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A Pathbreaking Analyzer for Higher Education

HEZER

[1]Kusal Ekanayaka, [2]Dimindu Ranasighe, [3]Moditha Punchihewa, [4]Shehan Jayasinghe, [5]Buddhima Attanayaka, [6]Hasrangi Withanage

[1,2,3,4,5,6]Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Abstract - **HEZER, a ground-breaking analyzer for higher education that aims to improve the decision-making process for people starting their educational journeys. The developed system makes use of web scraping techniques and cutting-edge machine learning algorithms to deliver individualized recommendations, with an emphasis on solving issues like limited advice, financial limits, career possibilities, and limited options. Students are helped in choosing their ideal degree programs by insightful opinions from both newcomers and professionals in the sector that have been gathered through surveys and questionnaires. HEZER includes a full range of functionality, such as budget planning, financial estimation, career analysis, and loan payback predictions. It is powered by cutting-edge technologies like React.js, Python, and machine learning methods like Random Forest Regression. It allows students to arrange their finances effectively by allowing them to predict future course prices. Carefully crafted research components offer individualized recommendations, financial advice, and perceptive analysis of commercial potential connected to chosen projects. The system's accuracy and dependability have been confirmed through meticulous integration and testing. HEZER establishes a new benchmark for customized recommendation systems in higher education, providing students with crucial tools to negotiate the challenging environment and make well- informed decisions. choices, ultimately leading to successful and fulfilling careers.**

Keywords: Higher education, Analyzer, Decision-making, Personalized recommendations, Machine learning algorithms.

I. INTRODUCTION

The importance of higher education in determining one's profession and chances for the future cannot be overstated. The process of choosing the best educational program, however, can be intimidating because students frequently face difficulties like insufficient guidance, budgetary limitations, unknown career prospects, and a large range of possibilities to pick from [1]. A new analyzer called HEZER has been created to solve these issues and aid young people in making wise selections.

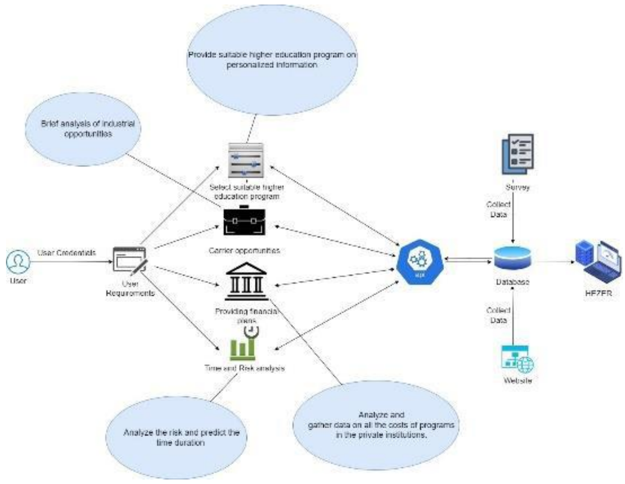

Figure 1: Overall System Diagram

HEZER represents a huge improvement in how students make decisions as they begin their educational journey. This analyzer offers a tailored and data-driven method to identify the most suitable higher education programs based on individual requirements and interests by utilizing cutting-edge technologies, such as web scraping and machine learning algorithms [2]. To guarantee the precision and dependability of the recommendations, important insights from surveys and questionnaires given to newcomers and members of the sector are included. These observations offer essential details about individual preferences and experiences while choosing degree programs, allowing the analyst to deliver thorough and personalized suggestions that take needs and goals into account [3]. This system's implementation incorporates cutting-edge tools like React.js and Python along with artificial intelligence techniques like Random Forest Regression. These technological advancements enable the system to offer a few features that aid students in their academic endeavors. A more comprehensive decision-making process is facilitated by notable elements like budget planning, financial estimation, career analysis, and loan repayment projections [4]. Financial restrictions are one of the main worries for students pursuing higher education. This worry is allayed by the system's incorporation of the capability to forecast course expenses, which enables students to wisely plan their financial obligations [5]. The analyzer helps students to make wise decisions about their future occupations

