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Context-Aware Computer Science Professional Skills Recommender System: A Taxonomy-Based Chatbot Approach

Edward N. Udo[1], Unwana I. Thomas[1], Okure U. Obot[1]

[1]*Department of Computer Science, University of Uyo, Uyo, Akwa Ibom State, Nigeria*

Abstract:
The development of a chatbot for context-aware professional skills recommendation in Computer Science (CS) addresses the need for personalized career guidance tailored to the dynamic nature of the field. The system employs advanced machine learning techniques, with Long Short-Term Memory (LSTM) models serving as the backbone for intent detection and context management. A structured taxonomy and knowledge base further enhance the system's ability to deliver precise recommendations, ensuring alignment with users' professional goals and skill needs. The implementation leverages the Flask Python web framework, chosen for its scalability, simplicity, and ability to support machine learning integration seamlessly. Key testing metrics showcase the chatbot's efficiency and accuracy, with a mean square error (MSE) of 2.042×10^{-6}, an absolute error deviation that peaks at 0.002, and an average response time of 47 milliseconds. These results demonstrate a high degree of precision and responsiveness, making the system suitable for real-time use. The chatbot's design incorporates a user-friendly interface to facilitate accessibility and ease of use for both students and professionals, ensuring widespread applicability. Feedback from participants during the evaluation phase was largely positive, with users commending the system's ability to generate relevant and context-aware recommendations. This chatbot contributes significantly to the domain of professional development tools, offering a robust solution for bridging the gap between users' aspirations and the skills required to achieve them. This work sets the foundation for further innovations in personalized learning technologies, particularly in areas requiring adaptive and context-aware capabilities.

Keywords: professional skills, conversational chatbot, context-ware, recommender system, LSTM, taxonomy, career path.

1. Introduction

The labour market is becoming increasingly complex and dynamic because employers of labour are looking for people with the requisite knowledge and skills that fit their organizational roles and goals while the job seekers are looking for jobs that match their skills. This introduces a challenge of identifying suitable matches [1].

Industry experts frequently express their belief that IT graduates are underprepared in terms of professional abilities and skills [2]. Today, the skills and competences of information technology practitioners are more crucial than ever. The requirements of the future may be very different from those of the present [3]. Future graduates must therefore be flexible, and the knowledge and abilities they gain must be dynamic and change-responsive. The continuous growth of IT jobs across various disciplines (e.g., cloud computing, cybersecurity, big data analytics) and the increasing reliance of companies on highly specialized IT professionals is making it difficult to choose an appropriate career in Information Technology [4].

The internet, because of its growth and universal access, has become a central market where training for acquisition of different skills are offered. As job seekers are assessed and ranked based on the skills they possess and how these skills relates to the competencies of the job requirements [5], the number of computing skills and people who are registering and undergoing trainings on these skills on the internet is increasing geometrically [6]. Selection of these computing skills becomes a huge problem especially when various factors including interest and certifications are involved. There is therefore an undisputable need to develop professional skills recommender system to guide people on the proper choice of skills relevant to their profession or the profession they may want to acquire skills in. The commencement of e-commerce in the early twentieth century paved way for the development of skills recommender system [7].

Skill recommendation system is a technology-driven solution aimed at suggesting relevant skills to individuals based on their discipline, area of interest, goals and their specific needs. Recommender system (RS) is among the leading system and tool available to users for the extraction of relevant information from the vast amount of data sources to help quicken the process of information seeking especially in this era of data exploration and utilization [8] and is capable of providing personalized recommendations by integrating user contextual information through analysis of the contextual parameters [9] or guiding the user towards interesting or useful resources within a large data space [10] based on the user preferences and try to predict which item is more appropriate to the users [11]. RS learn about a particular user by using existing data such as user profiles and their activities [12].

In recent times, job recommendation systems have gained popularity as useful tools for job to skill matching in the context of the labour market dynamics [13]. These recommendation systems make use of machine learning algorithms and data analytics techniques to give recommendations to employers using job seekers profiles, preferences and past behavior for enhanced efficiency of the overall hiring process [14].

In designing effective recommendation systems, several contextual factors that will impact on the choices of users, referred to as contexts [15] are considered along with the product and characteristics of the users. The term "context" does not have a general definition as it is applied in several areas of study such as data mining, mobile systems, marketing and management [16].

Context-aware system is a system or application that is capable of sensing, interpreting and responding to the users' environment, context or situation. Context aware computing enhances efficiency, engagement and experience by providing tailored responses that meet the users' circumstance. Context-aware recommendation system models and predicts users' preferences by explicitly adding new features of the data that represents available contextual information to the recommendation process. Recommendation systems that map content and available services to the preferences of users have grown and become very useful in domains ranging from e-commerce to online education [10] and also including computing, big data, Internet of Things, and information systems, due to the developments in ubiquitous computing and big data [17].

