Intelligent Career Advisor: Using NLP to Understand and Guide Career Paths

A Review

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Abstract— **Worldwide, the majority of students have difficulty identifying a career path following their completion of upper secondary school. Students frequently wonder what they will do after the 12th grade as they progress through the phases, which leads to a lot of uncertainty and second-guessing. In the recommended automated career counseling system, a student's academic journey becomes a critical component in guiding them towards a suitable professional path. The system effectively evaluates the student's entire profile by entering their tenth-grade test results and providing details about their extracurricular activities. The risk of academic misalignment is reduced and the risk of making bad professional decisions is raised by adopting a holistic approach. According on the student's academic standing and extracurricular activities, the system then generates personalized recommendations, encouraging a more informed and tailored approach to career advising.**

Keywords—Career Counseling, Classification, K Nearest Neighbor, Machine Learning Algorithms, Support Vector Machine.

I. INTRODUCTION

When choosing a job, consider additional considerations as well. The path one chooses is not solely based on what one hopes to achieve shortly after graduating. Understanding and being conscious of oneself, as well as one's skills and abilities, is the main focus of professional development advice. During this time, a variety of people (parents, teachers, fellow students, educational specialists, etc.) offer a lot of advice to each student, who then choose the course they wish to do. Students frequently regret their choice after selecting the wrong subject or stream. For example, there is a widespread misperception that students who perform exceptionally well in computer classes and earn the highest grades in the 12th grade would study in computer engineering.

This isn't the case in practice. Students in grades 11 and 12 as well as those currently enrolled in engineering programs took part in numerous rounds of discussion.

The suggested strategy takes a more customized and student-centered approach. Students actively participate in the system's evaluation process by entering the results of their tenth-grade tests and supplying details about their extracurricular activities. This interactive platform identifies and assesses a range of complete skill sets that are crucial for various career paths based on the student's academic performance and extracurricular activities. The approach looks at each person's unique profile rather than relying on an objective test to recommend career paths that best capitalize on their talents. Look at the following examples to gain a better grasp of the system's influence:

1) **Academic Prominence:** If a student consistently does well in math classes and actively participates in math- related extracurricular activities, the system may highlight their career choices in data science, analytics, or mathematics-intensive industries.

2) **Leadership and Teamwork:** If a student has demonstrated exceptional leadership skills through extracurricular activities like team sports or student government, they may receive recommendations for positions in management, project management, or entrepreneurship.

3) **Creative Aptitude:** For students who are passionate about the arts or creative endeavour's, the system may suggest career paths in design, marketing, or content creation based on their extracurricular activities and academic performance in related courses.

By interacting with the system and responding to questions that are specific to them, students can gain personalized insights on their unique skill sets. People are more capable of choosing their career path and are more cognizant of their interests and strengths because of this empowerment.

Additionally, the suggested method reduces the subjectivity frequently present in human advise by using artificial intelligence to deliver data-driven, objective recommendations, filling a significant gap in traditional career advising. This technological integration fits in with the expanding trend of digital transformation in education, where decision-making processes are being improved by the use of tools like natural language processing and machine learning. Additionally, the system can grow beyond individual use, providing educational institutions with a standardized platform to effectively mentor sizable student cohorts. It could develop into a dynamic tool that gradually adjusts to shifting industry demands and student needs by integrating real-time feedback mechanisms.

