2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon)
MIT ADT University, Pune, India. Apr 25-27, 2024

2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon) | 979-8-3503-6287-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/MITADTSoCiCon60330.2024.10575379

Conversational AI for Career Counseling

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***Abstract*— College students' life plans are heavily influenced by their career choices. Choosing the appropriate career is the most difficult decision in today's society. Many kids today are unsure about their future. They do have certain talents, but they are unable to identify them or place them in the appropriate domain. Different individuals advisevarious career alternatives, but the student must ultimately choose their job. For giving a focus to this we have built an innovative method for student career advising that combines ML for job prediction and RASA(NLU) framework for a chatbot. The work is about a website that gives you the whole information that is needed for the knowledge of every student. Concurrently, a sophisticated RASA(NLU) chatbot is being developed to engage students in meaningful and tailored interactions. To provide viable job possibilities, the ML-based career prediction model examines numerous aspects such as talents, educational background, and hobbies. The chatbot, on the other hand, uses natural language understanding and generation techniques to deliver personalized advice, answer questions, and lead students toward proper educational and career options. This dual strategy guarantees a thorough and productive career counseling experience, allowing students to make educated decisions regarding their future. Comparison of three differentMachine learning algorithms i.e. KNN, Random Forest, and Decision Tree was performed and KNN outperformed the other two. The accuracy obtained by this is 97% by use of the KNN model for job prediction. The integration of ML and NLU technologies contributes to a dynamic and personalized counseling environment, ultimately assisting students in achieving their professional aspirations.**

Keywords*— *RASA, chatbot, career counseling, machine learning, career guidance, KNN

I. INTRODUCTION

In recent times, the fusion of Natural Language Understanding (NLU) and Machine Learning (ML) has given rise to an innovative technology known as Conversational AI, which facilitates dynamic and personalized interactions between humans and machines. This technology has shown remarkable potential in diverse domains, transcending traditional boundaries and redefining human-computer interaction. A study by Ayanouz, Boudhir, and Benhmed introduces a pioneering smart chatbot architecture that leverages NLU and ML algorithms to provide efficient healthcare assistance. Moreover, Io and Lee's bibliometric analysis underscores the increasing interest in chatbots and conversational agents, revealing a growing acknowledgment of their significance [1]. Additionally, the practical application of Conversational AI within the realm of hotel bookings demonstrates its real-world adaptability [2]. The research provides a comprehensive overview of the methodologies, applications, and future potential of Conversational AI, highlighting its multidimensional impact [3]. A chatbot system employing AI and NLP serves as a tangible example of the technology's transformative capabilities [4]. Building upon the foundational studies, the research examines the role of Conversational AI in the context of career counseling, investigating the methodologies, applications, and untapped possibilities it offers to guide individuals toward their professional aspirations[5].

The utilization of Conversational AI in student career counseling has revolutionized the way educational institutions and career advisors interact with students. This technology enables students to receive personalized guidance, explore career opportunities, and make well-informed decisions about their future endeavors. In this work we aim to develop and implement a cutting-edge Conversational AI system for student career counseling. By understanding the context and preferences of each student, the AI chatbot will provide tailored career advice, recommend suitable educational paths, and suggest potential career trajectories based on the latest industry trends and job market demands.

II. LITERATURE SURVEY

The paper discusses the development of a chatbot that utilizes Deep Learning techniques, particularly Recurrent Neural Networks, The model used in this context is the BidirectionalLong Short-Term Memory (BiLSTM), a type of RNN that cancapture contextual information both from past and future inputs, making it suitable for sequence-to-sequence tasks likenatural language processing as mentioned in “chatbots as conversational healthcare agents”. The development aimed at an educational chatbot using 1000 question-answer pairs as training data. Utilizing random forest technique and ensemblelearning, the chatbot achieved 88.60% accuracy in classifying responses. It was deployed on Telegram for seamless communication between users and the chatbot as stated in “High Accuracy Conversational AI Chatbot Using Deep Recurrent Neural Networks Based on BiLSTM Model,".Thestudy investigates design and technical implementation issues, It is based on NLP, and machine learning as mentioned in "Chatbot: An Automated Conversation System for the Educational Domain,". choose the most suitable career options using Natural Language Processing and Machine Learning techniques, SVM and DT.