Chatbot development has grown; moving from basic rule-based systems to sophisticated natural language processing (NLP) models. Chatbots are now able to manage intricate discussions and offer individualized experiences. Chatbots are intelligent conversational computer programs that simulate natural human discourse and is capable of processing user inputs and generates result [18].

Students and graduates of Computer Science (CS) often struggle to map the academic knowledge acquired to professional skills demanded by the industries. Traditional tools and existing skills-gap recommender systems provide static lists or course recommendations, but ignore the facts that skill relevance depends on context like career goal, experience level and certification; and that users of these recommender systems prefer conversational, explainable guidance over dashboards.

While chatbot-based career tools exist, a taxonomy-based chatbot that recommends CS professional skills to graduates or those seeking to have certifications in computer related disciplines is lacking. This gap motivates the development of a context-aware CS professional skills recommender system that combines a taxonomy of CS skills (to enforce logical learning order), context modeling (to personalize user goals and preferences), and a chatbot (a retrieval-based system that uses Natural Language Processing for interactive and explainable recommendations). The system employs advanced machine learning techniques, with Long Short-Term Memory (LSTM) models serving as the backbone for intent detection and context management, to comprehend and adapt to user contexts, ensuring precise and tailored recommendations.

2. Related Works

Numerous studies have addressed and recognized the need for Information Technology graduates to develop their competencies [19, 20], and thorough examination of online job postings has revealed the evolving nature of these competencies. The emphasis is not on technical knowledge rather it is on individual skills and competencies [21]. There are also several works in literature that suggests relevant skills to individuals based on their specific needs, interests, and goals. [22] designed CaPaR (Career Path Recommendation) framework that analyzed user profiles and skills using text mining and collaborative filtering to provide career path and additional skill recommendations for related job vacancies.

[4] proposed a CareerRec, a machine learning-based recommendation system, to guide IT graduates in career selection based on their skills.

[23] adopted Artificial Neural Network technique to build a predictive model. Myers-Briggs Type Indicator (MBTI) physiological assessment test was used as a manual system to help users choose the best career. Data gathered from the MBTI categorization questionnaires were fed into the machine learning model to train the input traits in order to develop a better classification system. Confusion Matrix and K-Folds Cross Validation Methods were used to measure the performance of the model.

[24] presented machine learning-based course recommender that helped students in discovering relevant abilities and courses based on their previously taken courses, skills, and academic performance. The process of course recommendation began when a user accessed the URL and loaded the GUI. The users provided inputs based on preferences, the inputs were accepted and the course dataset was read from the backend server. Data filtration and collaborative filtering were applied to aid in the course recommendations.

[25] focused on the classification of learners into various groups based on their capabilities and interests using Naive Bayes, Support Vector Machine and Linear Regression algorithms to determine their learning style and recommended career choices that will best suit them. Naive Bayes Algorithm, which enabled data filtering using the Bayes Probability Theorem, was used to determine the degree of excellence in their recognized learning styles.

[26] developed the Skill Recommendation (SkillRec) system that recommended relevant job skills for a given job title by analyzing job descriptions and using word/sentence embedding techniques with a feed-forward neural network for job skill recommendations based on the job title representation.

[27] designed EduNexus, a system to give a cross-platform personalized recommendation on a course based on interest, set of skills and preferences using machine learning techniques including feature extraction, data mining and cosine similarity - comparing course contents in order to find similarities.

Some of these recommender systems look at only the job seekers interest and in the provision of generic jobs based on the users preferences (as indicated in their resume), without due consideration to their skills which will enhance their career growth.

Some other researches introduced the concept of context-awareness into their work, noting that context-awareness allows for a more organic conversational flow [28], as one stage is meaningless without reference to the others and a career path is inherently context-dependent.

[29] designed a context-aware recommender system that recommended undergraduate programs to students who have completed their high school based on their academic performance alongside other contextual factors like financial background, knowledge level, course of study and profession of interest and group. The context-aware recommender system used collaborative filtering and contextual modeling approach to design its predictive values for the various contextual factors. [5] proposed a context-aware sequence and token classification model to extract hard and soft skills from an applicant's curriculum vitae using representations from word embedding as features for Machine Learning classifiers. [30] created an intelligent chatbot to help job searchers with skill development and tailored recommendations using BERT model, SpaCy model and big language models.

The context-aware recommender systems available in literature focus purely on academic courses and not on CS professional skills recommendation. Moreso, no existing system combines taxonomy of CS skills/career path, context-aware personalization for professional goals, and chatbot user interface for interactive recommendation and explanation. This work combines these methodologies.

3. Methodology

The methodology for developing a chatbot for a context-aware computer science professional skills recommendation system is structured around data collection, preprocessing, model training, and chatbot integration.

