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Career Recommendation System using Artificial Neural Network

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***Abstract:** Artificial Neural Network is an important tool used in machine learning. The name 'neural' implies that it is a system that is derived from the human nervous system (brain) and is aimed at replicating the way humans comprehend. Neural Network is basically comprised of input layer, output layer and a hidden layer which consists of units that process the input data and transform them into the information that the output layer can utilize. There is a thing among the youth in choosing their career paths that they generally opt on either the recommendation of their colleagues or the job roles that are the highest paying in terms of salary. They lack the awareness of their strengths and skills that results in them choosing their career arbitrarily, which leads to frustration and demoralization. Besides, when the recruiters recruit the candidates, they need to evaluate them in many different facets. Therefore, there is a need for a system that can help such students in deciding a job role that is best suited for him/her which is in accordance with their skill set and other evaluation metrics which can now be achieved by the advancement in the field of deep learning. We propose an automated system using Artificial Neural Network which examines the personality traits of the individual along with academics and personal interests to predict which job role in computer science would be the best suited for them.*
***Keywords:** Career Recommendation, Artificial Intelligence, Machine Learning, Youth, Education.*

I. INTRODUCTION

For several years, information system supports in human resource management have been primarily focused on storing and tracking applicant data through applicant management systems. These systems aid in the internal processes and communication processes between the human resource management department and other departments. Recently, the increased amount of digital information and the emergence of e-business reform the way companies conduct business in different aspects. Initially, simple solutions are applied such as posting the job ads on the career unit of the corporate website. Then, using the experiences gained from these initial implementations, opportunities are identified, which leads to the establishment of other changes and enhanced e-recruitment platforms.

Artificial Neural Networks [1] is a data processing system consisting of a large number of simple, highly interconnected processing units in an architecture which is inspired by the structure of the cerebral cortex segment of the human brain. Therefore, neural networks can usually perform tasks that humans or animals excel at but which conventional computers often struggle with. For career recommendations, various parameters are considered, which makes it quite difficult to predict using traditional regression models. In the past few years, recommendation systems [2] have been widely utilized in various commercial platforms to offer recommendations to users.

Every field has various job roles which makes it challenging for any undergraduate student and recruiter to decide a well-suited job for students. Any student after graduation needs to decide which job role is best suited for him according to his profile. This is important for a long-term career plan. Similarly, for a recruiter it is very crucial to recruit a candidate after assessing him/her in all different aspects. With the use of a career recommender system, undergraduate students and recruiters can find the right job based on their personality, academics, interests, and other factors. Thus, they [7] have proposed an ensemble incremental learning system created by using these three machine learning algorithms namely, Artificial Neural Network (ANN), Support Vector Machine (SVM) and Decision Tree. This can be a very useful technique for offering the best career options for the student. Furthermore, in a research [14] it helped predict student’s estimated careers including student’s strengths and weaknesses.

II. LITERATURE REVIEW

Before we discuss the literature, it is useful to observe that in recent surveys on applications of recommender systems, job recommender systems and (more general) recommender systems in e-recruitment, are frequently not included. I.e., in the well-cited review on applications of recommender systems, Lu et al.