Data is collected from different sources like social sites, databases, etc.as stated in “Conversational Agents in E-Learning”. The paper presents a chatbot with a method for becoming a discussion member in a chat tool. The system efficiently supports students, enhancing their well-being and academic success. Uses NLPand ML as mentioned in "Online Career Counsellor System based on Artificial Intelligence”. The paper discusses various methodologies and approaches used in Conversational AI, including machine learning, deep learning, and reinforcementlearning. It highlights the use of Finite State Machines (FSMs) for dialogue management as stated in "Artificial Intelligence in Education” The proposed system is an anonymous and impartial chatbot designed to mentor students on career choices, program selection, and personal counseling. It uses tensor flow keras. The database used is basic and self-made and data is stored in JSON format. Accuracy - 0.9671, 0.9794, 0.9897 was constant, and also the limitations conclude that the model was overfitted if we changed some of the datasets. A frame-based dialogue management system for their conversational AI system uses machine learning techniques. The database was collected from 10 classes. Accuracy - 0.5570 = 55.7% as mentioned inthe paper

The paper Real-World Conversational AI for Hotel Bookings, mentions the use of machine learning models for intent classification, named entity recognition, and information retrieval, but it does not provide detailed information about the specific models used or their performance metrics

III. METHODOLOGY

In this work, we aimed to develop a dynamic website using HTML, CSS, PHP, and MySQL. The website allows users to register, log in, and participate in a domain-related questionnaire. Upon completion of the questionnaire, the system provides predictions or recommendations based on the user's responses using the K-nearest neighbors (KNN) algorithm. Additionally, a chatbot utilizing RASA’s NLU is integrated to enhance user interaction. Also for the comparison to get the best recommendation for the system, we have used three machine learning models – KNN, Random forest, and Decision tree to get the best accuracy.

Upon calculating the accuracy KNN model outperforms the other models. You can refer to Fig. 1 for the system architecture.

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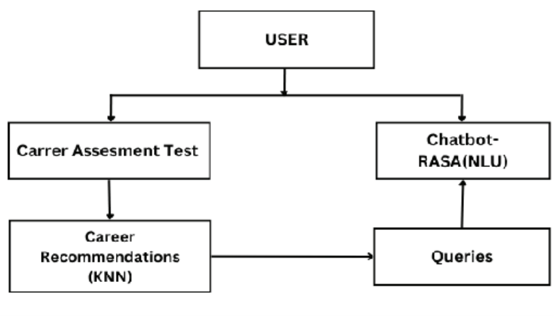


Fig. 1. Career Counseling System Architecture

For career recommendation and chatbot, the dataset is self-made. For career prediction, the data is pre-processed into the required format. For Example, the data in the data set will be stored in the form of words, nothing but alphabetic. It is converted into numerical format. For the Chatbot, the Dataset is self-made and contains intents and examples with colleges' names also so that the chatbot can provide colleges for the required course. The User Responses section involves answers to career-related questions. To create a diverse and tailored dataset, we conducted extensive research and compiled this information ourselves.

TABLE I. DATASET DESCRIPTION

Dataset Components	Details
Career Data	Job descriptions, skills, and educational requirements.
User Responses	Answers to career-relatedquestions
Pre-Processing Techniques	Feature Extraction

As the website has two parts *i.e.* career prediction and chatbot to emphasize it the given technologies are being explained.

