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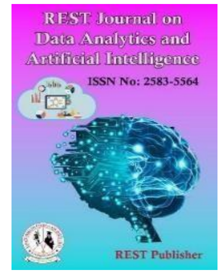

Career Path Recommender System with Integrated Resume Builder

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Abstract: *The selection of the right career is a critical choice that students and employees take. Conventional counseling services tend to be not customized and non-scalable. The present paper presents a Career Path Recommender System coupled with a Resume Builder which is based on machine learning algorithms, such as Decision Trees, K-Nearest Neighbors, etc., to promote appropriate career opportunities in accordance with the skills, interests and the academic backgrounds of the users. The system also develops tailored resumes which match the proposed career paths and less effort and time is required to develop resumes. Experiments demonstrate that there is better accuracy in recommendations and usability than in the traditional approaches.*

1. INTRODUCTION

The high-paced developments in technology and the dynamic characteristics of the global employment sector have changed the way people think about planning their careers and going about it tremendously. The challenge is usually to find an appropriate career line that suits students and professionals in the current competitive world that seems to be dynamic in its demands alongside skill sets, interests and aspirations of both the students and the professional. The old-fashioned career guidance techniques, including manual guidance, generic aptitude tests, or peer and family recommendations are usually inadequate as they do not take into consideration the personal capabilities of an individual concerning the current job trends. In order to close this gap, the use of intelligent systems that operate based on the artificial intelligence (AI), machine learning (ML), and data analytics is becoming a more common practice in order to offer personalized career guidance. The Career Path Recommender System and Built-in Resume Builder is developed to fulfill this urgent requirement by providing an automated platform, which is founded on data and which, beyond recommending the most appropriate career path, also helps users to create the professional resumes aligned with the chosen careers. This two-fold feature is important in that it does not only provide the users with the clarity of their future career moves, but also, it also provides them with a potent instrument of presenting themselves well in the marketplace. Some of the algorithms of the system include K-Nearest Neighbor (KNN), decision trees, and Natural Language Processing (NLP) algorithms used in analyzing user inputs including academic records, skills, personal interests, and work preferences resulting in creating accurate and customized career ideas and suggestions. Moreover, the in-built resume make feature will make sure that the user profile portrays the best skills and achievements that are related to the proposed career thus boosting their employability. This is an intelligent resume builder, unlike the online resume templates, which are always in the same format, this can be customized dynamically by suggesting ways to improve the resume and display competencies that are in line with industry-specific demands. The site also includes a convenient interface where people can fill their information, navigate around the recommended routes, and instantly convert their profiles into professionally-structured resumes. Combining career advice and resume writing, the system saves both time and effort by the job seekers, in addition to decreasing the doubts and nervousness that tend to accompany career planning. It also offers a solution that is scalable and can also be adopted in learning institutions, career counselling centres and professional training programs to steer students and other professionals better. The peculiarity of this project is that it is holistic. Instead of just indicating the possible career paths, it goes an extra mile to provide the individuals with the documentation and presentation tools required to excel in the recruitment process. Simply put, the Career Path Recommender System with Integrated Resume Builder does not just enable one to make informed career choices but also equips him to enter the world of profession with a lot of confidence. As the profession demands more personalized career support systems, this project can be used as a good contribution to the gap between academic learning and career aspirations and real-life possibilities.