[81] do not mention the application area of e-recruitment, the same holds for the earlier review by Felfernig et al. [41]. Also, although most papers on neural networks in job recommender systems were published after 2018, the survey on (deep) neural networks in recommender systems (including a section on application areas) also neglects this application [11]. From the HR perspective, job search and recommendation are also not always mentioned as an application area, as opposed to candidate selection, while in the end these systems do determine who will be in the applicant pool in the first place [111]. One possible explanation could be that, from a technical perspective, the problem of job search and job recommendation is little different from a general information retrieval/recommendation task. Job seekers frequently use ‘general-purpose’ search engines and online social networks to search for jobs (e.g., [56, 32, 66]). Furthermore, many job recommender systems we will discuss in this paper could very well be used in other application areas (and vice versa). Nonetheless, we will argue that factors such as the large amount of textual data, the reciprocal and temporal nature of vacancies, and the fact that these systems deal with personal data does require a tailored approach, and the sheer volume of contributions make it clear that this application area should not be neglected. Previous surveys on job recommender systems, which consider JRS contributions before 2012, include Al- Otaibi and Ykhlef [5] and Siting et al., though especially the latter survey is very limited in scope. More recent is the survey on recommender systems in e-recruitment by Freire and de Castro [43]. Although our work has some overlap, we especially wish to address some of the limitations of the work by Freire and de Castro in this paper. Even though the work by Freire succeeds in collecting a substantial number of contributions in the JRS application domain, they seem to fail to properly classify these contributions, making it difficult to see patterns in this literature. A clear example of this is that approximately 20% of the contributions discussed in their paper is labeled as hybrid, whereas another 33% is being labeled as “other”. Although the reader would later find that the “other" category includes for 25% contributions using (deep) neural networks, this still leaves a large number of contributions with an unsatisfying label. Furthermore, as shown by Batmaz et al. [11], there is a considerable development within the class of (deep) neural networks applied to recommender systems, which we also find in job recommender systems. This aspect is neglected by Freire and de Castro. The classification given by Freire and de Castro is understandable, given that so many contributions use mixtures of collaborative filtering and content-based techniques, and given that these are presented by the contributions themselves as hybrids. However, these labels do not provide much insight into what these contributions actually entail. Furthermore, Freire and de Castro [43] focus solely on methods and validation, whereas we, among other subjects, will also take into consideration ethical considerations. We will also put special emphasis on job recommender systems which, often successfully, take into account the reciprocal and temporal nature of job recommendations. As many contributions use one of the data sources made available through data science competitions for training and validating job recommender systems. Most noticeably, these include the *RecSys 2016* and *RecSys 2017* competitions ([1], and [2] respectively), using a dataset from the job board, and the *CareerBuilder 2012* Job Recommendation Challenge [60], which was hosted by CareerBuilder on Kaggle[21, 61]. All three datasets contain data with respect to candidate profiles, vacancies and online interaction between the two. Another resource often used is the Occupation Information Network an English-based job ontology that is frequently used in knowledge-based job recommender systems. We will use the terms *vacancy*, *job posting*, and *job* somewhat interchangeably throughout this paper to represent the *item* in the classical recommender system setting, whereas job seekers are considered as *users*. Although, as in the early paper by Vega[116], job seekers are still often described by their resumes, some current e-recruitment systems allow for descriptions that move beyond self-descriptions of one’s professional self. Here one should think of the social connections one can observe on (professional) social networks. When we speak of *resumes*, *CVs*, *user profiles*, or *job seeker profiles*, we assume these are synonyms and may contain additional information (such as social relations) beyond the self-description. Last, we will sometimes speak of “textbook" or “off-the-shelf", by which we mean methods one can find in popular machine learning/pattern recognition textbooks such as by Bishop [16] and Flach [42], or Aggarwal [3] in the case of commonly used recommender systems.

III. REQUIREMENTS & SPECIFICATION

A. Requirements

1) Functional Requirements

- The user should upload their details like personality traits, academics and personal interests.
- Operations and functions of this application are made error-free. The users will be capable of operating effectively.
- The application consists of modules that simplify the process for users. They only need to provide input and wait for recommendations to be generated.
- The user can generate recommendations in multiple graph formats.

2) Software Requirements

For developing the application the following are the Software Requirements:-

- Python
- Django

Operating Systems supported:-

- Windows 7
- Windows 8
- Windows 10
- Windows 11

Technologies and Languages used to Develop:-

- Python

Debugger and Emulator:-

- Any Browser (Particularly Chrome)

3) Hardware Requirements

For developing the application the following are the Hardware Requirements:-

- Processor: Pentium IV or higher
- RAM: 2 GB
- Space on Hard Disk: Minimum 120 GB

4) Algorithm Used

- *Artificial Neural Network (ANN):* An Artificial Neural Network (ANN) is an information processing model that is inspired by the human brain which makes computers to understand things and make decisions in a human-like manner. Computer programming allows the artificial neural network to behave like interconnected brain cells.
- *Support Vector Machine (SVM):* Support Vector Machine (SVM) is an algorithm of supervised machine learning. It is used for both classification and regression, though it is best suited for classification problems.
- *Decision Tree:* A decision tree is an algorithm of supervised machine-learning which is used for both classification and regression problems. It is a tree-like structure in which each internal node denotes the feature, branches denote the rules and the leaf nodes denote the result of the algorithm. It is also used in Random Forest algorithm to train on different subsets of training data.

B. Specification

1) Applications

- Students wanting to pursue engineering as a career but are not sure about the stream can use this Website as an advisor.
- This system can be used by educationalists who aim to search engineering streams.
- There are different prediction techniques that help recommendation systems to obtain data.

2) Advantages

- The predictions are highly relevant: The course recommendations are likely to be highly relevant to the user's unique interests and are not biased by course ratings from peers with dissimilar career goals.
- Recommendations are transparent: The process by which a recommendation is generated can be made transparent, which may increase students trust in the recommendations.
- New items can be recommended immediately: Unlike collaborative filtering, content-based filtering does not require a user to interact with an item before it can be recommended. Moreover, Next Level ensemble approach is cable of hinging on data outside the user's basic query. This can be a useful technique for automatically expanding the search scope when the user's query does not yield any matching courses.

3) Future Scope

- For now, we are building a recommender system that only recommends branches of engineering so in the future for candidates whose interest lies outside of the project domain, the machine will give them a generic output instead of recommending a specific branch.
- Since all the branches of engineering are not equally popular, it is difficult to get a large dataset to train an unbiased model.