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by revealing potential career pathways and corresponding industry prospects [6]. Through integration and testing procedures, the system's effectiveness and dependability have undergone thorough validation. This verification guarantees the accuracy and dependability of the analyzer's personalized advice and recommendations. The system raises the bar for decision-making support in higher education and as a result, giving students the skills, they need to successfully negotiate the challenges of the higher education landscape [7]. This study seeks to provide a thorough description of the system's implementation and evaluation. The system's technical details, including the use of web scraping methods, machine learning algorithms, and cutting-edge technology, will be thoroughly examined. In addition, the approach taken to gather opinions from experts in the field and beginners will be covered, emphasizing the system's full features and advantages such financial planning, career analysis, and loan repayment projections [8]. The goal of this research is to show the system's effectiveness and potential for directing students toward rewarding occupations. Technology helps to improve the entire higher education experience and gives people the power to make wise decisions about their educational path by offering individualized recommendations and addressing the issues they face [9]. An important step forward in resolving the difficulties students confront while making decisions is the creation of an inventive analyzer for higher education. By utilizing cutting-edge technologies, combining insightful information, and providing customized recommendations, this analyzer equips students to successfully negotiate the intricacies of the higher education scene. With the help of this research paper, you will gain a thorough grasp of how this cutting-edge system was put into use and evaluated, as well as information on its technical components, evaluation process, and extensive features. It seeks to illustrate the exceptional effectiveness and potential of this method in directing students toward successful and fulfilling careers through thorough study and review. This research helps to shape a future in which students may genuinely prosper and realize their full potential by improving the whole experience of higher education and giving people the resources, they need to make educated decisions about their educational journey.

II. LITERATURE REVIEW

Higher education's environment is continually changing, and more and more students are looking for assistance to choose their course of study wisely. When it comes to meeting the various demands and difficulties that students experience, traditional approaches to advising and decision-making frequently fall short. Personalized recommendation systems, web scraping methods, machine learning algorithms, and technologies like React.js and Python, which serve as the basis of HEZER, a ground-breaking higher education analyzer, will all be covered in this literature study.

A) Providing the Most Suitable Higher Education Program based on Personalized Information

To help students choose the best academic programs based on their unique preferences and interests, personalized recommendation systems have become an important topic of research in the field of higher education. Such systems have been developed and are effective because of numerous studies that use a variety of strategies and techniques. A personalized recommendation system for higher education that makes use of collaborative filtering approaches was put forth by Li and Ye [10]. The technology developed individualized program choices by examining student profiles and course data, considering elements like academic background, interests, and professional objectives. This strategy showed how collaborative filtering may be used to provide students personalized recommendations. A content-based recommendation system using machine learning techniques was introduced by Guruge and Kadel [11]. The system examined program descriptions, curriculum information, and course materials to match students' interests, talents, and professional objectives with pertinent degree programs. This content-based strategy worked well at matching the preferences of the students with the right program alternatives. Liu et al. [12] investigated the integration of recommendation algorithms with students' social connections and interests by including social network analysis into the recommendation process. The method tailored recommendations for higher education programs to individuals' social and professional networks by considering connections with classmates, academic groups, and business professionals.

A hybrid recommendation system was created by Wu et al. [13] by fusing collaborative filtering and content-based techniques. In this method, collaborative filtering was used to record user preferences and content-based analysis was used to suggest programs based on similarities in requirements and course material. The recommendation of appropriate higher education programs used the hybrid technique, which showed better accuracy and coverage. Samin and Azim [14] suggested a knowledge-based recommendation system that makes use of knowledge graphs and semantic analysis. The system suggested higher education programs that matched individuals' interests, job objectives, and knowledge areas by pulling information from numerous sources, including academic databases and career resources. A hybrid recommendation system that integrated deep learning and collaborative filtering techniques was introduced by Obeid and Lahoud [15]. To uncover complex patterns and relationships from many data sources, the system used deep learning models in conjunction

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with collaborative filtering to gather user preferences. For college students, this hybrid strategy produced precise and individualized program suggestions. Hurana's system for context-aware suggestions [16] took location and time into account among other contextual factors. Contextual considerations were incorporated into the recommendation process so that the system could deliver individualized program choices that were catered to needs and circumstances. Through the application of user preference modeling approaches, Mcginity [17] created a preference-based recommendation system. To develop personalized profiles and suggest the most appropriate higher education programs in accordance, the system examined users' prior experiences, preferences, and feedback. This preference-based strategy proved successful at addressing unique needs and preferences. These works use a range of strategies to develop personalized recommendation systems for higher education, including collaborative filtering, content-based analysis, social network analysis, hybrid models, knowledge-based approaches, deep learning, and context awareness. By combining and leveraging these advancements, the HEZER analyzer aims to provide a cutting-edge method for recommending the finest higher education programs based on personalized information.