3.1Data Collection

Information regarding top computing careers, required technical skills, specializations and certifications were gathered from industry databases, online job portals, and academic sources which were used to build taxonomies of career paths for five (5) computer science skills - Cyber Security, Artificial Intelligence, Software Engineering, Data Science and Internet of Things. The taxonomies were used to build the intent and response knowledge-base for the chatbot which were stored in json format. The dataset was represented as a lists data structure in order to manipulate the data elements and was converted to data frame before the preprocessing. Figure 3.1 is a preview of the dataframe.

```
Dataset Preview as DataFrame:
                                   Pattern Tokens         Intent
0                                         [hello]      greetings
1                                     [hi, there]      greetings
2                            [nice, to, meet, you]      greetings
3          [hi, ,, any, career, counsellor, here, ?]      greetings
4  [How, do, I, embark, on, cybersecurity, career]  Cybersecurity

Vocabulary Size: 73
Sample Vocabulary: [',', '.', 'analyst', 'and', 'any', 'architect', 'are', 'assurance', 'auditor', 'bye']
```

Figure 3 1 *Dataset Preview as Dataframe*

3.2Data Preprocessing

The data was preprocessed using the following Natural Language Processing (NLP) techniques:

Tokenization- Text and sequence of characters were broken into smaller units (individual words or characters) called tokens, to ensure that they were of uniform length. Text were encoded into numerical representations word embedding. These tokens are words, phrases, symbols and any other meaningful units based on the specific task at hand. For instance, the sentence "I need a career path in cybersecurity" was tokenized into ["I", "need", "a", "career", "path", "in", "cybersecurity"]. Vocabulary was defined to capture the semantic relationships between words. The Natural Language Toolkit (NLTK) Python Library was used to achieve this.

Lemmatization- Words were reduced to their base or root (lemma) so that different forms of inflected words can be normalized and treated as the same. For example, the words "run", "running", and "ran" would all be reduced to the lemma "run". Similarly, "goes", "going", and "went" would all be reduced to the lemma "go".

3.3Model Building

An LSTM-based model was employed to understand the user queries and generate skill recommendations based on context. LSTM, a type of Recurrent Neural Network (RNN) was chosen due to its ability to handle sequential dependencies in text, thereby enabling the chatbot to retain context and provide more relevant recommendations.

This model was implemented using Keras Python library, consisting of an input layer, an embedding layer, an LSTM layer, a Flatten layer, and a Dense (output) layer.

The input layer specified the shape of the input data to be received by the model. Embedding layer converted the integer indices (words) into dense vectors of fixed size. LSTM layer sequenced the tasks to be processed for the next layer. Flatten layer flattened the input data into a one-dimensional array while the Dense layer mapped the input data to the output data.

3.4Model Trainingand Testing

The Model was trained with Epoch, Loss, Accuracy and Adam Optimizer function using 75% of the labeled career path data, learning the relationships between user queries, skill requirements, and respective professional certifications. This was done by plotting a graph of Model Accuracy against Loss. 25% of the dataset was used for the model testing.

3.5Model Deployment

The trained LSTM model was integrated into a chatbot application using Flask Python Framework. The chatbot's interface was built with Django, a python web Framework, to allow real-time interaction with users. Finally, iterative testing and fine-tuning were performed to optimize response accuracy, ensuring that the chatbot effectively personalizes professional skill recommendations for users based on their background and career goals. The chatbot interface prototype design is shown in Figure 3.2