II. PROPOSED SYSTEM

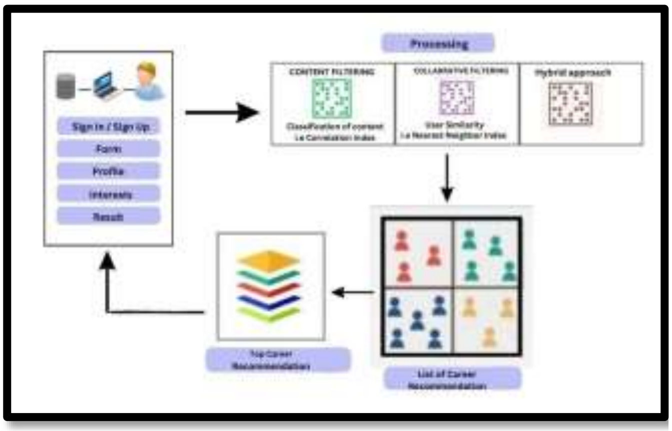

Fig. 1 Architecture Diagram of the recommended system

II. OVERVIEW OF THE PROPOSED SYSTEM

In the procedure, a candidate's skill set is analysed using the system depicted in Figure 1. After registering, the user completes questionnaire assessments in which they enter the results of their tenth-grade tests and provide details about their extracurricular activities, among other things. Students participate actively in the system's assessment procedure. This interactive platform identifies and assesses a range of complete skill sets that are crucial for various career paths based on the student's academic performance and extracurricular activities. These data will be saved in a database and processed using a variety of methods, such as collaborative filtering, content-based filtering, and hybrid approaches. Following this, machine learning algorithms and data extraction techniques will be used. Show the user's highlighted strengths based on that, and the algorithm will offer the best career paths accordingly.

III. LITERATURE SURVEY

Reema Goyal et al. (2021) explain the concept of an Intelligent Career Advice Chatbot (ICCC) designed to provide career advice to students in the tenth and twelfth grades. By responding to inquiries, encouraging learning, and offering guidance when one chooses a career path for additional study, the ICCC aims to assist students. There are several benefits to developing an intelligent chatbot for career advice. Firstly, it provides students with an easy and scalable method of receiving academic and professional assistance. Making career counseling more widely accessible could reduce the strain for educators who work as human career counselors. Furthermore, the chatbot may be able to provide personalized recommendations based on each user's responses by utilizing machine learning techniques, which would increase the effectiveness of the advice provided. If students' queries are addressed and help in choosing a career for additional education is given, they may make better decisions and do better academically. There might be some problems even if the research makes no mention of negative impacts. It is challenging to guarantee the accuracy and reliability of the chatbot's support. If the machine learning algorithms or the questions are poorly thought out or outdated, students may be given false information that could lead to them making poor career decisions.

Shaikha Al-Dhari et al. (2023) emphasize the significance of choosing a career as a critical decision that people must make in both their academic and professional lives. The primary focus is on the techniques used by machine learning and artificial intelligence to predict and recommend career paths. The use of data analytics to predict employment decisions has several benefits. First, it uses artificial intelligence and machine learning to give people personalized job guidance based on insights from data. Better career choices and possibly more lucrative and fulfilling work could come from this. One possible drawback is the over-reliance on data analytics when making professional decisions. Although these approaches can provide useful information, it's likely that they fall short in taking into consideration the intricate elements of professional decisions.

Muskan Sharma et al. (2022) present Career and Personal Mentorship for Higher Secondary Education, offering guidance and support to students enrolled in higher secondary education. The primary objective of this system is to assist students in making informed decisions about their academic programs, career paths, and personal development opportunities. The goal of the proposed chatbot-based solution is to provide students with a platform where they can seek assistance anonymously, without fear of discrimination or condemnation. Conventional mentoring sessions can be very time-consuming, and not all students may be able to attend them. The chatbot has made it easier for students to seek help whenever they need it by offering a round-the-clock substitute. It ignores concerns around the chatbot's understanding of and ability to handle challenging emotional or private circumstances that children might encounter. Furthermore, the effectiveness of the chatbot in providing tailored and pertinent mentorship is determined by the caliber of its training data and the accuracy of its algorithms. Making sure the chatbot is appropriately trained and updated frequently to satisfy students' evolving needs is an important aspect that should have been discussed.

Muhammad Arif et al. (2019) explain how the study specifically highlights the need for career counseling as a means of enhancing graduates' employability. It argues for the development of a personalized career counseling strategy that is tailored to the particular needs of each student and the shifting demands of the job market. The essay emphasizes how supporting tailored career guidance might increase employability. By better aligning their skills and interests with available job openings, graduates can increase their chances of landing a job after graduation. One of the primary problems is implementation difficulties. Personalized career counseling may provide significant challenges, necessitating the establishment of substantial infrastructure, skills, and resources.

John Robert D. et al. (2020) discuss the challenges junior high school students in the Philippines face while deciding on a professional route within the parameters of the K-12 curriculum. According to the research, guidance counselors can determine the optimum academic path for senior high school students by using a web-based career track recommender system driven by Deep Neural Networks (DNNs). There are many potential benefits to using DNN in a web-based career track recommender system. For instance, it can improve the efficacy of guidance counselors by automating the process of identifying the most appropriate academic tracks for children. Then, counselors might be able to provide more tailored guidance and support to individuals who need it most. A DNN-based model would not accurately capture the intricate interplay of an individual's interests, skills, passions, and values that goes into choosing a career.