B) Most Convenient and Affordable Financial Plan after Analyzing User's Information

One of the biggest concerns for students is their inability to afford higher education. Researchers have focused on developing systems that evaluate users' performance to overcome these concerns financial data and offer personalized financial plans. Brobi and Pillai [18] created a financial planning system for higher education that uses machine learning algorithms to forecast tuition costs, living costs, and potential scholarships to give students individualized financial plans. The system considered factors including family income, academic achievements, and chosen programs to provide students with straightforward and affordable financing options. Epple and Romano [19] developed a financial assessment model using data mining techniques that helps students to evaluate the cost of their chosen programs and construct effective financial plans. The system analyzed historical financial data, including tuition costs, accommodation costs, and other expenses, to provide accurate predictions and aid students in making informed financial planning decisions. Harnisch [20] provided a method for predicting the length of loan repayments based on individual financial situations by using past loan data and machine learning algorithms. By taking into account factors including income levels, loan amounts, and interest rates, the system provided personalized insights into loan payback plans, enabling students to better manage their finances.

Barr and McClellan [21] developed a budgeting and financial management system for college students. The system combines financial data, such as income, expenses, and savings goals, to give personalized financial plans and recommendations. Students might keep track of their spending, set objectives for their budgets, and get real-time feedback on their financial condition in order to promote good financial habits. A crowdsourcing-based financial planning system was presented by Hamadi et al. [22] to gather and analyze financial data from various sources. The system gathered information on opportunities for part-time employment, scholarships, grants, and money-saving strategies, providing students with complete and up-to-date financial planning options. Fakeeh et al. [23] developed a decision support system for the management of financial aid in higher education. To ensure that students received the most suitable and affordable financial aid, the system developed tailored financial aid packages that maximized the allocation of grants, loans, and scholarships. It accomplished this by incorporating institutional policies, financial assistance rules, and student profiles. Durband and Britt [24] devised a technique to help college students become more financially literate. The system included interactive modules, instructional resources, and financial planning tools to improve students' understanding of financial concepts and promote responsible financial decision-making. Parker [25] recommended a system for assessing financial risk for college students. By analyzing financial information including income, expenses, and credit history, the system identified potential financial risks and then provided individualized recommendations to lower those risks. This proactive strategy aimed to protect students from monetary issues and ensure a positive academic experience.

Numerous studies have been conducted on personalized recommendation systems for higher education and financial planning to meet the challenges faced by students along their educational journey. This study has demonstrated the effectiveness of numerous techniques, including collaborative.

Personalized program recommendations and useful financial advice are delivered using filtering, content-based analysis, social network analysis, and machine learning algorithms. By fusing the strength of personalized information analysis with careful financial planning, the HEZER analyzer intends to take advantage of these advancements and provide students with the knowledge they need to make informed decisions about their higher education. HEZER's cutting-edge features and capabilities are designed to enhance the entire higher education experience, paving the way for prosperous and fulfilling careers by guiding students toward the most suitable programs and relieving their financial concerns. a succinct analysis of the industrial opportunities linked to certain programs.

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Understanding how commercial opportunities and career prospects relate to courses is crucial for students. Numerous studies have looked at and made recommendations for industrial prospects. Seo and Hong [26] proposed an industrial analysis system that gathered information on the sector from online sources using text mining techniques. By monitoring job postings, professional networks, and trade periodicals, the system provided insights regarding the labor market and employment opportunities related to curricula. Students were able to choose their educational pathways with the aid of this technique based on how well their interests matched up with market demands. Bulbul et al. developed a machine learning-based career analysis system. to evaluate business trends [27]. The algorithm used detailed data on industry growth, job market trends, and skill needs to select programs that were in line with projected job demands. The approach helped students make well-informed decisions about their educational path by considering factors including growing industries, in-demand positions, and anticipated growth areas.