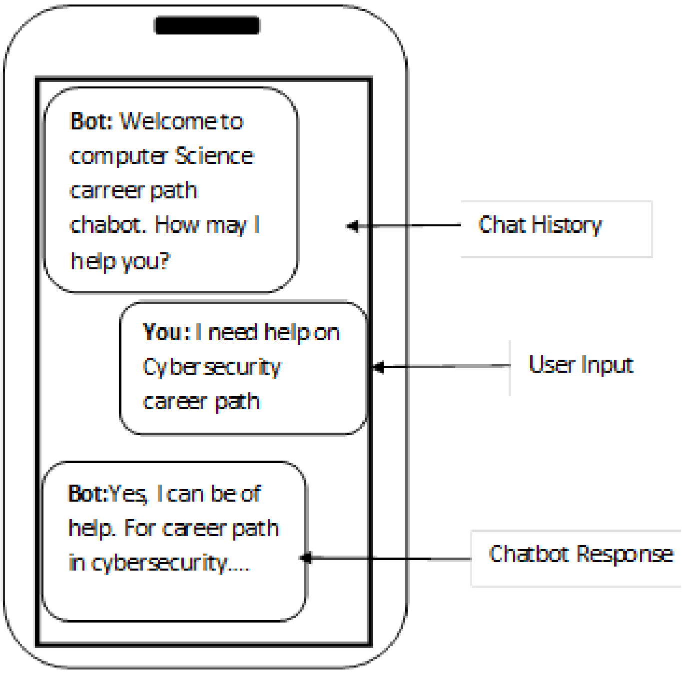

Figure 3 2 *Chatbot Interface Prototype Design*

3.6QuestionnaireDesign

To create a realistic and representative dataset for training the chatbot, questionnaires were carefully designed to capture typical queries and expressions from four (4) target groups: Non-IT Professionals, IT Professionals, Secondary School Students and University Computer Science Students. The questions for each of the group reflected the language and technical knowledge typical for the group. A total of 30 responses were collected from each group, giving a total of 120 sample data; ensuring a balanced dataset that captures both simple and complex intents. Figure 3.3 - 3.6 shows selected responses from each target group and their associated plots.

