

Elevare—AI Career Suggestion Portal: Helping Students by Binding the Solutions at One Place

Divyam Manchanda¹, Ravikant Jangir¹, Nikita Malik^{2,*}

Abstract

The selection of suitable career has become very difficult and it's complexity is being increased day by day, due to advancement in technology and number of professional fields. conventional approaches of suitable of occupation focus on aptitude tests that in fact do not consider the variability in skills. This paper introduces a new AI-powered career suggestion portal called Elevare, which attempted to help students choose a career occupation based on research. The main focus and purpose of this paper would be to develop a model that would be able to predict the occupation as well as provide a skill gap report. The proposed system includes the combination of a classification system based on the Random Forest model and a web-based system based on MERN stack using Python machine learning (ML) microservice. Student profile using academic background, technical skills and interests is analyzed using TF-IDF vectorization to be able to better predict the career in which they will fit. The efficacy of the proposed method in career prediction is proven by the practical analysis, which is much better than the traditional classification systems particularly in dealing with varying and specific career categories to work with. The proposed system also enhances the user experience through the conversion of career predictions into instructive activities in customized learning paths. Apart from career recommendations, users are also given dynamic roadmaps. The results show that Elevare serves to bridge this gap between the student potential and industry expectations in order to make career planning more structured, transparent and outcome - oriented.

Keywords: AI-based career recommendation, skill gap analysis, random forest classification, TF-IDF text vectorization, personalized learning roadmap, MERN stack with machine learning integration

INTRODUCTION

Career selection is one of the most significant choices in the academic and professional lives of students. With technological growth and the introduction of other fields of career, students are now exposed to a great variety of options. However, the availability of choices does not always lead to clarity. Many students do not know what career opportunities they wish to pursue, what they like, or what they are capable of doing. This mismatch between potential and direction has raised the need for intelligent and organized systems in career guidance [1, 2].

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Background and Context

Career confusion among students has become a common problem because of the changing requirements in the industry and the lack of awareness of the new jobs available. Traditional career counseling methods often operate on the basis of manual evaluation, aptitude evaluation, or general advice that may not be accurate enough to capture a person's capability. As a result, students often make decisions based on incomplete or outdated information. In recent years, the fusion of Artificial Intelligence in the

education sector has demonstrated the possibility of solving these challenges by creating data-driven and individual advice [3, 4].

Motivation and Significance

Despite ready access to online resources, information rather than clarity can be a problem for students. There are Platforms that provide courses based on career advice, have a large amount of content, but no structured and personalized direction according to different individuals. This is a source of confusion that complicates things for students. The motivation for this work is to create a system that recommends suitable career options and guarantees clear and personalized suggestions. This intelligent system will not only analyze user profiles and offer focused recommendations but will also provide them with dynamic roadmaps.

Research Problem/Hypothesis

Existing career recommendation systems largely concentrate on career prediction based on few parameters such as academic competence or personality [5, 6]. While these systems can give recommendations, they cannot tell students how to get to the careers they are recommended for. Integrated systems for career prediction, skill gaps, and learning guidance are lacking. The hypothesis of this study is that the combination of career prediction, skill gap analysis, and personalized roadmap generation can result in more effective and informed career decision-making [1, 7].

Objectives of the Study

The present study aims to create an intelligent career recommendation system that provides end-to-end guidance. The specific objectives are to predict appropriate career choices using machine learning (ML) methods, visualize differences between students' skills and those needed in the industry, and provide a customized learning map. Additionally, the objective of this study is to present these insights in an interactive dashboard that will help improve user understanding and engagement.

Structure of the Paper

The remainder of this paper is organized as follows. Section 2 reviews related work and current approaches to career guidance. Section 3 presents the methodology and experimental design of the proposed system. Section 4 provides the results and performance analysis. Section 5 covers the findings, implications, and limitations. Last but not least is Section 6 that concludes the paper with the future research directions.