Duggirala introduced a big data analytics and natural language processing-based, industry-driven program recommendation system. [28]. The strategy compared industry demands with students' interests, abilities, and career ambitions in order to provide personalized recommendations for higher education programs. This tactic aimed to bridge the gap between industrial needs and educational possibilities by letting students select curriculum that fit those needs. Aljohani and Aslam [29] recommended utilizing a data-driven technique that mined and evaluated comprehensive employment market data to assess industry potential. The system used machine learning techniques to identify new markets, desirable skills, and career trajectories. The strategy gave students in-depth knowledge of industry trends and opportunities, enabling them to choose courses that would enhance their employability and prospects. Kim et al. [30] developed an industry-specific recommendation system employing collaborative filtering techniques. By analyzing students' preferences, courses relevant to the industry, and career paths of graduates, the algorithm proposed courses that would equip students with the knowledge and abilities needed for various professions. This industry-focused strategy's objective was to increase students' marketability.

A paradigm for industrial opportunity analysis that combines social network analysis and machine learning methods was suggested by Lam et al. [31]. The method discovered industry trends, job placement rates, and alumni success stories by considering the links between educational institutions, industry professionals, and alumni networks. With the help of this thorough study, students were able to make well-informed choices by considering the potential career paths linked with various curricula.

Brockmann and Clarke [32] knowledge-based system, which recommends programs based on business potential, makes use of ontologies and semantic analysis. The system suggested programs that matched students' career objectives and the needs of businesses by obtaining and evaluating industry-related knowledge from various sources, such as job advertisements, company profiles, and professional networks. An industry-focused program recommendation system that makes use of data mining techniques was put out by Massaro et al. [33]. To provide insights into the industrial prospects connected with various programs, the system examined industry-related data, including job descriptions, skill requirements, and industry reports. Students were able to match their educational choices to the job trajectories and growth industries that interested them thanks to this method. These studies offer insightful information about market dynamics, skill requirements, and industry trends by utilizing diverse techniques like text mining, machine learning, social network analysis, and big data analytics. By combining these strategies, the HEZER analyzer intends to give students a thorough study of the industrial opportunities connected to programs, enabling them to make educated decisions about their educational and professional routes.

C) Implementation of a System that Analyzes Risk and Predicts Time Durations

Analyzing the risk factors associated with educational programs and estimating the length of time needed to complete them have drawn a lot of interest in the research literature. To address these issues, academics have suggested several models and approaches: Salihoun et al.'s [34] risk analysis framework used statistical models and data mining approaches to evaluate the hazards related to various educational programs. The framework considered elements including entrance standards, the difficulty of the curriculum, and employment prospects to give pupils a thorough awareness of the potential hazards involved. This methodology gave students the tools they needed to choose their programs wisely by using data-driven analysis. A time duration prediction model was created using machine learning techniques and historical data in a study by Suhaimi and Rahman [35]. This model sought to predict the length of time needed to complete a program based on a variety of variables, such as course load, academic performance, and student characteristics. The program produced precise forecasts by utilizing machine learning, assisting students in efficiently organizing their academic future.

The Analytic Hierarchy Process (AHP) was used by Divjaket al. [36] to offer a framework for risk assessment and decision-making for higher education programs. To evaluate the risks related to various programs, the framework included

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several variables, including program repute, career prospects, and financial concerns. This framework provided a systematic method for assessing risks and assisting students in their decision-making process by utilizing AHP. A deep learning-based methodology was used in another work by Christou and Tsoulos [37] to forecast the length of higher education programs. Intricate patterns and linkages within historical data, including student profiles, course information, and academic achievement, were captured by the model using a deep neural network. This model accurately predicted time durations by utilizing deep learning, which helps students efficiently organize their instructional timelines. Research on risk analysis of college education programs utilizing grey relational analysis was done by Shen et al. [38]. To assess the risks related to various educational programs, the study considered a few risk indicators, such as infrastructure, program accreditation, and the qualifications of the teachers. Students and decision-makers benefited greatly from the complete risk assessment made possible by the grey relational analysis technique.