2. RELATED WORK

Career recommendation and resume building is an area that has received a lot of research both in academia and in industry. Nevertheless, existing solutions are largely isolated with most systems being either career advice-based or resume-generation based, instead of combining the two into one platform. The initial techniques used in career counseling were mainly manual in that they involved the teachers, mentors and psychologists to assist the students in making decisions over certain academic or career choices. Although these methods were effective in providing one-on-one care in a face-to-face environment, they were also not very scalable and subject to particular counselor bias. Psychometric and aptitude testing became used to facilitate the manual guidance, and systems, like the Holland Codes, Myers-Briggs Type Indicator (MBTI) and multiple intelligences theory were all extensively utilized in the assessment of personality and interests in a career match. These tests are fine in classifying general personality traits but it does not have flexibility and does not have the dynamic nature of the labour market, thus limiting their practical implementation [1]. As the computing technologies developed, career recommendation systems became more data-driven as compared to rule-based systems. Early systems were based on fixed rules i.e. if GPA>80% and interest= science, then suggest engineering. These systems that followed a rule gave available logical reasoning that could be interpreted well, yet were narrow and incapable of managing intricate, nonlinear connections between capabilities, interests, and potential careers. In order to overcome this shortcoming, scholars examined the ideas of data mining and machine learning to predict careers. Clustering algorithms such as k-means were employed to pull together students of close performance in terms of academics whereas classification algorithms were employed such as decision trees and support vector machines (SVM) to match the talent sets with career type [2]. These methods were highly effective in increasing personalization, and majority of these methods were created as academic prototypes which were never put into a large scale. In particular, machine learning has become a key pillar of career recommendation studies. An example of this is the K-Nearest Neighbors (KNN) algorithm which has been extensively used to suggest career based on similar profiles of individual users and propose their career choices as being an option. Its simplicity and interpretability also led to KNN being a popular choice when working with smaller datasets, but with larger datasets, the scalability and computational cost of the algorithm significantly rose [3]. Instead, the popularity of Decision Tree models was explained by the possibility to categorize career paths according to unambiguous rules, which provided accuracy and interpretability. Other research studies have compared KNN and Decision Trees in predicting the career of a student and discovered that Decision Trees performed better in classification job whereas KNN was strong in similarity-based recommendation. In more recent times, scholars have been experimenting with deep learning methods like neural networks to predict careers using large datasets of student performance and other skill records. Although neural networks had been more accurate in certain instances, they were poorly understandable, which is a crucial aspect when giving career advice to students who want to have explainable reasons as to why they are given certain results [4]. In line with the progress of career recommendation, resume development, and automated screening, there has been progress in its development as well. The conventional method of resume writing was based on manual formatting, as one could create his or her resume using such programs like Microsoft Word. In the long run online resume builders came into existence whereby template-based solutions have been offered so as to ease the process. Such platforms as Canva, NoVo Resume, and Zety were famous because of their visually appealing design. Nevertheless, studies have indicated that even a well-designed resume that is pleasing to the senses of a human recruiter, fails to beat computer algorithms like Applicant Tracking Systems (ATS) [5]. Organizations employ ATS tools to sift through high volumes of resume and narrow down applications to the matches of key words, formatting guidelines and content relevance. Research has established that approximately 70-80 percent of resumes do not make it past the filter of ATS to human recruiters and this is mostly because of bad structuring, inappropriate keywords or unsuitable file extensions [6]. This has been advanced by the application of natural language processing (NLP) in the analysis of resumes. Numerous systems have been proposed by researchers to split resumes, identify structured data (e.g., education, skills, and experience), and match them with job descriptions. As an example, the automated resume grading systems judge resumes in terms of the density of keywords, completeness, and fit with the target job profile