Vignesh S. et al. (2021) offer a fresh answer to the difficulty of choosing an appropriate career route, which is one that many students face after completing upper secondary school. Even at the age of 18, many students lack the maturity and understanding needed to make informed career decisions, according to the authors. One of the advantages of this technique is that it can significantly reduce the number of students who make bad career choices. By using objective assessments and AI algorithms, it may provide customized recommendations based on individual skill sets, increasing the likelihood that students would select careers that align with their interests and skill sets. However, there are some possible limitations to consider. First off, the quality of the assessment questions and the availability of a sizable dataset are key factors that determine how accurate the system is.

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Punjab Mane et al. (2020) discuss the major difficulty of assisting students in making well-informed career decisions in an era of expanding professional possibilities and opportunities. A smartphone application that helps high school students choose a career route based on their ability, hobbies, and personality traits is presented in the study. One of this paper's key advantages is the way it integrates psychology and technology to provide career advice. By considering the student's aptitude to follow a particular course, personality traits, hobbies, and other factors, the technique attempts to deliver more precise and customized recommendations. On the downside, the article ignores any potential limitations or challenges associated with the implementation of the recommended career guidance application.

Min Nie et al. (2018) examine the crucial choice that students must make about their careers and how it impacts their life planning. Job appraisers have previously employed diagnostics and questionnaires to identify the various factors that may influence students' job choices. It offers a practical, data-driven method for predicting students' preferences for jobs. By using behavioral data, this method may significantly increase the accuracy of career projections, empowering students to make more educated decisions. The subjectivity associated with traditional employment advising methods may also be reduced by the model's emphasis on data-driven insights. When collecting and evaluating student behavioral data, certain privacy regulations and laws must be adhered to. Inappropriate handling of sensitive personal data may result in ethical dilemmas and privacy concerns. Furthermore, depending too heavily on behavioral data may obscure certain crucial non-behavioral factors that influence employment choices, such as personal convictions, hobbies, and contextual circumstances.

Vishal D. et al. (2022) recommend developing a mobile application for Android that provides comprehensive details on institutions, eligibility requirements, costs, and more to address these problems. The application's objective is to assist students, both domestically and internationally, in selecting the best school and course for their interests and qualifications. The Android career coaching mobile app offers several possible benefits. By incorporating features like institution ranking, scholarship opportunities, and campus placement prospects, the application may help students find colleges that provide a well-rounded education, improving their entire college experience.

Pavel Kiseleva et al. (2023) emphasize the importance of personality traits in career counseling and investigate how machine learning might be applied to social network data analysis to predict these traits. This paper presents the idea of social constructivism as the foundation for machine learning methods applied in career counseling. It is emphasized that this theory is empirically supported by the AUC-ROC measure calculation utilized in career counseling modelling. It offers a practical and evidence-based method for predicting college students' preferences for jobs. By using behavioural data, this method may significantly increase the accuracy of career projections, empowering students to make more educated decisions. In its analysis of the findings, the study highlights the empirical backing for the theoretical underpinnings of social constructivism in the context of career counseling. Even though specific experimental results are not discussed in this review, the research emphasizes the importance of understanding how professional identities are created within social networks and how values influence this process. The study highlights the importance of values in career development and argues that this process could be enhanced by incorporating machine learning into social networks. Even if the article implies that this approach would be beneficial, a more in- depth analysis of the experimental data would provide crucial information regarding its effectiveness and utility.

IV. METHODOLOGY

The Oracle of Prediction, Skill Enlightenment, and Skill Discovery—shown in Fig. 2, where the full process was completed—are the most important parts of the methodology. After the evaluation is complete, candidates are informed of their specific performance in several skill categories. The Prediction parts of the second module then come into play

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In this instance, predictive operations are performed using a machine learning algorithm that operates seamlessly in the web application's backend and makes use of the applicants' scores from the prior module.