(a)Non-IT Professionals

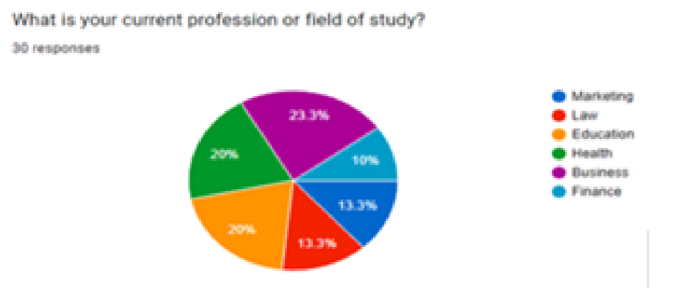

Figure 3 3 A *Response to Question 1*

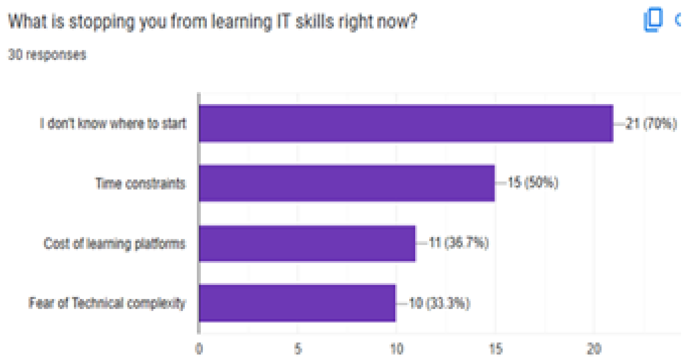

Figure 3 3 B *Response to Question 5*

(b)IT Professionals

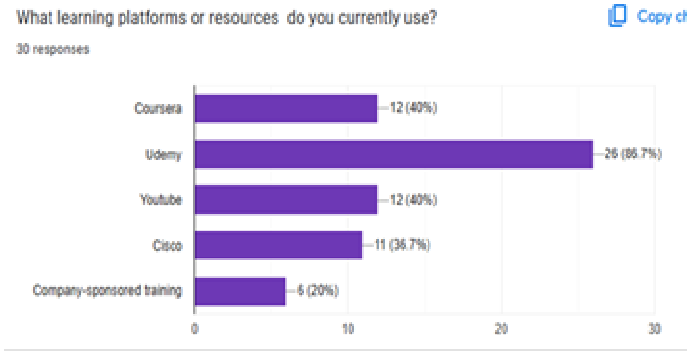

Figure 3. 4 A *Response to Question 10*

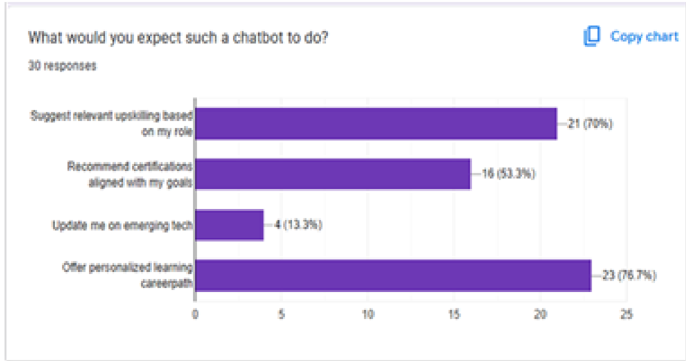

Figure 3 .4 B *Response to Question 12*

(c)Secondary School Students

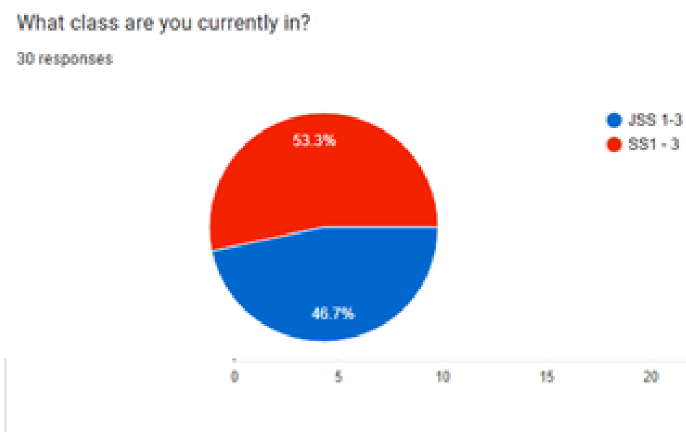

Figure 3. 5 A *Response to Question 12*

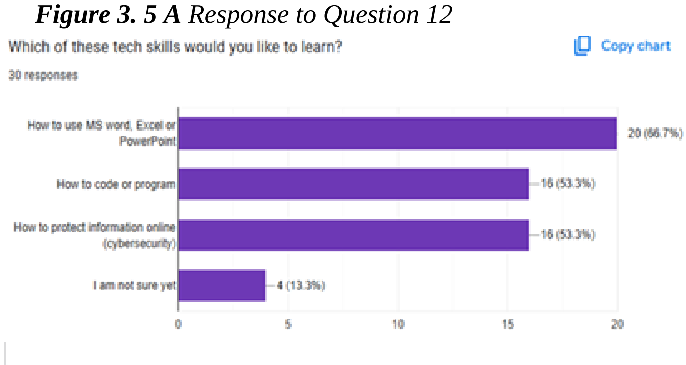

Figure 3 .5 B *Response to Question 16*

(d) University Computer Science Student

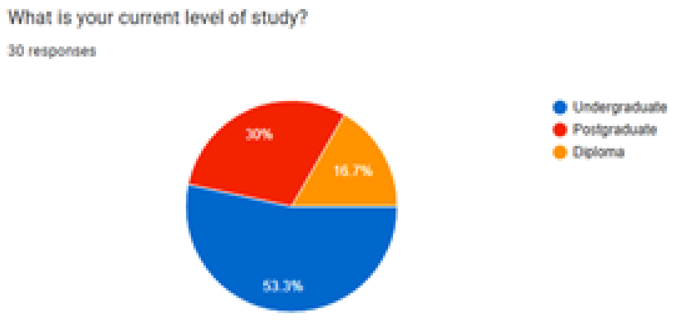

***Figure 3. 6 A** Response to Question 18*

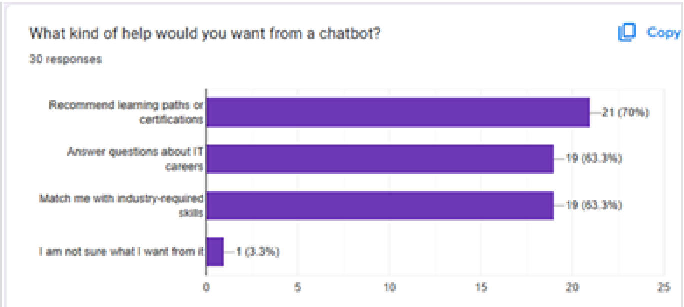

***Figure 3 .6 B** Response to Question 22*

The responses from the questionnaires were preprocessed, labeled, and organized into training and testing datasets. This approach ensured that the chatbot learned from real user input patterns and vocabulary unique to each group. The diversity in language style and technical terminology among groups posed challenges but was necessary for building a robust model that can generalize well.

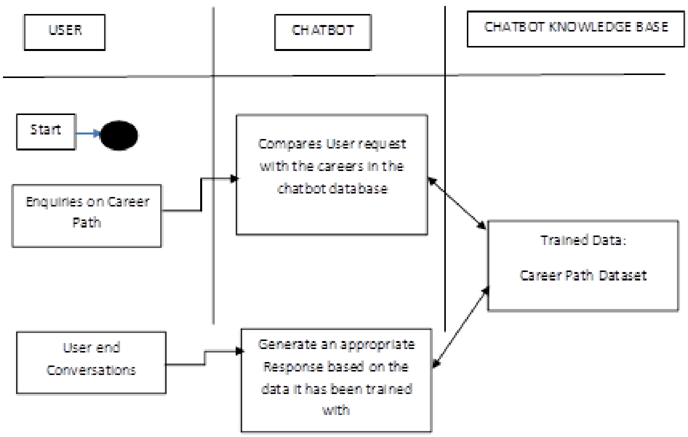

***Figure 3 7** Response to Question 22*

4. Results

The performance of the model was evaluated using accuracy, precision, recall and F1-Score metrics. Precision-recall curves (PRC), shown in Figure 3.8 were plotted for each of the target groups to analyze the trade-off between precision and recall across different classification thresholds. This graphical representation offers deeper insight into how the model behaves beyond a fixed threshold, highlighting strengths and weaknesses in detecting user intents.