LITERATURE REVIEW / RELATED WORKS

The problem of career guidance has been extensively studied both in the research area and in the practical sphere. With the rise in complexity of the job market, various approaches have been tried to help students make the right decision about their careers. These methods are available in a wide range, from traditional academic performance analysis to sophisticated machine learning-based systems for recommendations. In this section, existing work in the domain of career guidance is reviewed, methodologies of different approaches are compared, gaps in research in this domain are identified, and the proposed system is explained.

Overview of Existing Work

Early-career guidance systems were mostly based on academic data mining, where student grades and subject performance were used as inputs to predict appropriate career paths. These systems came to believe that academic performance alone was a good predictor of future success. While such approaches deliver structured predictions, practical skills and personal interests are frequently neglected [8].

Another popular approach is grounded in psychometric and personality tests. These systems analyze answers to questionnaires and relate perceptions regarding personality traits to predetermined careers.

Although are quite effective in understanding behavioral tendencies, they are technically shallow and do not consider industry-specific skill requirements [6, 2].

More recent systems are more focused on skill gap analysis based on resumes, in which the user's resumes are compared with job descriptions to identify missing skills evident in resumes. While these systems offer useful insights for job seekers, they assume that their users already have a transparent career goal in mind. Learning path generation systems have also appeared with their ability to provide structured paths of skills to learn, but they typically require predefined career targets and have no predictive capability [9, 3].

Comparison of Previous Approaches

Academic-only models provide simplicity and ease of implementation; however, the predictions are often generic and do not consider individual interests and/or working conditions [8]. Personality-based systems offer psychological matches but fail to consider technical aptitudes, thus rendering their recommendations implausible in skill-driven areas such as technology and engineering.

Resume analyzers work well for professionals who are looking to further develop their careers; however, they are not suitable for students who are still searching for a career [10]. These systems do not help users find the right role and only optimizes the right skills only for known roles. Learning path generators help reduce information overload by organizing learning resources; however, they rely heavily on user-defined goals and do not provide guidance on career choice [9, 3].

In comparison, most of these systems solve only one aspect of career guidance, either prediction or analysis and learning, rather than providing a holistic and complete solution to the problem. This approach makes people dependent on multiple platforms, creating more confusion than clarity. Different platforms must be searched for each feature. Table 1 shows a comparison of previously conducted studies.

Research Gaps Identified

Firstly, very few solutions are available to support users throughout the entire process of discovering careers and developing skills. While most systems provide either career suggestions or skills recommendations, they often fail to link these two aspects.

Second, many career guidance systems are primarily static systems that base their suggestions on a one-time assessment of the user's abilities and preferences.

Lastly, few systems can generate structured learning road maps after providing a career prediction for the user, and therefore, the user becomes lost as to what he/she should be doing next. These shortcomings indicate an urgent need for a high-level and adaptive career guidance system [1, 4].

Elevare's Solutions to Addressing these Gaps

The proposed system (Elevare) is different from previous systems in that it provides an integrated workflow that allows users to start with career predictions, then proceed to identify skill gaps, and generate a personalized roadmap for the user to follow to reach their career objectives. Thus, users will receive not only recommendations for careers; they will also have access to professional advice on how they can pursue those career objectives. With the use of a combined approach of machine learning and a scalable web-based architecture that is capable of dynamic interactions, the system will allow for appropriate levels of dynamic interaction and scaling of the system as required by the number of users. The inclusion of the skill gap analysis function will assist in closing the gap between suggested careers and industry needs.

Additionally, the road map generation function will take skills or knowledge areas that are absent and create a "learning" based action plan to eliminate "information overload." The ability to continuously update the user's profile, allowing the user to return and/or refine their profile, is another example of a type of feedback-related career guidance process supported by the proposed system. Therefore, the integration of these functions represents the primary novelty of this proposed system.

THE METHODOLOGY/EXPERIMENTAL DESIGN

This section describes how the Elevare Career Recommendation System was developed using all available methodologies (design, implementation, and evaluation). The primary focus of the methodology/design of the experimental design, as presented in Table 2, was to develop a career guidance system that utilized web-based technology combined with ML techniques to create an end-to-end career guidance solution. In addition to ensuring that the methodological approach was systematic in terms of the data flow, that the predictions were adequate, and that the results could be interpreted meaningfully, it was also essential that the system would be capable of being scaled up and/or modified.