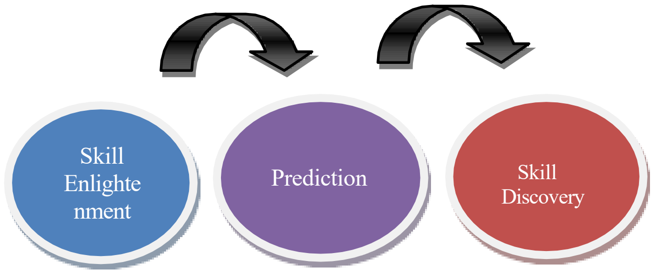

Fig. 2 Process Flow

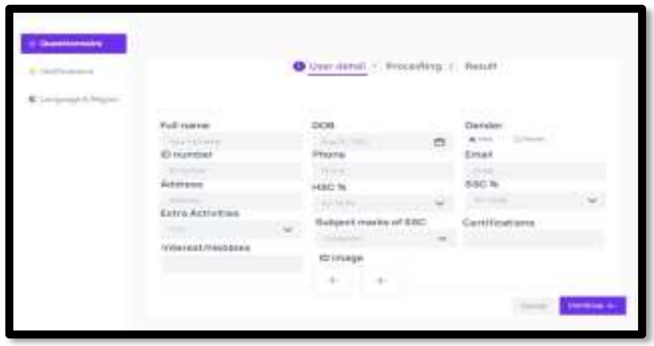

Fig 4. Questionnaire Assessment Test Dashboard

The second segment's outcome is the prediction of the ideal department for each candidate's profile. The last section is called "Skill Discovery," and it thoroughly evaluates applicants' performance. This comprehensive assessment is offered in multiple formats, providing candidates with a comprehensive and in-depth comprehension of their outcomes.

A. *Skill Enlightenment*

A user interface called "Pathfinder AI," which is intended to offer career recommendations, was created for the system. This interface acts as a thorough manual, guiding users through many aspects of the topic to improve the content's efficacy.

Users can interact on the Pathfinder AI website by using their personal user accounts. To view customized career recommendations, each user must either sign in or create an account. (User Profile: Log in or register.)

1) *The system interface is shown below:*
2) *Register and log in as indicated in Figure.3*
3) *Making banners as seen in Fig. 3*
4) *Questionnaire selection as mentioned in Fig.4*
5) *Fig.4 list popular categories.*

Fig 3. Dashboard of Pathfinder AI

which are intended for enrolment. The register page collects user data and stores it in the database.
The user is then taken to the login page, where they are required to enter personal information, including their academic history, extra circular reports, and interests. The suggestion offers accurate and pertinent career suggestions based on the user's form data. The three best career pathways are suggested for an individual to follow. For the backend, Python was used. The suggested approach connected the front-end and back-end using Python Flask. Depending on the information entered, it also used cosine similarity to estimate the user's career. The cosine similarity of two vectors is a measure of their similarity. Using keywords, it may be used to record how close together objects are on a dataset. The closeness between two vectors (A and B) is obtained by dividing the dot product by the magnitude value. Data is transformed into the format required for cosine similarity using Pandas, a fast and effective data frame for data manipulation. Additionally, NumPy files are used.

B. *The Oracle of Prediction*

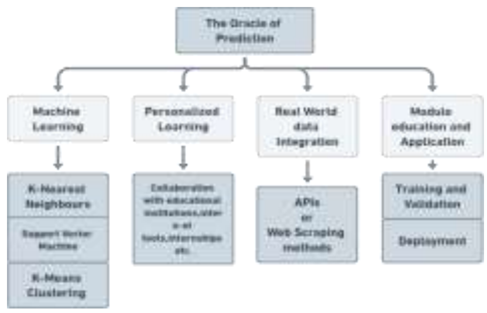

Fig 5. The Oracle of Prediction Module

Support Vector Machines (SVM) and AdaBoost algorithms are used to verify the model's accuracy during the pre-deployment stage. These cutting-edge methods were used to optimize the system and guarantee that it could provide accurate and trustworthy career recommendations

To improve the model's capacity to assess user data efficiently and give consumers precise and knowledgeable counsel as they navigate their career choices—discussed below—the performance of Support Vector Machine and AdaBoost was evaluated. These testing initiatives demonstrate the dedication to provide a strong and trustworthy career suggestion system.