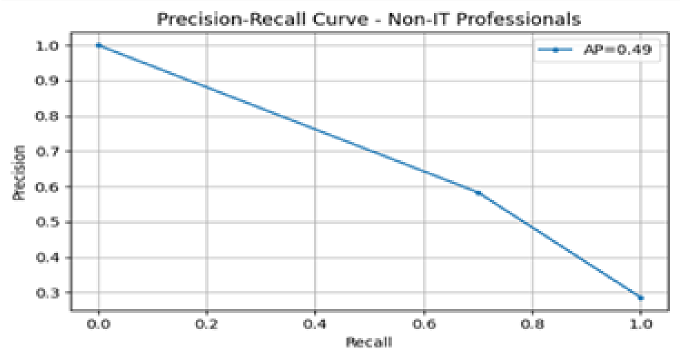

***Figure 3. 8 A** PRC plot for Non-IT group*

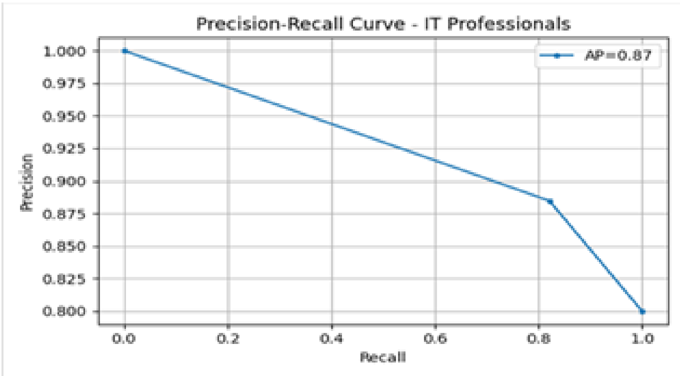

***Figure 3 .8 B** PRC plot for IT group*

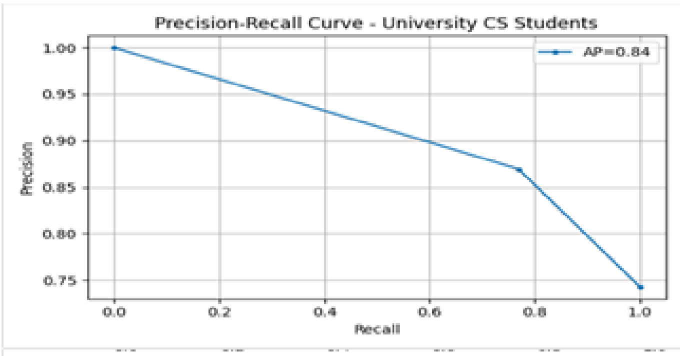

***Figure 3. 8 C** PRC plot for CS Students*

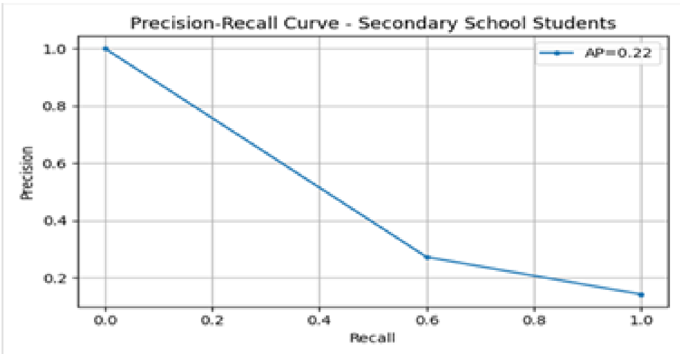

***Figure 3. 8 D** PRC plot for SS Students*

The PRC plots provided the following insights:

IT Professionals and University Computer Science Students curves showed high precision across a wide range of recall, indicating consistent performance.

The curve for Secondary School Students dips steeply, illustrating challenges in maintaining precision when recall improves.

Non-IT Professionals curve showed moderate balance but with some trade-offs.

Variations in precision and recall reflect differences in language familiarity, query complexity, and contextual understanding.

Table 4.1 shows the summary of the performance metrics for each target group using the confusion matrix (CM) analysis shown in Figure 3.9a - 3.9d.