To facilitate a clear understanding of the methodology, the study was designed sequentially, where each stage of development utilized the input from the previous stage. This structured methodology assisted in limiting inconsistencies and facilitated the ability to manage the data flow throughout the system. From the standpoint of methodology, the objective was to make the methodology reproducible; therefore, the same inputs consistently produced the same outputs, which is a required characteristic for any experimental machine utilizing machine learning.

Experimental Setup

The equipment set up in our lab was designed to allow us to develop and conduct both full-stack web applications and Machine Learning experimentation within the same physical area.

All experiments were run on a typical laptop computer for web application development, which had sufficient computing resources (memory and CPU) to perform the three main tasks associated with each ML operation (data cleaning and preparation, training the predictive model(s), and executing real-time predictions). An overview of the dataset is presented in Table 3.

All aspects of the system's software functionality were implemented as a single system (both front-end and back-end) utilizing the MERN Stack, and Python was used to implement the ML algorithms. Structured career recommendation data was also utilized for the purposes of experimentation and testing; the data was obtained from Kaggle.

System Structure and Algorithm

The system consists of a client-server layered architecture and a machine-learning microservice. The system architecture is illustrated in Figure 1. A layered architecture was used to separate the three key elements of interaction with the user, the logic of the application, and the processing of analytical data. In the client layer, implemented with React.js, the system collects all inputs (e.g., education history, skills, interests, etc.) entered by the user through an interactive interface. The input collected in this manner is then transmitted to the server layer using RESTful API calls.

In the server layer, which was built using Node.JS and Express.JS, there exists a central coordinator. The central coordinator authenticates users, validates the requests submitted to the system, and interacts with the machine learning component of the system. The analytical portion of the system will be created as a standalone Python microservice. This microservice operates independently of the main server of the system and is responsible for processing the user input on a single machine.

To make predictions about careers, the textual attributes of the user's input are converted into numeric vectors using the TF-IDF method [11–14], enabling the system to consider both the importance of the skills and interests claimed in the user's profile.

Table 1. Comparison with related works.