Based on a variety of characteristics, including curriculum design, faculty qualifications, and industry relevance, Asilturk and Cunkas [39] concentrated on risk analysis of educational programs. Their investigation used a thorough methodology that combined qualitative and quantitative analyses to analyze the hazards related to various projects. The framework provided a comprehensive view of risk analysis, boosting students' comprehension of the advantages and potential drawbacks of various educational initiatives. Fuzzy logic and decision trees were combined in the risk evaluation model Oqaidi et al. [40] suggested for higher education programs. To determine the overall risk level associated with various programs, the model considered several risk characteristics, including program popularity, employment rates, and alumni happiness. The model provides a systematic and understandable method to risk analysis, assisting students in their decision-making process using fuzzy logic and decision trees. Wang et al. presented a risk assessment methodology built on Bayesian networks to further improve risk analysis in higher education programs. To analyze the risks related to various programs, the framework included a variety of risk indicators, such as academic performance, financial factors, and program repute. This framework presented a probabilistic approach to risk analysis by utilizing Bayesian networks, allowing students to assess and compare the hazards of various educational programs. These studies show the various strategies and models created for the application of systems that assess risk and forecast the length of time needed for educational programs. Researchers have significantly aided students in their decision-making process and assisted them in navigating the intricacies of higher education by using data mining techniques, statistical models, machine learning algorithms, and other cutting-edge technologies. The purpose of implementing such technologies, like the HEZER analyzer, is to give students insightful information so they may make educated decisions about their academic careers.

III. METHODOLOGY

The methodology section describes the strategy and methods used in creating the HEZER analyzer, a system created to make suggestions for customized higher education programs based on data about individual students. In this section, the methodology's many steps - including data collecting, data preprocessing, feature extraction, the creation of a tailored recommendation algorithm, and the evaluation metrics used to gauge the system's efficacy—are described in depth. The HEZER analyzer seeks to match students with the best higher education programs based on their academic background, interests, career objectives, and preferences by employing this methodology. To ensure transparency and reproducibility in the creation of the HEZER analyzer, the methodology section offers a thorough knowledge of the procedures and methods used to accomplish this objective.

A) To Provide the Most Suitable Higher Education Program based on Personalized Information

1) Data Collection: A detailed data gathering procedure was created to compile pertinent information from students, including their academic history, interests, professional objectives, and preferences, in order to deliver individualized higher education program suggestions. The algorithm was able to provide customized recommendations by gaining a thorough grasp of each student's individual profile and requirements thanks to this detailed information. Surveys, questionnaires, and student profiles were used in conjunction with one another during the data gathering procedure to gather the required information. In order to collect particular information about the students' educational history, such as their academic accomplishments, standardized test scores, and extracurricular activities, surveys and questionnaires were meticulously created. These tools also sought to learn more about the students' interests, objectives for their careers, and preferred academic specializations. Students were also able to share further information or insights into their personal preferences and objectives by responding to open-ended questions. Student profiles were used to supplement the surveys and questionnaires and improve the data collection process. These profiles included relevant details including academic credentials, recommendation letters, and personal statements. The system may gain insightful knowledge about the students' academic performance, expertise areas, and personal characteristics by accessing these profiles, thus

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enhancing the dataset. Careful measures were taken to safeguard the data's confidentiality and privacy to guarantee the data's accuracy and dependability. To protect the students' information, strict data protection procedures were put in place while following all applicable privacy laws and ethical guidelines. The collecting of data was done in the strictest of confidence, with the students given thorough explanations of its use and purpose before their informed consent was obtained.

2) Data Preprocessing: To assure quality and consistency, a rigorous preprocessing step was taken with the collected data. Data cleaning techniques were used to eliminate inconsistencies, mistakes, and outliers. Data normalization was done to standardize all of the data's features, and the right imputation techniques were used to fill in any missing values.

3) Feature Extraction: From the preprocessed data, significant features that were pertinent to program selection were extracted using a variety of methodologies. GPA and results on standardized tests were seen as important measures of academic accomplishment. The identification and extraction of skills, credentials, personality traits, and interests. To identify the most important qualities, feature engineering approaches including dimensionality reduction and text mining were used.