A. Career recommendation

In the career recommendation phase, the system employs the K-nearest neighbors (KNN) algorithm to deliver individualized career options to the user. The algorithm determines the k most comparable users from the dataset based on the user's replies to the engineering domain- related questionnaire, taking into account their prior career decisions and achievements. It then proposes jobs that similar users have taken, to guide the user toward prospective career pathways that are consistent with their interests and abilities. By identifying trends in the datasetand understanding the career paths of similar persons, the system provides personalized career suggestions to assist the user in making educated decisions about their professional journey. Various models were used but the best accuracy we got was of the KNN model *i.e.* 97.1% which is better as compared to the others.

B. ChatBot:

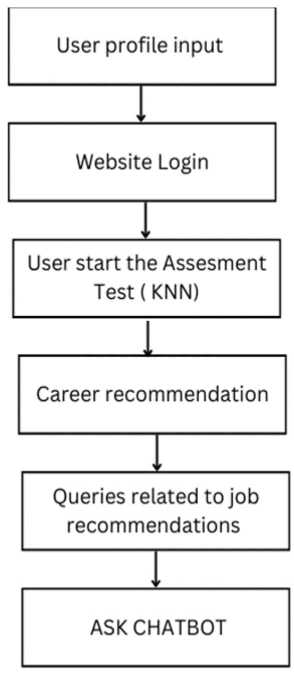


Fig. 2. Career.ly Flow Diagram

The development of the career counseling chatbot followed a structured methodology, commencing with the comprehensive collection of diverse career-related texts to ensure relevance and quality. Subsequently, rigorous data preprocessing techniques were employed to cleanse the gathered information, eliminating noise and irrelevant content. NLP techniques formed a pivotal aspect of the process. Text classification algorithms were applied, leveraging NLP to categorize and organize the wealth of career-related data into coherent and meaningful categories or intents. Additionally, clustering algorithms were utilized, facilitating the grouping of analogous career-related texts and enhancing the organization and structure of the gathered information.

The implementation phase involved the use of Rasa NLU, which began with meticulous training data preparation. The collected data was meticulously annotated with intents and entities, forming the foundation for training the Rasa NLU model. This was complemented by the implementation of a robust model architecture within Rasa NLU, empowering the system to proficiently understand user queries by adeptly extracting intents and entities. Further, the NLU pipeline in Rasa was meticulously configured, defining essential components like tokenizers, featurizers, and classifiers to optimize performance. By utilizing Rasa's natural language understanding (NLU) capabilities, the chatbot was able to learn to understand user inquiries and convert inputs into understandable intents and entities. This gave the system the ability to identify and classify user intentions that are particularly linked to career counseling. Then, conversation flows were carefully crafted, fusing activities to provide contextually relevant answers based on identified intents and entities. This allowed users who were looking for career advice to receive personalized assistance and direction. The systemflow Diagram in Fig. 2 describes the integration inside thewebsite to illustrate the flow of the system.

Algorithm 1: College Recommendation Algorithmwith NLU and Entity Extraction

Input: User Query Q

Output: Recommended College

1. Identify Intent:
   I(intent) <- NLUModel(Q)
2. Entities(Q) <- Entity Extraction(Q)
3. while (S(entity)):
   R(entity) <- f(A(entity), C(entity))
4. While (S(entity)):
5. if (A(entity) <- h(R(entity), P(entity)))
6. Recommend Top Colleges:
7. return top colleges based on scores
8. End of Algorithm
9. End of Algorithm

IV. RESULT

The outcomes outline the career suggestion and chatbotimplementations in a dynamic website.

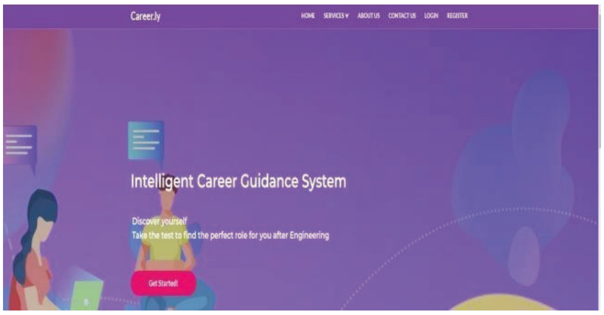


Fig. 3. Home Page

Fig. 3. describes about the home page, login and registration part combined with PHP and MYSQL. The students would be registered through a very simple method either by email id or Mobile number. The logincredentials would be created and would be validatd through every login attempt. Students Can See Various Fields.