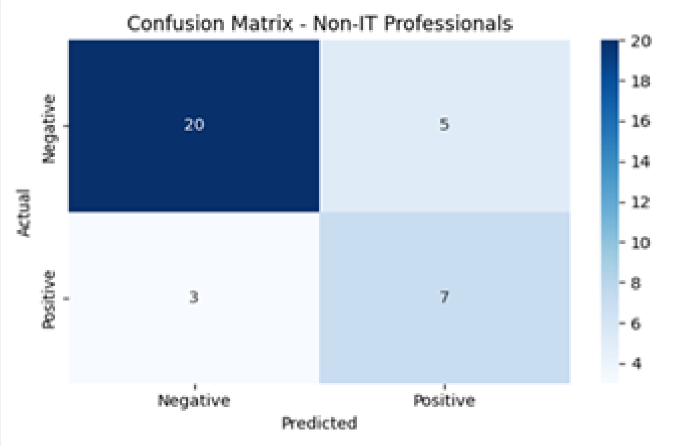

Figure 3 .9 A *CM for Non IT Group*

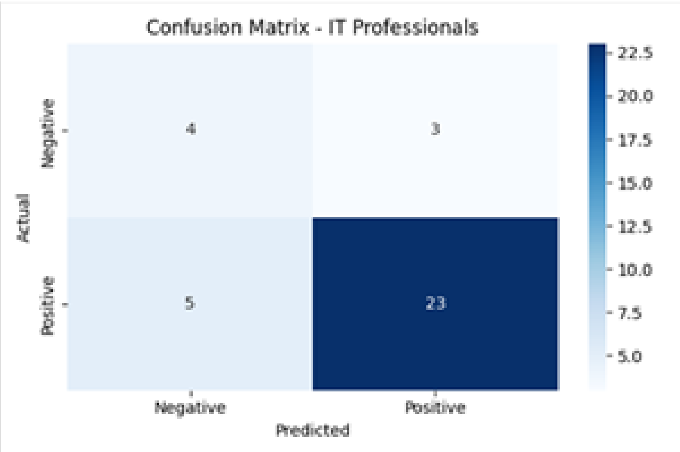

Figure 3 .9 B *CM for IT Professionals*

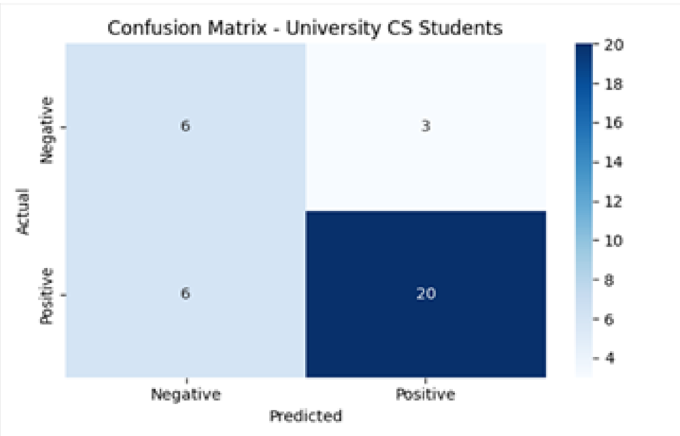

Figure 3. 9 C *CM for University CS Students*

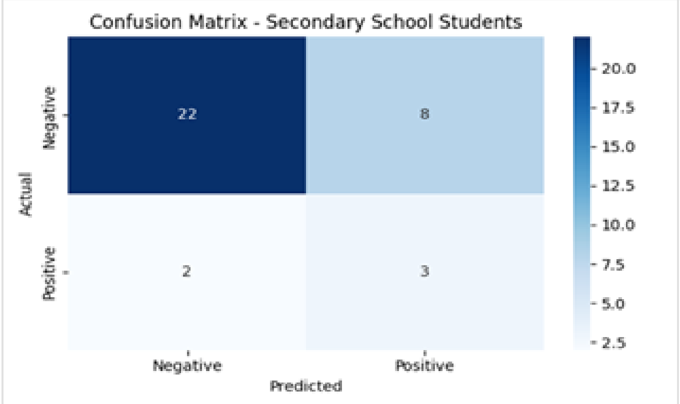

Figure 3 .9 D *CM for Secondary School Students*

Table 4.1 Summary of Confusion Matrix Performance for each Group

User Group	Accuracy	Precision	Recall	F1-Score
Non-IT Professionals	0.77	0.58	0.70	0.64
IT Professionals	0.77	0.88	0.82	0.85
Secondary School Students	0.71	0.27	0.60	0.38
University CS Students	0.74	0.87	0.77	0.82

The group-wise result in Table 4.1 shows that the chatbot demonstrates particularly strong performance in technically aligned user groups, while revealing notable gaps in generalization to less technical audiences.

For IT professionals, the model achieved 77% accuracy, with high precision (88%), recall (82%), and an F1-score of 85%, indicating a well-balanced ability to correctly classify both positive and negative intents. Similarly, University Computer Science students yielded a high F1-score of 82% and an overall accuracy of 74%, suggesting that users with domain familiarity interact more effectively with the system's language model and intent structure.