4) Evaluation Metrics: Evaluation metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were used to evaluate the efficiency and accuracy of the personalized recommendation system. These measures evaluated the model's prediction errors, enabling a thorough assessment of how well it recommended the best higher education options. The HEZER analyzer was able to successfully deliver individualized suggestions for higher education programs based on data about specific students using this methodology. The development of an efficient system that matched students with the best educational programs based on their personalized information was made possible by the data collection, preprocessing, feature extraction, personalized recommendation algorithm using the Random Forest Regressor model, and evaluation metrics.

B) To propose the Most Convenient and Affordable Financial Plan after Analyzing User's Information

1) Financial Data Collection: Students' pertinent financial data was gathered in order to offer customized and reasonable financial plans. This comprised information on their earnings, savings, spending, and any prospective financial aid or scholarships for which they might qualify. Each student's complete financial information was gathered using surveys, financial questionnaires, and documents.

2) Financial Analysis: To determine the overall cost of the chosen higher education programs, the obtained financial data underwent careful investigation. This analysis took into account a number of financial factors, including tuition costs, living expenditures, costs for books and supplies, transportation, and other incidental expenses. Accurate estimates for the various cost components were obtained using historical data and industry benchmarks.

3) Financial Planning Algorithm: Based on the student's financial data and the anticipated program fees, an algorithm was created to suggest customized and practical financial strategies. The association between the student's financial characteristics and the program costs was modeled using both linear regression and random forest techniques. These algorithms forecast each student's financial needs based on pertinent traits and historical financial data.

4) Affordability Assessment: Detailed analysis was done to determine whether the suggested financial options were affordable. The student's financial situation, loan possibilities, and future repayment periods were all taken into consideration throughout this evaluation. The recommended plans' suitability for the student's budget and alignment with their financial objectives were assessed using financial ratios and indicators as part of the affordability analysis. The length and viability of loan payback choices were estimated using loan repayment prediction models. .By employing this concept, the HEZER analyzer sought to provide individuals pursuing higher education with individualized financial plans that were both practical and reasonable. The development of a system that offered students customized financial plans to assist their educational journey required the collecting of financial data, its analysis, the deployment of a financial planning algorithm, and an affordability evaluation.

C) Brief Analysis of Industrial Opportunities Associated with Selected Programs

1) Industry Data Collection: Relevant industry-related data was gathered in order to provide insights into the industrial potential linked to selected initiatives. This involved compiling data on employment trends, employment rates, new industrial developments, and market demands. To compile thorough industry data, sources including internet job boards, industry reports, governmental databases, and professional networks were used.

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```python
# Example data for testing
new_data = {

    'University': ['SLIIT'],
    'Specialization': ['Cyber Security'],
    'Employability': ['Associate'],
    'Job_Role': ['System Architects']
}

new_data['University_encoded'] = map_jason('university_mapping.json',new_data['University'][0])
new_data['Specialization_encoded'] = map_jason('specialization_mapping.json',new_data['Specialization'][0])
new_data['Employability_encoded'] = map_jason('employability_mapping.json',new_data['Employability'][0])
new_data['Job_Role_encoded'] = map_jason('job_role_mapping.json',new_data['Job_Role'][0])

new_data = pd.DataFrame(new_data)
```

Figure 2: Industrial Data Testing

2) Text Mining and Analysis: Utilizing text mining techniques, useful information was extracted from the data collected about the industry. Online sources such as job ads, industry reports, and information retrieval methods were examined using natural language processing algorithms. This required locating important phrases, concepts particular to the industry, and competencies related to various programs.

3) Industry Mapping: Based on their curriculum, skill requirements, and potential career routes, the chosen programs were mapped to certain industries. This involves identifying the industries where graduates of each program might be able to find employment by examining the program syllabi, course descriptions, and learning outcomes. In order to help students comprehend the market landscape and how their chosen program aligns with future job options, a mapping method was used.