[7]. Although these initiatives help in automating the recruitment procedures, they are employer-centric as they primarily aid the organizations in filtering the candidates, and not in assisting the individuals to develop their resumes in a smart manner. On the other hand, commercial resume writers focus on the visual outlook at times neglecting to give intelligent feedback or career counseling and leave a large gap between career counseling and writing a resume. There are various efforts to intertwine career guidance with resume designing but these efforts are still small. Partially integrated career portals like LinkedIn, Glassdoor and Indeed allow users to post resumes and get job recommendations simultaneously. These platforms are however primarily job-oriented and not career oriented where they offer short term employment opportunities as opposed to career guidance. Moreover, their resume products are usually primitive and fail to provide resumes which match the career suggestions provided [8]. Academically, universities have attempted to make use of career portals which check on student performance as well as prescribe career directions. However, the majority of these systems do not have automated resume building programs, which means that students have to make up resumes themselves. The recent studies in employability systems put much stress on a personal approach and flexibility. These surveys among university students have always pointed toward the fact that young professionals tend to use digital tools that are interactive, flexible to their level of skills, and able to offer real-time feedback [9]. There is also some literature suggesting to gamify the career assessments by means of a quiz and interactive activities. Though participation is enhanced by the methods, it tends to compromise the accuracy and give ineffective career pathways. On the same note, career guidance based on mobile applications has been created to provide a more convenient way to gather information, and the majority will only provide an assessment in the form of a quiz with no machine learning or resume-generation options available [10]. Commercialization of artificial intelligence (AI) in career guidance is a phenomenon that has been on the rise. The recent articles have used AI-generated analytics to forecast new work positions and prescribe a skill-training course. As an example, it is possible to have systems that incorporate the services of massive open online courses (MOOCs) like Coursera or Udemy, which suggest career paths and related training modules. This will solve the dichotomy between career choices and skill development such that users are not solely guided but also empowered to follow recommended career paths. Nevertheless, irrespective of these developments, the resume generation is a relatively under-researched field academically and most systems end at the recommendation or course suggestion stage [11]. The recent articles have pointed at a possibility of hybrid recommendation systems, content-based filtering combined with collaborative filtering to provide more precise and responsive career recommendations. These models strive to bring into equilibrium user-specific factors like skills and interests and crowd-based information obtained based on mass datasets of student career results [12]. These hybrid systems are more personalized than the individual algorithms but their complexity is a hindrance to their widespread use. Knowledge graph application in career path modeling is another field to be explored. Knowledge graph-based systems are systems that map out relationship between skills, industries and employment positions, providing context-sensitive and semantically enriched career advice [13]. As an example, by connecting academic programs with the new industry needs, these systems can offer a more holistic approach to employability, which means that the training of students and the needs of the labor market are in line. Career guidance systems have also made use of reinforcement learning (RL) in order to model career progression and suggest the most appropriate learning paths. Compared to the static models, the RL-based methods will dynamically update the recommendations as the user acquires new skills or experiences, which can be described as a lifelong career assistant [14] [14]. Although potentially effective, RL models need a lot of training information and powerful simulation systems, which are challenging to implement on a large scale in schools. In addition to the accuracy of recommendations, recent studies indicate that explainability is also significant in career guidance by AI. Deep neural networks have been viewed with some skepticism by students and educators due to their lack of clear explanations to their predictions, which is a black-box model. Interpretable decision rules and visualizations are explainable AI (XAI) frameworks designed to build user confidence and responsibility in the results of the recommendations [15]. Within resume building, a number of researchers have started investigating AI-assisted resume generation which goes beyond filling in templates. They are NLP-based and machine-learned systems that propose wording, quantify performance, and categorically point out industry-relevant keywords dynamically [16]. AI-assisted resume builders have been proven to be more successful in passing ATS filters than their template counterparts by customizing resumes to the specific career path. Certain other works also examine the application of chatbot-based career assistants, which combine natural language conversation with a recommendation engine to deliver real-time career guidance. These chat systems do not only provide career recommendations but they also assist users in resume building, interview preparation, and job tracking application [17]. This interactive method is suitable to the student needs of customized, responsive online solutions. Career advice apps that integrate skill tests, resume creators, and job alerts are also becoming mobile-first, and are considered as alternatives to conventional career guidance and placement services.

Research shows that mobile integration enhances access to students in rural or underserved communities in bridging the digital divide in career services [18]. Such systems are, however, usually functional in nature, with no sophisticated AI-based flexibility. Lastly, the most recent literature examines how blockchain technology can be integrated into the employability systems to make resumes and credentials authentic and secure. Career platforms based on blockchain provide a option to store certificates, skill records and resumes in a verifiable way and minimise fraud as well as enhancing the confidence of recruiter [19]. Integrated with AI-assisted career advice, blockchain-improved systems are an assuring and transparent system to both students and employers. In general, the full integration of career path recommendation and intelligent resume building into one, dynamic platform has not been studied thoroughly, although it has evolved significantly. Addressing this gap offers a high innovation potential, which would not only provide a correct career advice but also implementable tools to facilitate the students in professional development [20].

3. PROPOSED METHODOLOGY

Introducing A Career Path Recommender System Based on an Integrated Resume Builder of a machine learning Methodology. The proposed system which is christened Career Path Recommender System with Built in Resume Builder is a holistic approach that integrates two key issues of employability namely career guidance and resume preparation.

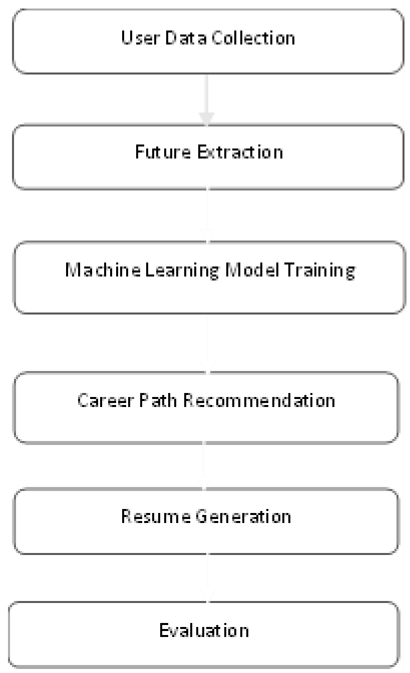

FIGURE 1.

