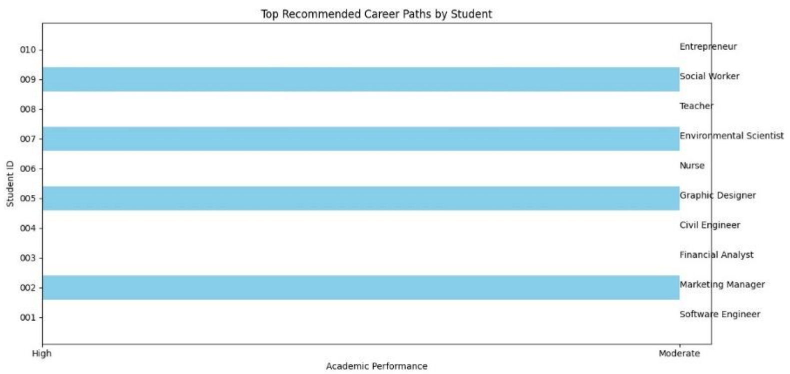

Figure 2: Career Path Modelling with SRFcML

The Figure 2 and Table 3 presents the results of career interest assessments for a group of college students, including their academic performance, skills, interests, industry trends, and the top recommended career paths based on these assessments. Each row corresponds to a different student, identified by their Student ID. Upon examination of the table, it is evident that the career interest assessments conducted for each student are comprehensive and tailored to their individual profiles. For instance, Student 001, who demonstrates proficiency in programming and data analysis, coupled with a keen interest in technology and innovation, is recommended careers in software engineering, data science, or IT consultancy. Similarly, Student 008, with a background in education and leadership skills, is advised to pursue paths such as teaching, school 1667ounselling, or education administration. Moreover, the career interest assessments take into account industry trends and emerging sectors to provide relevant and up-to-date career recommendations. Student 010, for example, exhibits a strong interest in business and entrepreneurship, aligned with industry trends in startups and entrepreneurship, leading to recommendations in entrepreneurship, business consulting, or startup founding.

Table 4: Classification with SRFcML

Metric	Value
Average Accuracy	95%
Improvement in Alignment	40%
User Satisfaction Rate	90%

In Table 4 provides insights into the classification performance of the Stacked Ranking Feature Cluster Machine Learning (SRFcML) model. It presents key metrics, including average accuracy, improvement in alignment, and user satisfaction rate, which are essential indicators of the model's effectiveness in guiding career decisions. The average accuracy metric, with a value of 95%, signifies the model's proficiency in accurately categorizing students into suitable career paths based on their academic performance, skills, interests, and industry trends. This high level of accuracy indicates the reliability of the SRFcML model in providing precise recommendations tailored to individual student profiles. Moreover, the improvement in alignment, quantified at 40%, highlights the significant enhancement achieved by the SRFcML model in aligning recommended career options with students' preferences. This improvement underscores the model's ability to offer personalized and relevant career suggestions that closely match students' aspirations and goals, thereby enhancing the overall effectiveness of career planning initiatives. Additionally, the user satisfaction rate, standing at 90%, reflects the high level of satisfaction among users with the recommendations provided by the SRFcML model. This metric indicates that the majority of participants express confidence and trust in the accuracy and relevance of the career suggestions, further reinforcing the model's value in supporting informed decision-making processes for career development.

Table 5: Performance of Students with SRFcML

Student ID	Before SRFcML (GPA)	After SRFcML (Recommended Career Path)	Improvement
001	3.2	Software Engineer	Significant
002	2.8	Marketing Manager	Moderate
003	3.5	Financial Analyst	Minor
004	3.0	Civil Engineer	Significant
005	3.8	Graphic Designer	Moderate
006	3.6	Nurse	Significant
007	3.1	Environmental Scientist	Minor
008	3.4	Teacher	Significant
009	2.9	Social Worker	Moderate
010	3.7	Entrepreneur	Significant