1) **Machine Learning:** K-Nearest Neighbours is the machine learning algorithm used for classification, as seen in Fig. 5. Using formulas like Minkowsky, cosine similarity measure, chi square, Euclidean distance, and correlation, this supervised learning approach determines the distances between each neighbor to classify the target variables. K-Nearest Neighbor is an excellent fit for classification problems since it can be used to many datasets and obtain accuracy of over 90%

The K-Means Clustering approach is used to achieve machine learning clustering. Each value merges with the cluster with the closest mean after n observations are divided into K clusters using the K-Means Clustering algorithm. In this framework, K-Means Clustering is mostly used to provide secondary and tertiary recommendations and to group the departments that are most closely correlated with the candidate's performance.

By combining several models, ensemble techniques such as Random Forest, Gradient Boosting, Support Vector Machines, etc., can improve prediction accuracy.

2) **Personalized Learning:** The suggestion engine should also be developed to present students with individualized learning plans depending on the outcomes of their assessments. These courses may include relevant textbooks, online resources, extracurricular activities, and internships.

Students will have access to the resources they need to improve their skills if educational institutions work together to incorporate the suggested courses into their curricula.

3) **Real-World Data Integration:** Included data from real-world sources that provide information on market trends, industry demands and pay figures for different career paths. With this knowledge, students may make informed decisions.

APIs: Gathering up-to-date data from job-search websites, official labor statistics, or sector-specific websites through APIs or web scraping techniques.

4) **Model Education and Application:** Model works on following stages

Data Preprocessing: Complete comprehensive data preprocessing, such as feature scaling, missing value resolution, and categorical variable encoding, to prepare data for training.

Training and Validation: To train machine learning models, need a large and representative dataset. Make use of techniques such as cross-validation to assess models' performance.

Deployment: To use the trained model as a web service or API to make predictions in real time on the website. Consider utilizing containerization with technologies like Docker to guarantee successful deployment.

C. Skill Discovery

Employed state-of-the-art data visualization techniques, like interactive dashboards, to provide a comprehensive assessment of the student's performance and recommended career paths.

Comparative Analysis: Assign students to examine several career options side by side while accounting for variables such as anticipated earnings, job opportunities, and school requirements. Putting in place a feedback system to allow students to provide suggestions for the career counseling process and support the system's continuous development.

Key points of Highlighted System:

1) User Interface: An application was created to make it easy for students to finish examinations and receive career guidance on their phones. included a chatbot feature to provide guidance and advise whenever needed during the career planning process.

2) Integration with Educational Institutions: Include AI-powered chatbots on school websites to provide real- time career guidance and answer often requested questions.

3) User Feedback: By incorporating suggestions from instructors, counselors, and students, a user feedback loop will allow for ongoing customization and improvements.

4) AI mentorship: Provide a platform that enables students to ask AI-powered mentors questions about their professions and receive guidance from them.

5) Social Integration: Provide students with the chance to connect and communicate online with others who share their career interests.

6) Language Support: Provide support for many languages in order to serve a diverse student body.

VI. RESULTS

To test the classification model's performance, the confusion matrix in Table 1 computes its precision, recall, accuracy, f-measure, and error-rate. The following are the formulas for the performance measurements indicated above:

TABLE 1. CLASSIFICATION METRICS

Parameter	Formula
True Positive (X) =	X/(X+Z)
False Positive(Y) =	Y/(Y+Q)
False Negative(Z) =	Z/(Z+X)
True Negative (Q)=	Q/(Q+X)
Precision(p) =	X/(X+Y)
Recall(r) =	X/(X+Z)
Accuracy =	(X+Q)/(X+Y+Z+Q)
F-Measure=	2*(p*r)/(p+r)
Error-rate=	1-accuracy

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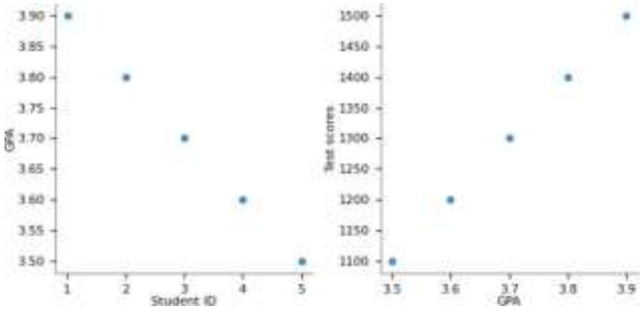
TABLE II. STUDENT DATA