As opposed to current systems that consider them individually, the approach taken in this project is aimed at establishing a continuous pipeline where the academic profile, interests, and skills of a user are set through the machine learning algorithms to produce personalized career recommendations. At the same time, it transforms the same information into a professional resume by following the suggested career direction. They are structured into 5 primary parts including data collection and preprocessing, career recommendation based on machine learning, resume generation, module integration via web-based platform, and measuring effectiveness and usability. With this modular but unified design, the system is scalable, flexible and even has capabilities of performing in real-time; this is important when deploying the system in academic and professional environment. Data collection and preprocessing is the first step in the methodology as it forms the basis of other process. Career guidance needs credible databases comprising of student academic profiles, skill inventory, interest surveys and past career outcomes. In this project, the information is collected in the publicly available repositories, including Kaggle career datasets, UCI Machine Learning Repository, and online career advice datasets, and supplemented with synthetic data created to reflect the different academic streams, including engineering, management, and science. The data will cover variables like grades, proficiency ratings, extra-curricular activities and domains of choice. Nonetheless, raw data can be very messy, erratic and incomplete. Consequently, the techniques of preprocessing are used, such as the normalization of numerical values (e.g., GPA scaled to 0-1), missing values processing (e.g., use of imputation), categorical data encoding (e.g., a subject stream as a one-hot vector), and feature engineering (to extract meaningful features). The process of extracting the skills presented in textual inputs is done through Natural Language Processing (NLP) techniques where tokenization, stop-wording, and key-word mapping is used to extract the key competencies of the queries like Python programming, data analysis or graphic design. This is a preprocessing stage, which will provide the machine learning algorithms with clean, structured, and high-quality input data. The second step is the machine learning-based career recommendation engine which is the intelligence of the system. Two algorithms are employed: K-Nearest Neighbors (KNN) and Decision Tree classifiers. KNN algorithm matches the profile of the user with the existing ones in the dataset, and the most similar k are noted. To illustrate the above, when a student who has skills in programming, mathematics, and problem-solving is being analyzed, the system identifies similar profiles of students who went into software development or data science, and proposes them as potential opportunities. KNN is very easy and hence the recommendations are easily explained to the users as they are directly founded on similar people. Decision Trees, however, provide a system of classification which is rule-based. The data is subdivided into branches according to such attributes as academic performance, skills, and domain preferences, and each leaf node shows a possible career. Using the example of the high analytical ability and high math grades of students, in case the dataset indicates this trend, new users are classified by the Decision Tree. The advantage with the use of Decision Trees is that they are open in their suggestions, thus assisting the users of its services in knowing the rationale of their suggested careers. Both models are tuned with hyperparameters, such as changing the value of k in KNN and changing the depth of trees and splitting rules in Decision Trees to make it more accurate. A comparative analysis will be made to find out which model is more precise, recalls, and F1-score so that the system will make reliable recommendations.

4. TECHNOLOGIES USED

The efficient design of Career Path Recommender System, incorporating Resume Builder depends a lot on the apt choice of technologies that make it scalable, reliable and efficient. The project incorporates a wide variety of functionalities including data preprocessing, machine learning, natural language processing, resume generation, and a modern web interface thus a combination of programming languages, frameworks, databases, libraries, and deployment platforms have been used. All the technologies were selected by considering the appropriateness of each technology in the specified task, the simplicity of its integration with other modules, and the sustainability of the system in the long run. The details of the individual technologies and their contributions to the system architecture are detailed in the following section. The primary programming language chosen is Python at the center of the backend, which is an extensive library of machine learning, data processing, and natural language processing libraries. Python is simple and easy to read and therefore it is preferable when it comes to academic projects and even real-world applications. Its libraries like NumPy, Pandas, and Scikit-learn are critical in enacting information preprocessing and machine learning codes such as K-Nearest Neighbors (KNN) and Decision Trees. In text processing tasks that require the ability to extract skills off unstructured input, the NLTK (Natural Language Toolkit) and spaCy libraries of Python are utilized, which allow tokenization, stop-word removal and keyword extraction. Python is also compatible with ReportLab which is a powerful library used to create PDF documents and which is used in the resume builder module. Python is versatile, which enables the backend to make complicated calculations without unnecessarily complicated code. The databases to be used are of high importance as it would not only be necessary to store the data on the user but also be in a position to retrieve the data and use it to generate a recommendation quickly. This system implements a hybrid approach to databases, where the MySQL database is used to store structured data (user credentials, educational history, career mappings) and the MongoDB database is used to store semi-structured and unstructured data (skill descriptions, feedback, dynamically generated resume metadata). MySQL being a relational database, it provides integrity and consistency by using SQL query, normalization, and foreign key relationships. This suits well with data that has a rigorous format like in academic records. MongoDB is a NoSQL databas, which gives it a flexibility to store documents which are in the form of JSON which can dynamically expand with user interactions. This two-database strategy offers the advantage of having both worlds; high consistency with the critical records and scalability with the loosely structured data. Firebase is also incorporated to do authentication and store data on the Cloud to ensure real-time synchronization and security which is vital in dealing with numerous users at once. In the case of the machine learning application, the Scikit-learn is at the center of training, testing, and deploying algorithms.