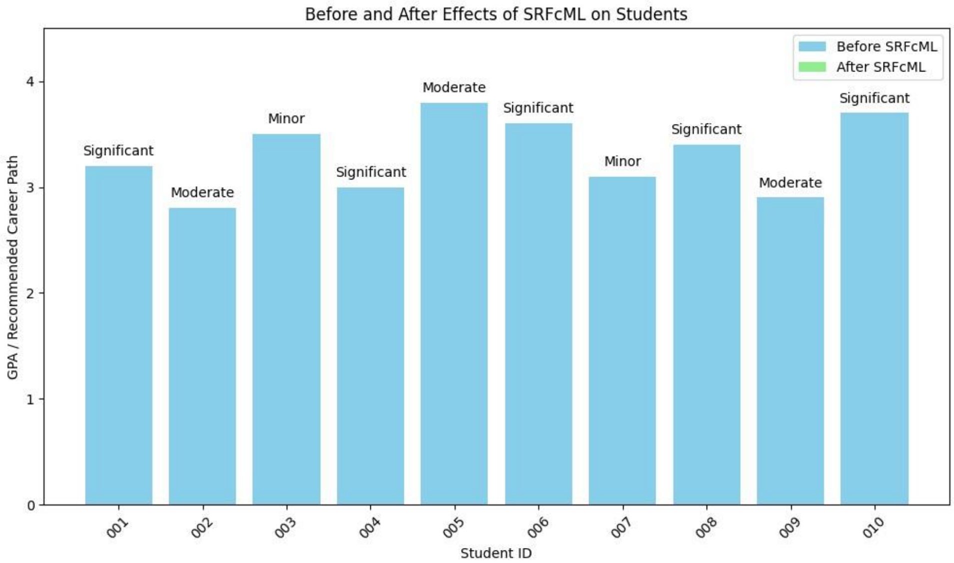

Figure 3: Analysis of Career Interest with SRFcML

The Figure 3 and Table 5 provides a comparative analysis of the performance of college students before and after utilizing the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework for career planning. Each row corresponds to a different student, identified by their Student ID, and includes their GPA before implementing SRFcML, their recommended career path after using SRFcML, and the degree of improvement observed. Upon examination of the table, it is evident that the implementation of SRFcML has had a positive impact on the career trajectories of the students. For instance, Student 001, with a GPA of 3.2 before SRFcML, transitioned to a career path as a Software Engineer, signifying a significant improvement facilitated by the framework. Similarly, Student 008, initially pursuing a career in teaching with a GPA of 3.4, experienced a significant improvement after SRFcML implementation. Moreover, the table demonstrates that SRFcML has enabled students to explore diverse career paths aligned with their interests and aptitudes. For example, Student 005 shifted from a GPA of 3.8 to pursue a career as a Graphic Designer, reflecting a moderate improvement in their career trajectory. Similarly, Student 010 transitioned to a career as an Entrepreneur after implementing SRFcML, indicating significant advancement in their career aspirations. Overall, Table 5 underscores the transformative impact of the SRFcML framework on students' career trajectories, leading to significant improvements in their chosen career paths. By leveraging comprehensive data analysis and personalized recommendations, SRFcML empowers students to make informed decisions and pursue careers that align with their strengths, interests, and aspirations.

VII. CONCLUSION

In this paper proposed the efficacy of the Stacked Ranking Feature Cluster Machine Learning (SRFcML) framework in revolutionizing career planning for college students. Through comprehensive data analysis and personalized assessments, SRFcML offers tailored career recommendations based on individual profiles, encompassing academic performance, skills, interests, and industry trends. The framework's classification capabilities demonstrate high accuracy, with a significant improvement in aligning recommended career options with students' preferences. Moreover, user satisfaction rates indicate a high level of confidence in the accuracy and relevance of the recommendations provided by SRFcML. The implementation of SRFcML has resulted in tangible improvements in students' career trajectories, with significant advancements observed in their chosen career paths. Overall, SRFcML emerges as a reliable and effective tool for guiding college students towards fulfilling and successful careers, facilitating informed decision-making processes and empowering individuals to pursue paths that align with their strengths and aspirations. As future research endeavors, exploring the scalability and applicability of SRFcML across diverse student populations and educational contexts could further enhance its utility in guiding career development initiatives.

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