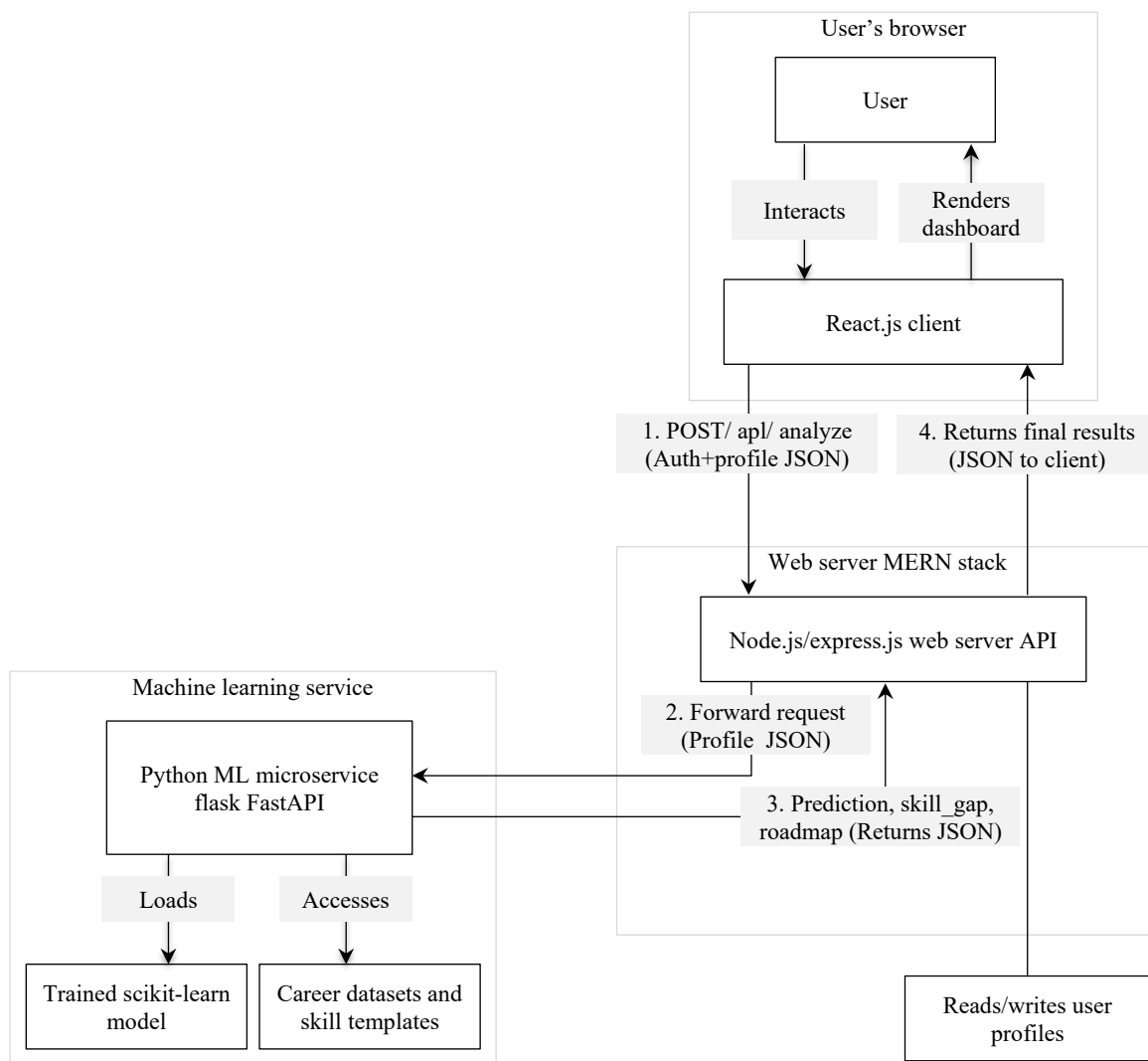
Study	Key focus	Methodology	Dataset / tool used	Limitations
Liu S et al. (2023) – learning path recommendation using knowledge graph [1]	Personalized learning path and dynamic sequence	Knowledge graph construction + path optimization	MOOC metadata, course dependency graphs	No career prediction; no explicit skill gap Analysis
Wu W et al. (2025) – multi-dimensional knowledge graph recommendation [5]	Adaptive multi-factor learning path generation	Multi-dimensional Knowledge Graph + similarity ranking	Educational content datasets	It only Focuses on learning and is not career-oriented
Li A et al. (2026) – personalized learning path via KG [6]	Learner-centric path recommendation	Knowledge graph + preference modelling	Course catalogues + learner logs	Does not guarantees career classification and job alignment
Gander (2021) – hybrid career pathway system [9]	Dynamic career progression modelling	Hybrid ML (content + collaborative filtering) + temporal modelling	Career transition datasets	Requires large historical datasets are complex in implementation
Nongnuch (2025) – career recommendation using deep learning [3]	Prediction of careers from text features	Word embeddings + BiLSTM	Resume and job description datasets	Limited roadmap They are static after trained once
EI-Keiey (2025) – career recommendation via feature selection [8]	Optimization of career predictions	Feature selection + ML classifiers	Student academic & skills dataset	No roadmap making mechanism
Latha R (2025) – skill gap analysis system [10]	Skill mismatch detection	NLP skill extraction + clustering	Resume + job postings data	No career discovery module; limited adaptability
Guo et al. (2023) – radardmath adaptive system [14]	Mastery-based learning adaptation	Knowledge graph + mastery detection	Educational mastery datasets	Designed for academic mastery, not complete career suggestions

Table 2. Experimental design and system configuration.