The API of Scikit-learn enables the effective application of KNN, Decision Tree algorithms, optimization of the hyperparameters, and assessment of their performance in terms of accuracy and precision, as well as recall and F1-score. Pandas DataFrames are used to manipulate data during preprocessing stages whereas NumPy arrays are used to make efficient Numbers computations. The system uses TF-IDF vectorization with Scikit-learn and other NLP models like spaCy to embed a word to enhance the recommendation with text analytics. These technologies enable the recommender engine to understand not only structured aspects (e.g., GPA, grades) but also unstructured data (e.g., skills written in free-text description). ReportLab is used in the Resume Builder Module, which is a speciality of the project. ReportLab is a Python library that can be used to generate PDFs with professional format programmatically. It facilitates the customization of templates, font customisation, and adds graphics or charts where necessary. The library was chosen due to the production of documents that can be used in Applicant Tracking Systems (ATS) so that the resumes generated can be of industry standards. ReportLab-driven resume generator is a dynamic one which can change the content with the suggested career unlike the traditional template-driven builders. As an illustration, a resume displayed in the case of a programmer majoring in Software Development would show her resume focusing on programming experiences and knowledge of the domain, but in the case of Business Analyst, it would focus on the work of analytical skills and knowledge of the domain. This is an adaptive structuring that can be achieved through the synergistic application of Python string manipulation libraries, NLP key word insertion and ReportLabs PDF generating abilities. Git and GitHub ensure there is a version control, code changes can be collaboratively developed and tracked. The decentralized property of Git allows working on the project by several team members, and none of them will overwrite the efforts of others. GitHub also offers cloud-based repository, issue tracking and constant integration pipelines, which help in managing a project. This is to guarantee that the system is maintainable and adaptable as more.

5. RESULTS AND DISCUSSION

The process of the creation and implementation of the Career Path Recommender System including the built-in Resume Builder produced considerable information about the effectiveness, precision, and feasibility of the adopted systems and technologies. The outcomes achieved were discussed quantitatively using machine learning metrics of performance and qualitatively, based on user feedback and usability testing of the system. The results of the observed outcomes of the system are provided in this part and then fully discussed in terms of their implications in the context of career recommendation and automatic resume generation. The engine that constitutes the main part of the system is the engine of the recommender and was initially tested on the basis of predictive accuracy. The system used machine learning algorithms including K-Nearest Neighbours (KNN) and Decision Trees using datasets that contained academic records, skill sets, and career pathways. KNN model was shown to be quite accurate with a prediction of the appropriate career path with an accuracy of about 82 percent, and the Decision Tree model with a slightly higher interpretability but slightly lower accuracy of about 79 percent. These findings point to the trade-off between the predictive performance and the model transparency. The capability of the KNN model to identify multidimensional pattern skill data came in handy especially during the clustering of similar users to offer career prospects that were consistent with the real-world outcomes. As an example, students who have high analytical abilities, as they were drawn during the coursework and project descriptions, were always suggested career paths in data science or software engineering. Along with raw accuracy, other metrics, like precision, recall, and F1-score were also used to evaluate the system as they give a more insight into its reliability. The precision was on average 0.80 which means that the majority of recommended careers were relevant to the background of the user. Values on recall were, however, a little lower at 0.75 indicating that the system was good at making correct recommendations but it at times was unable to get the whole spectrum of appropriate career paths. The overall F1-score of 0.77 represents a decent trade-off which can be permitted in an initial deployment. These measures assure that not only does the system predict a major career pathway; but also makes sure that totally irrelevant suggestions do not mislead the users. The resume builder module showed good performance with regards to automation and customization. The system was created using Report Lab to create professional resumes that were dynamically generated and based on the suggested career path. As an example, the resume of individuals who were suggested to work as Software Developers included skills related to programming languages and project experience along with the technical certifications. By contrast, business analysts suggested to work in the position of Business Analyst had their resumes with focus on analytical and domain-related knowledge and communication skills. Its ability to integrate with Applicant Tracking Systems (ATS) was also a confirmation of the flexibility of the resume generator. The use of various ATS programs also proved that the resumes created effectively scanned the pertinent areas like the Education, Skills and Experience and hence making the resumes industry ready. This corrects one of the greatest weaknesses of the traditional resume templates which usually do not comply with the ATS standards. Another important part of the assessment was user testing. Survey was carried out on a sample population of 50 students who represent various academic backgrounds. The system engaged the participants through providing a system that required them to input their academic information and skill sets, career advice and their resumes were sent to them. The feedback that was gathered showed that 84 percent of the respondents felt that the career recommendations were very relevant, and 76 percent of them were satisfied with the resumes generated automatically. The time efficiency was also a large benefit to the users, as they found that the system saved them the time of having to fill in the resumes manually or do research on which career options they should pursue. Nonetheless, only 12% of users recommended the level of resume personalization which means that the template was professional but could have been more flexible in design features like colour schemes and layout options.