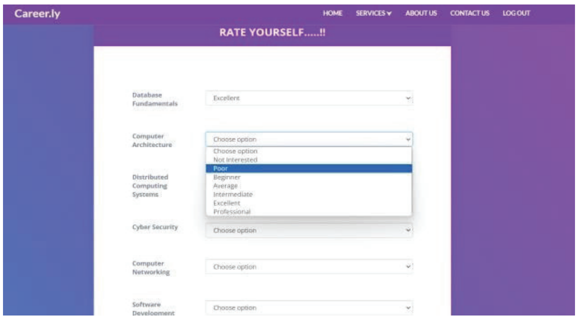


Fig. 4. Questionnaire

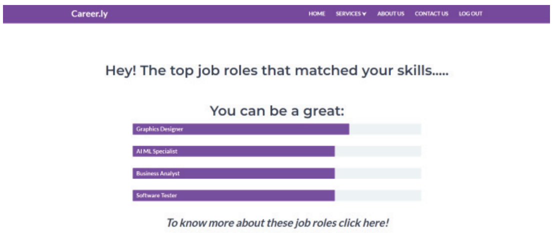


Fig. 5. Career Recommendations

Fig 4 and fig 5 respectively depict the questionnaire andthe career recommendations that the user will get basedon the level of interest he or she has about that specific subject. The model was trained using KNN, Random Forest and Decision Tree classifier and the accuracy are 97.13%, 86.4%, and 33.04% respectively. The KNNmodel was best fit, Also the user can get additional information on specific recommended career by the website refer fig. 6.

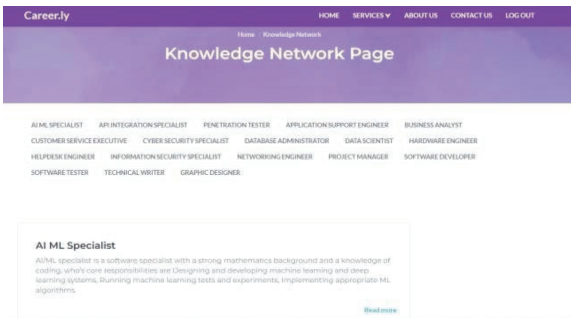


Fig. 6. Offered courses

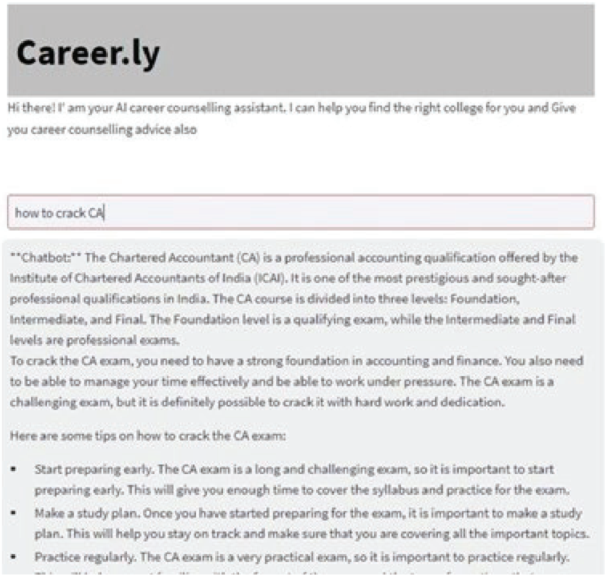
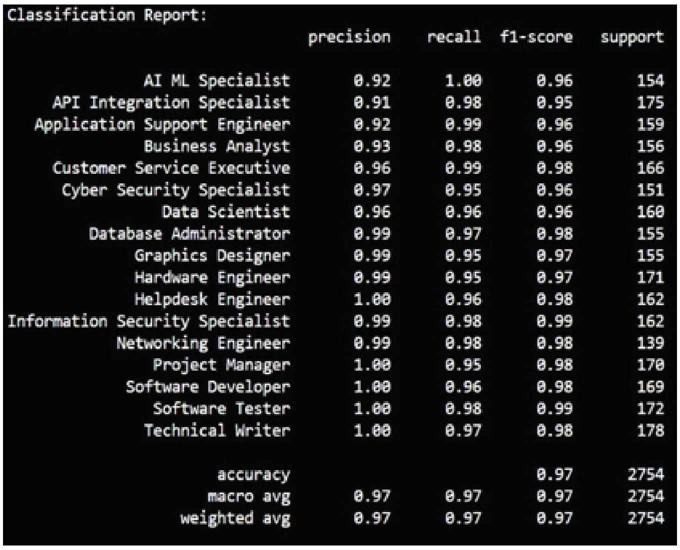