Module	Configuration	Purpose
Dataset	1,195 raw records → 1,194 processed samples; class imbalance handled	Multi-class career prediction training
Feature engineering	TF-IDF (max_features=2000, ngram_range = (1,2), stop_words='english')	Text-to-vector transformation
Train-test split	80:20 split (955 train, 239 test), stratified sampling	Fair and unbiased evaluation
Algorithms evaluated	Logistic regression, SVM, decision tree, random forest	Model benchmarking
Final model	Random forest (weighted F1-score = 0.8065)	Robust career classification
ML deployment	Python (Scikit-learn) + Flask API (Port 5000), model serialized via joblib	Real-time inference microservice
Backend	Node.js + Express.js (REST API, JWT authentication)	API orchestration and security
Frontend	React.js (SPA) + Tailwind CSS	User interaction and dashboard visualization
Database	MongoDB Atlas (Users, CareerSkillMap, resources, assessments)	Persistent storage and roadmap data
Skill gap logic	Set difference: target_skills – user_skills	Missing competency detection
Performance	End-to-end response time < 2 seconds	System efficiency validation

Table 3. Dataset overview.

Parameter	Value
Total Raw Records	1,195
Total Processed Records	1,194
Raw Dataset Shape	(1195, 12)
Processed Dataset Shape	(1195, 7)
Selected Predictive Features	4
Target Variable	Career
Train-Test Split Ratio	80% : 20%
Training Samples	955
Testing Samples	239

**Figure 1.** System architecture.

The conversion of these attributes will enable the system to apply a Random Forest classification algorithm to generate career predictions [12]. The modular design of the system will also ensure that if the prediction model needs to be modified or replaced, it may be done without having to perform extensive modifications to the existing web application [13].

Table 4. Evaluation metrics of random forest model.

Metric	Value
Accuracy	0.8368
Precision (Weighted)	0.7987
Recall (Weighted)	0.8368
F1-Score (Weighted)	0.8065
Train-Test Split	80% : 20%
Training Samples	955
Testing Samples	239
Feature Dimension (TF-IDF)	2000 Features

Evaluation Metrics

To verify that how effective the career prediction model was, various measures of performance, as presented in Table 4, were used. Accuracy was used to test the overall accuracy of the predictions in the model. However, because career datasets often have unequal numbers of various career categories, if one only relies on accuracy, one may mislead oneself to the wrong conclusion.

Precision and recall were analyzed carefully to understand how well the model performs on both common and less common career categories. High precision is important to ensure that the predicted careers are relevant, and high recall is important to ensure that suitable career options are not overlooked. By taking these measures holistically, the tendency of biased predictions was reduced in this system. The incorporation of weighted evaluation metrics further ensured that the overall performance evaluation was not dominated by more powerful classes in society, making the evaluation system fair and balanced.

Therefore, further measures like precision and recall were used to analyze the correctness and completeness of predictions for individual career classes. Here, the weighted F1-score was given more importance because it provides a broken point of measure, considering the combination of precision and recall, as well as class imbalance. This makes the evaluation more reliable and reflective of the prediction performance in real-world use [1, 2].

Experimental Workflow

The Elevare system provides users with comprehensive career guidance by following a predetermined step-by-step process to evaluate user input data. Users enter their profile details via a web interface, where they have the option to add academic data, skills, and areas of interest. When the user data are entered, they undergo preprocessing, which is used to normalize the text and convert the text to features so that the format can be utilized for model training.

The run-on results after processing are then taken through the Random Forest Classifier which generates a ranked list of possible careers. In accordance with the predicted career that has the highest ranking, a comparison of the user's current skills and a predetermined list of required skills for the career role will be conducted via a skills gap analysis.

Once completed, a customized learning path will be created based on the identified missing skills that correlate with the appropriate learning resources. Finally, all of the results (career recommendation, identified skills gaps, and the suggested road map) will be made available to the user in an interactive dashboard to provide a full cycle of the experiment from the initial input to actionable recommendations.