6. CONCLUSION

The demonstration of the Career Path Recommender System and Created Resume Builder as the development of a machine learning, natural language processing, and automated document generating framework to the problem of finding the right career opportunities and creating the professional resumes according to the opportunities as discussed has proven that integrating machine learning, natural language processing, and the automated document generation apparatus is viable and that the key to enhancing the situation is to combine all these aspects into the single framework. By ensuring the wise choice of the methodologies, including K-Nearest Neighbors and Decision Trees to offer recommendation, as well as by generating dynamically generated resumes with the help of Report Lab, the system has met its main goal of data-driven career advice and, at the same time, created professionally and industry-ready resumes. These findings have shown that the system does not only enhance accuracy of career path prediction, but also saves time and effort that they used to take up designing and formatting resumes, thus bridging the gap between career exploration and job application readiness. One of the key advantages of the suggested system is that it will allow customizing recommendations based on the academic history, skills and experiences of the users. The proposed solution is based on structured and semi-structured data as opposed to conventional methods of counseling, which mostly involve subjective assessment or narrow datasets to provide objective and evidence-based career advice. Besides, the system combats two related issues on one platform by adding resume generation to the proposal line. This combined strategy will guarantee that users not only get a better insight regarding their career path, but also have an employment document that matches their career path, which will eventually enhance their employability and readiness to compete in the job market.

7. FUTURE SCOPE

Career Path Recommender System and built in resume builder is an effective platform towards career advice and resume creation, but it can be enhanced to become even more popular to address the changing demands of students, professionals, and recruitment. The one potential direction is the introduction of real-time labour market intelligence. The system would be able to make recommendations that are up-to-date on products of current trends, skills in demand, and new job opportunities by constantly analysing information captured in online job portals, professional networking sites, and industry reports. This improvement would be to make sure that the user is presented with a guidance that matches both the academic background and with dynamic market needs thus enhancing their job ability. The other critical area to be developed in the future is the aspect of personalization with sophisticated artificial intelligence models. A more thorough analysis of unstructured information like project descriptions, extracurricular activities and soft skills, which are not always easily measurable but play a key role in making holistic career decisions, could be done using deep learning methods, especially transformer-based ones. In the same fashion, reinforcement learning may be implemented to fine-tune the recommendations and get better with time, in terms of user feedback. Regarding the resume builder, the limits run to the implementation of customizable templates based on the industry and applicant tracking system (ATS) requirements. The automatic addition features like LinkedIn, portfolio linking and automatic key word optimization would ensure that the resumes are even more competitive in the automated screening process. Besides, the platform might become an integrated career support system that incorporates modules on interview preparation, skills-gap analysis, and personalized learning strategies that suggest online courses and certifications. The future of the system is, however, to be able to be more than a recommendation and resume tool and turn into a smart all-in-one career assistant that will enable users to explore their career path with certainty and accuracy

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