Fig. 7. Chatbot Interface

The most unique and significant part of the study is the Chatbot that students can use for guidance on any relevant doubts they get about the career recommended.

TABLE II. ACCURACY OF KNN MODEL FOR DIFFERENT VALUES OF N

Value of "n"	Accuracy
3	96.80
4	96.65
5	97.13
6	95.57
9	96.73



Classification Report:

	precision	recall	f1-score	support
AI ML Specialist	0.92	1.00	0.96	154
API Integration Specialist	0.91	0.98	0.95	175
Application Support Engineer	0.92	0.99	0.96	159
Business Analyst	0.93	0.98	0.96	156
Customer Service Executive	0.96	0.99	0.98	166
Cyber Security Specialist	0.97	0.95	0.96	151
Data Scientist	0.96	0.96	0.96	160
Database Administrator	0.99	0.97	0.98	155
Graphics Designer	0.99	0.95	0.97	155
Hardware Engineer	0.99	0.95	0.97	171
Helpdesk Engineer	1.00	0.96	0.98	162
Information Security Specialist	0.99	0.98	0.99	162
Networking Engineer	0.99	0.98	0.98	139
Project Manager	1.00	0.95	0.98	170
Software Developer	1.00	0.96	0.98	169
Software Tester	1.00	0.98	0.99	172
Technical Writer	1.00	0.97	0.98	178
accuracy			0.97	2754
macro avg	0.97	0.97	0.97	2754
weighted avg	0.97	0.97	0.97	2754

Fig. 8. Classification Report

To prove that the accuracy presented by us is the best we have assumed different values of N for classification and Fig 9 gives a brief explanation of how the accuracy is 97%.

The proposed solution provides the students with all the guidance that they need to get their ideal vocation which they should choose and is early enough to understand student's inclinations, enhance understanding of their personality types, educate on the various options, enable them for their career planning, development, and guidance, provide guidance on a continuous basis, make information available on career, education, etc. through sources, and be a partner in the overall journey

V. CONCLUSION

The study was a success in terms of establishing an interactive and educational platform for anyone interested in exploring technical disciplines. The team designed a user-friendly website that allowed smooth user registration, login, and participation in a domain- specific questionnaire by using a variety of web development technologies such as HTML, CSS, PHP, and MySQL. Theuse of the K-nearest neighbors (KNN) algorithm enabled individualized career forecasts basedon user replies, hence improving the user experience. Furthermore, theaddition of a chatbot that uses RASA introduced an interactive aspect to the platform, delivering real-time guidance and information. The study introduces an innovative integration of ML forpredictive career analysis and RASA(NLU) for a personalized chatbot, fundamentally transforming the landscape of student career counseling. The work not only exhibited technical competence, but it also underscored the significance of using machine learning,Rasa, NLU tools to provide targeted assistance and insights to persons beginning their careers.

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