```python
# function for save mappings to json file
def create_json_file(file_name, encoded_list, pure_list):
    mapping ={}
    for i in range(len(encoded_list)):
      if pure_list[i] not in mapping:
        try:
          mapping[pure_list[i]] = int(encoded_list[i])
```

Figure 3: Industry Mapping Function to Json

4) Career Opportunity Analysis: To determine the prospective job chances and growth prospects connected to each chosen curriculum, the gathered industry data underwent examination. This investigation includes finding patterns and correlations between program properties and market demands using machine learning methods, in particular the random forest approach. The association between program characteristics, such as courses, talents, and certificates, and the accompanying employment options was modeled using the random forest algorithm. Students benefited greatly from this study' insights regarding the labor market and possible career paths related to their chosen programs. The HEZER analyzer sought to give a thorough study of industrial opportunities linked to particular higher education degrees by using this methodology. The collecting of industry data, text mining and analysis, industry mapping, and analysis of job opportunities were essential steps in providing students with important information so they could choose their programs and career routes wisely.

D) Implementation of a System that Analyzes Risk and Predicts Time Durations

1) Risk Factors Identification: Key risk criteria were identified to create a system that analyzes risk connected with higher education programs. Program difficulty, dropout rates, employment rates, market demand, and other pertinent indicators were some of these variables. A thorough list of risk factors was created after significant research and professional consultation.

2) Risk Data Collection: To compile pertinent data on the indicated risk variables, data collecting was done. In addition to historical program data, student records, industry reports, and other pertinent datasets were also used. The information gathered included details on individual programs, statistics about student performance, program completion rates, and market trends pertaining to employment possibilities.

3) Risk Analysis Model: To evaluate the potential hazards related to various programs, a risk analysis model was created. To assess the gathered data, this model used statistical models and data mining techniques. The patterns and connections between risk factors and program outcomes were found using techniques like clustering, classification, and regression. The effects of each risk factor on the success or failure of the program were quantified and evaluated using statistical models, such as logistic regression or decision trees.

4) Time Duration Prediction Model: A prediction model was created with the use of machine learning techniques to forecast the amount of time needed to finish the application. The model took into account features including course load, academic achievement, program complexity, and other pertinent characteristics. Using historical data on program time and related characteristics, machine learning algorithms such as linear regression, decision trees, or random forests were employed to train the model. As a result, the model was able to identify trends and connections between the input variables and program completion time, resulting in precise forecasts. The HEZER analyzer used this methodology in order to create a system that accurately assessed the risks related to higher education programs and forecasted the time needed to complete the program. A comprehensive system that assisted students' informed decision-making required the identification of risk factors, data collecting, construction of risk analysis and time duration prediction models, and application of machine learning algorithms.

IV. CONCLUSION AND FUTURE WORKS

The HEZER analyzer is a powerful tool that helps students makes informed decisions about their higher education. It utilizes various methodologies, including

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personalized information analysis, financial planning, industrial analysis, risk assessment, and time length forecasting. By analyzing individual information, the system matches students with the best programs based on their academic backgrounds, hobbies, career objectives, and preferences. The system provides practical financial advice, allowing students to make informed choices based on their financial situation and loan options.

The HEZER analyzer also helps students understand the industrial potential of their chosen programs by gathering industry-specific data, text mining tools, mapping programs to industries, and analyzing career chances. This knowledge helps students match their educational goals with the needs and potential of the sector. The system also analyzes risk and predicts time duration, allowing students to assess potential hazards and time requirements.

However, there are still areas for improvement. The accuracy and efficiency of the personalized recommendation system can be improved by incorporating more sophisticated machine learning algorithms and methodologies. Techniques like deep learning, reinforcement learning, and hybrid approaches can be explored to identify more complex patterns and interactions in student data and program properties.

By expanding the scope of data collection, including extracurricular activities, internships, and student feedback, the HEZER analyzer can provide more thorough insights into students' preferences and program characteristics. The system's relevance and adaptability can be ensured by adding real-time data sources and student feedback loops.

The HEZER analyzer can produce up-to-date suggestions by regularly updating industry data, job market trends, and program information. It can also evaluate potential dangers by extending the analysis of risk factors and using advanced models. Additionally, the system can assess program quality and success rates by considering factors like program accreditation, faculty expertise, and student support services.

User-friendly mobile applications and interfaces can further enhance the HEZER analyzer's usability and accessibility. By continuously enhancing and increasing its capabilities, the HEZER analyzer can play a vital role in helping students make educated decisions and shape their educational and career trajectories.

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