Student ID	GPA	Test score	Extracurricular Activities	Chosen Career
1	3.9	1500	Debate team, math club	Software engineer
2	3.8	1400	Science Olympiad, robotics team	Doctor
3	3.7	1300	Band, student council	Lawyer
4	3.6	1200	Art club, drama club	Architect
5	3.5	1100	Soccer team, video game club	Engineer



. Fig 6. 2-d Distributions

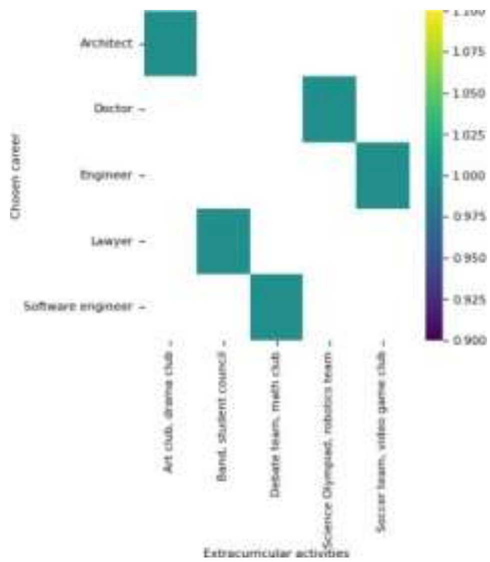


Fig 7. 2-d categorical distributions

Using classification approaches such K-Nearest- Neighbor, Support Vector Machine, and Adaboost algorithm, prediction results were determined from the above inferred Table 2, and their performance metrics were computed.

The k-nearest neighbor algorithm, also referred to as KNN or k-NN, is a supervised learning classifier that predicts or classifies how a single data point will be clustered based on closeness.

The SVM outperforms the k-NN in terms of classification speed and accuracy, even though both methods provide images with a respectable degree of classification accuracy. Adaptive boosting, or AdaBoost, is an ensemble machine learning technique used for a range of classification and regression applications. It is a supervised learning strategy that turns several weak or base learners into a strong learner to classify data.

TABLE III. PERFORMANCE MEASURES

Classification Technique	Accuracy	Precision	Recall	F1 score
SVM	90%	85%	95%	90%
KNN	80%	75%	85%	80%
Adaboost	95%	90%	95%	92%

According to Table 3, the classification method that is shown to be the most effective classifier in terms of accuracy and F1 score is the Adaboost algorithm.

Based on the classification performance indicators in Table 2, we constructed training and testing sets from the dataset.

It is recommended to employ an 80/20 split, where 20% of the data is used for testing and 80% is used for training.

Train an Adaboost classifier, Support Vector Machine, and k-nearest neighbor on the training set. K=3 is the value used for the k-nearest neighbor classifier. Choose a Support Vector Machine kernel function. The kernel function is used to transform the data before the Support Vector Machine classifier makes a prediction. One popular kernel function for classification issues is the radial basis function (RBF). Modify the hyperparameters of the Support Vector Machine classifier. The Support Vector Machine classifier's performance is influenced by its hyperparameters. A grid search could be used to find the optimal hyperparameter values. Lastly, set the weights of the Adaboost training examples to match one another. Using the practice materials, a slow learner was trained. identified the training set error made by the weak learner. Modify the training instance weights based on the error of the weak learner. Repeat the procedures until the desired outcome is achieved. Make assumptions regarding the test set.

Below, Equation (1) represents the sum of squares of the distance of each data point to its assigned vector m_k.

$$J = \sum_{i=1}^{I} \sum_{J=1}^{J} r_{ij} \, ||(x_i - m_i||^2 \tag{1}$$

1) *I is to total number of data points,*
2) *J is the number of clusters*
3) *X_i is the vector of measurement i*
4) *M_j is the mean for cluster j*
5) *R_{IJ} is an indicator variable that indicates whether to assign x_i to j.*

Hence, The Adaboost classifier has the highest F1 score, followed by the Support Vector Machine and k-nearest neighbor classifiers. This indicates that the Adaboost classifier is the best performing classifier on this dataset overall, considering both precision and recall.