RESULTS AND ANALYSIS

This section examines and evaluates the results from the experimental tests based on the operation of the Elevare career-recommendation system. The focus of this evaluation is to assess the efficiency of the machine learning model, compare the model against a baseline, and interpret the results in terms of their practical relevance. The success of the system will be evaluated by considering both the numeric-accuracy of the system and its usability/personalization in the actual work environment of career counseling.

RESULT PRESENTATION

The results of our experiments indicate that the proposed system is capable of providing correct and appropriate recommendations for students' careers. All multiple classification models were trained and evaluated on the prepared dataset, and the performance of each model was assessed using standard evaluation methods. The output results from the experiments are represented in tabular and graphical formats to ensure that all results are clearly understandable and interpretable.

Random Forest model demonstrated superior performance when comparing it against the other models based on the majority of the assessment metrics. Sample outputs from the system illustrated that users with a similar academic background and a variety of skills were directed toward a variety of potential career paths, illustrating the system's capability to create personalized recommendations for users.

The Dashboard was also able to effectively display the predicted careers, the required missing skills, and the planned learning path for users, thus supporting the accuracy of the end-to-end data flow as well as the visualization of the results.

Figure 2 shows the results page for the project, showing how the real-time prediction output is shown along with confidence-based recommendations and personalized roadmaps. All of these have been rendered seamlessly together, therefore validating the overall system architecture and responsiveness.

Comparison to Baseline Models

To prove the success of the proposed method, several baseline machine learning models were compared with the random forest classifier. The baseline models included logistic regression, support vector machines (SVM), and decision trees. Logistic regression was used as a linear baseline model that was quite simple and could not provide the ability to model the complex and non-linear relationships that exist in textual career data. Table 5 shows the performance of the different models.

The SVM model performed mediocrely, especially on well-separated career classes. However, its performance decreased for less frequent career categories, suggesting the presence of sensitivity to class imbalance. The Decision Tree model performed better than the linear models because of its ability to capture non-linear patterns, but had tendencies towards instability and overfitting when exposed to the sparse, high-dimensional feature space created by TF-IDF vectorization.

Unlike that, the Random Forest model proved to be more efficient as it aggregates the predictions of multiple decision trees [12]. This ensemble approach helped lower the variance and improved generalization. Consequently, Random Forest received the best overall accuracy and a much better weighted F1-score, making it the most suitable model to deploy to the Elevare system [4, 12].

Table 5. Model performance metrics.

Model	Accuracy	Precision (Weighted)	Recall (weighted)	F1- score (weighted)
Logistic regression	0.6611	0.6412	0.6611	0.6205
SVM	0.6569	0.6509	0.6569	0.6243
Decision Tree	0.6713	0.6809	0.6871	0.6711
Random forest	0.8368	0.7987	0.8368	0.8065