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We express gratitude to all our team members for their collective efforts and hard work in completing this project and also for their intellectual support throughout the course of this work.
We consider this opportunity as a big milestone in development of our career. We will strive to use gained skills and knowledge in the best possible way, and we will continue to work on the improvement of these skills, in order to attain desired career objectives.

V. CONCLUSION

This project proposes an efficient ANN model for predicting a well-suited job-role for the Computer Engineering student. The developed model is apt for the analysis of many objective factors for a person with qualified knowledge, and skills. This recommender system can be used by any IT based recruiter to hire a candidate appropriate for the job. Additionally, an individual as a Computer Engineering fresher can find out the domain that they are qualified for based on their profile and the ones who are unaware of their career. The proposed model used 15 parameters to predict one of the six job-roles with an accuracy of 94.9%. Hence, ANN model gives more accurate results to traditional machine learning models.

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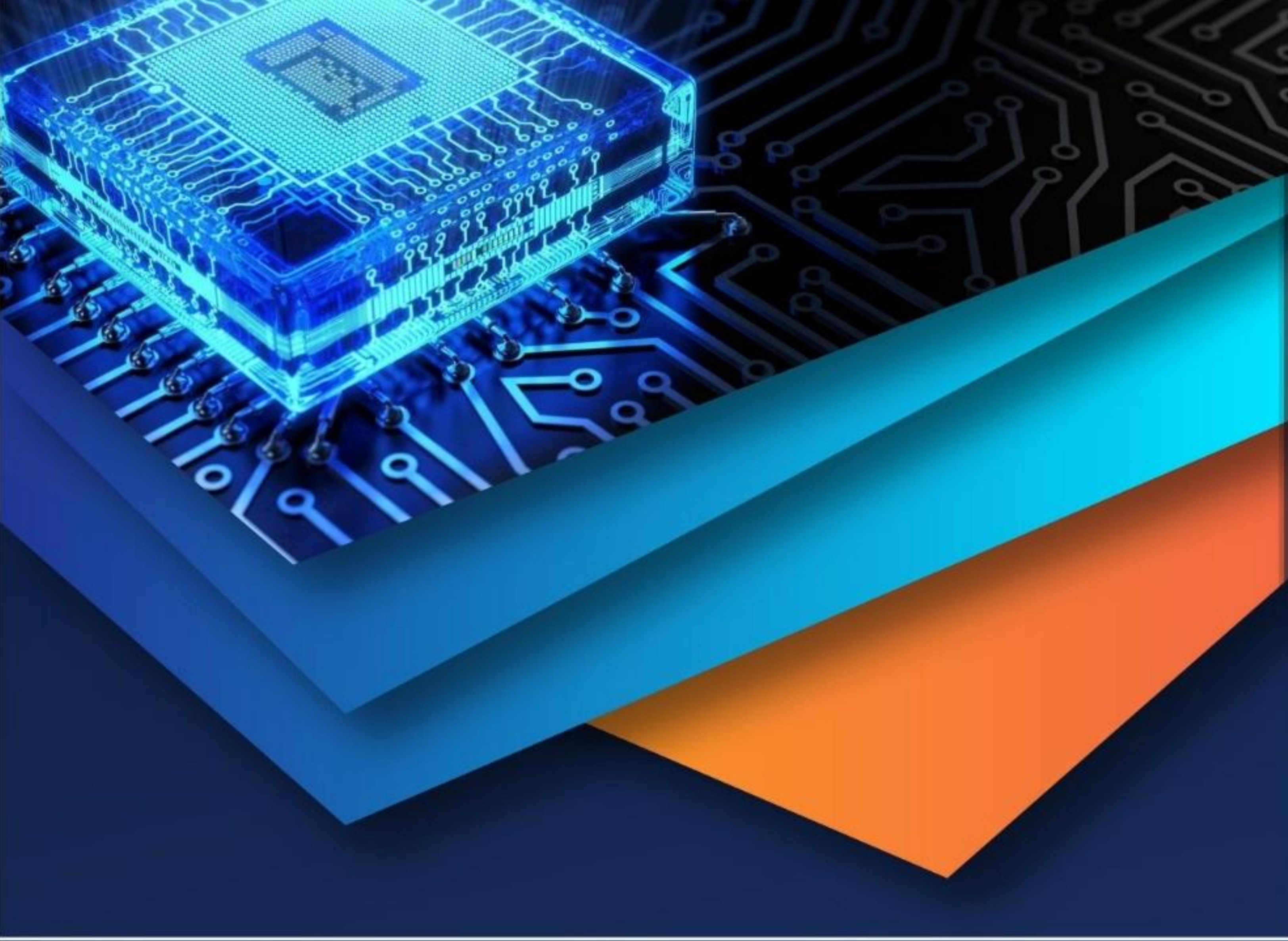

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