By contrast, non-IT professionals, though achieving 77% accuracy, experienced a sharp drop in precision (58%) and F1-score (64%**)**, indicating a higher incidence of false positives. This reflects some mismatch between user phrasing and the model's trained vocabulary, which is more tuned to technical terminology.

The lowest performance was observed among secondary school students, with precision at 27% and an F1-score of 38%, despite a 71% accuracy rate. This discrepancy suggests the model struggled to generalize to queries with simpler or more informal language, often misclassifying intent. The confusion matrix results for this group highlighted a higher number of false positives and false negatives, indicating that additional training data or rephrasing support may be necessary for improved performance.

The accuracy of the chatbot model was measured by comparing the accuracy it provided against a predefined training epoch and its loss analysis. The chatbot LSTM model achieved an accuracy rate of 89%, as shown in Figure 3.9, indicating a high level of precision in identifying the appropriate skills for various user contexts. Figure 3.10 shows the model accuracy over loss.

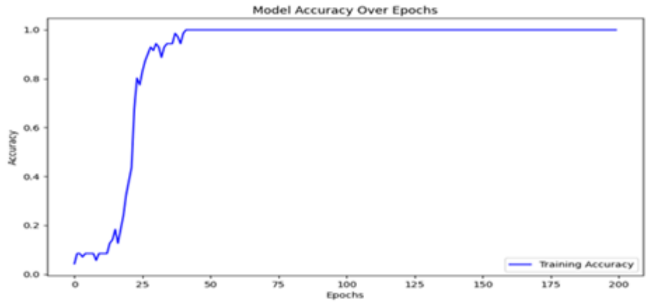

Figure 3 .10 *Model Accuracy over Epochs*

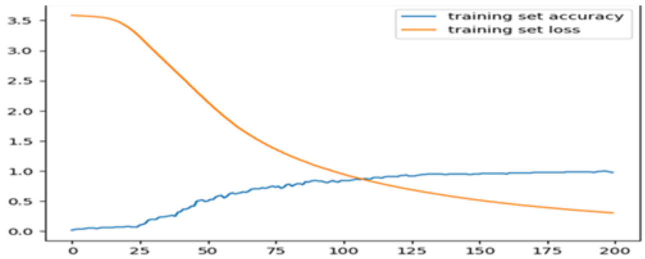

Figure 3 11 *Model Accuracy over Loss*

4.1ErrorAnalysis

The Mean Squared Error (MSE) of 2.042759919236951e-06 was gotten from the training set. The value indicated that the model's predictions were very close to the actual labels in the training data. The absolute error plot displayed in Figure 3.11 provides a visual way to assess the consistency of the model's performance. An absolute error of 0.002 suggests that the deviation between the predicted and actual value for the 70th sample is minimal. Therefore the model performed well since the error was closer to the lower end of the error range.

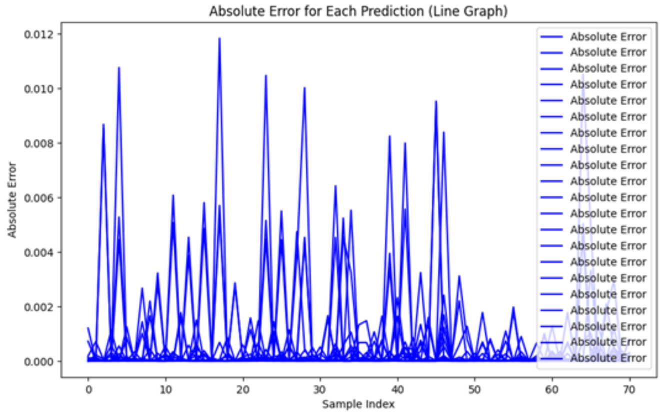

Figure 3 .12 *Model's Absolute Error*

5. Conclusion

The Development of a chatbot for context-aware computer science professional skills recommendation systemhas proven to be a valuable tool in enhancing career development processes. By leveraging machine learning and NLP, the system can provide personalized and contextually relevant advice to users, thereby bridging the gap between their current skill sets and their career goals. The chatbot's ability to process natural language inputs and provide intelligent recommendations makes it a significant improvement over traditional, static career guidance systems. The successful implementation and testing of this system demonstrate its potential to be a useful resource for individuals seeking to advance their professional skills.-

For future improvements, it is recommended that the chatbot be integrated with a broader range of data sources to increase the accuracy and relevance of its recommendations. Incorporating real-time labor market information and expanding the chatbot's database of skills and career paths could further enhance its utility. Additionally, continuous updates and refinements to the machine learning models used in the system are suggested to ensure that the chatbot remains current with evolving industry standards and user expectations. Finally, exploring the deployment of the chatbot across multiple platforms, including mobile applications, could increase its accessibility and impact on a wider audience.

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