VII. CONCLUSION

Envisioning Tomorrow is a significant breakthrough in AI-driven career advising that provides tailored suggestions by combining the K-Nearest Neighbor method for skill categorization with the K-Means Clustering strategy for department choices. The Adaboost classifier demonstrates the system's present effectiveness and demonstrates that it can outperform traditional career advising methods. Future developments could focus on enhancing algorithms for increased accuracy, incorporating additional features like psychometric testing, promoting increased user involvement, incorporating feedback from the sector, and implementing continuous learning strategies. To continuously enhance the process of providing students with knowledgeable and tailored career guidance, Envisioning Tomorrow lays the groundwork for an adaptable and dynamic career counseling approach.

VIII. FUTURE SCOPE

Although the "Envisioning Tomorrow" system is a groundbreaking development in AI-driven career counseling, there is much room for improvement in terms of its usability, precision, and social impact. To keep the system flexible, inclusive, and in line with the changing demands of students and the global labor market, future advancements could concentrate on a few crucial areas.

The incorporation of sophisticated psychometric tests is one important area for development. A more comprehensive picture of each student's profile may be possible by include instruments to assess personality traits (such as the Big Five Personality Model), emotional intelligence, and intrinsic motivations in addition to academic achievement and extracurricular activities. For example, even though their marks indicate otherwise, a student with high conscientiousness and creativity might be more suitable for positions in innovative entrepreneurship than traditional engineering. The method might provide suggestions that are in line with talents as well as long-term professional and personal fulfillment by collaborating with psychologists and utilizing proven psychological frameworks.

The incorporation of labor market data in real-time is another crucial improvement. Although the current system depends on static inputs like test results and activities, it could be made to reflect current and future demands by connecting it to dynamic sources via APIs, such as job boards (like Indeed and LinkedIn), official labor statistics (like the U.S. Bureau of Labor Statistics and India's Ministry of Labor), or industry-specific trend reports. For instance, the system might give priority to associated career routes for students with the necessary skills if data shows a sharp increase in demand for engineers with expertise in renewable energy by 2030. By extracting new job titles and abilities from online job advertisements, web scraping techniques could further augment this and enable the system to adjust to quickly evolving fields such as biotechnology, green technology, and artificial intelligence.

Another top aim is increasing the system's accessibility. In order to serve a variety of student demographics across the globe, future versions of the program, which is now geared toward a particular demography (such as Indian pupils after the tenth grade), could support numerous languages, including Hindi, Spanish, Mandarin, or Arabic. By adapting recommendation algorithms to local educational systems, social norms, and employment market situations, cultural quirks could be taken into consideration. For example, an urban student may be guided toward competitive metropolitan businesses, whereas a student in a rural area may receive recommendations that emphasize local prospects or online learning pathways. "Envisioning Tomorrow" would be positioned as a universal career coaching tool due to its global scalability.

Immersion technologies like virtual reality (VR) and augmented reality (AR) could be a game-changing addition. Before choosing a career path, students could "experience" a day in the life of a software engineer, doctor, or architect thanks to these tools that mimic work environments. A VR module may, for instance, allow a student to explore a virtual hospital, engage with patients, and do simple tasks, giving them a concrete idea of if medicine is something they are interested in. When combined with AI-driven performance feedback, these simulations may boost decision-making confidence and lower the risk of mid-career transitions brought on by misalignment. Within a few years, partnerships with tech firms that specialize in VR/AR (like Microsoft and Oculus) could make this possible.

IX. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to everyone who helped us finish this research and make "Envisioning Tomorrow" a reality. This initiative is the result of teamwork, steadfast assistance, and priceless insights from a wide range of people and organizations, to whom we are deeply grateful.

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We are incredibly grateful to our mentors, whose advice has been a lighthouse for us during this trip. We received crucial guidance from their knowledge of machine learning, natural language processing, and educational technology, which enabled us to successfully negotiate the challenges of developing and deploying an AI-driven solution. Their helpful criticism, tolerance, and support in times of doubt were essential in helping us polish our concepts and guarantee the accuracy of our approach. Additionally, we appreciate their willingness to offer their time and expertise, which enhanced this paper's conceptual and technical features.

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GitHub link : https://github.com/Anushka800/AI-Powered-Counselling/tree/main