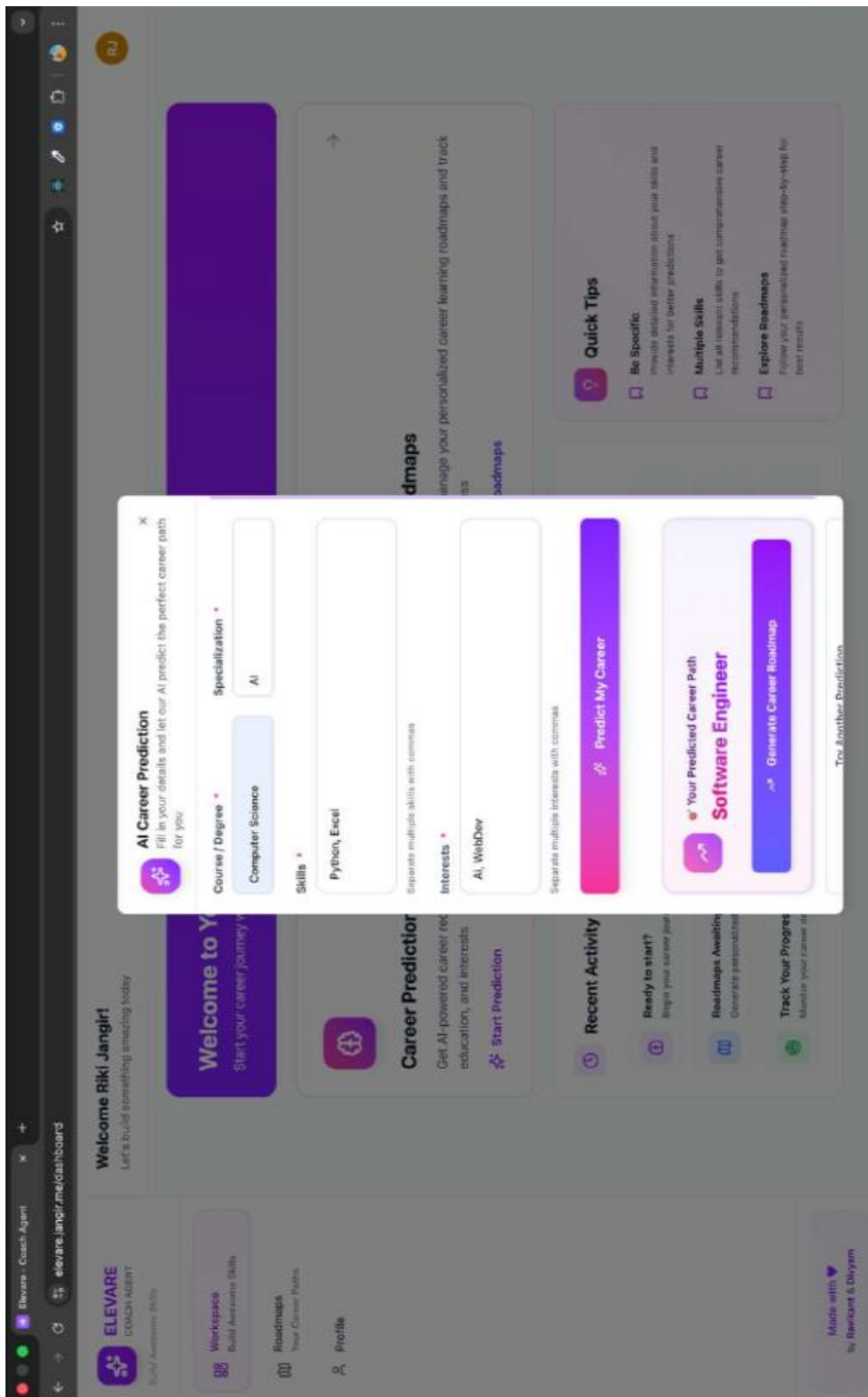


Figure 2. Result page

What We See and What We Understand

One of the conclusions drawn from analyzing the experimental results is that ensemble-based machine learning methods affect career predictions because they provide ways to represent both textual and multi-dimensional information [12]. Among all the models examined, the Random Forest model performed particularly well in predicting less common career niches and career paths, which is a key requirement for a career guidance system that supports a diverse group of students. Because this model can achieve a Macro F1 score significantly greater than the Decision Tree Model, it is possible to say that the Random Forest Model is demonstrably superior when identifying less common career paths.

In addition to having the ability to identify less common career paths, another major advantage of using the Random Forest model is its ability to balance the confidence in making predictions with providing an explanation for those predictions. By generating the probability of each student's potential career path, the system can avoid giving the student a rigid, "one-size-fits-all" career path recommendation. Additionally, the research results support the hypothesis that a multi-factor analysis approach is beneficial in selecting a career path [8, 2]. Therefore, the inclusion of the student's skills and interests along with their academic history is a valuable input in determining the relevance of the career path predictions made by the system.

Finally, the consistency of the predictions made by the model across multiple test sets indicates that the model can produce consistent and unbiased predictions.

The confusion matrix shown in Figure 3 indicates a strong diagonal dominance, showing that, for the most part, the different career categories have been correctly classified. Misclassification occurs infrequently and randomly.

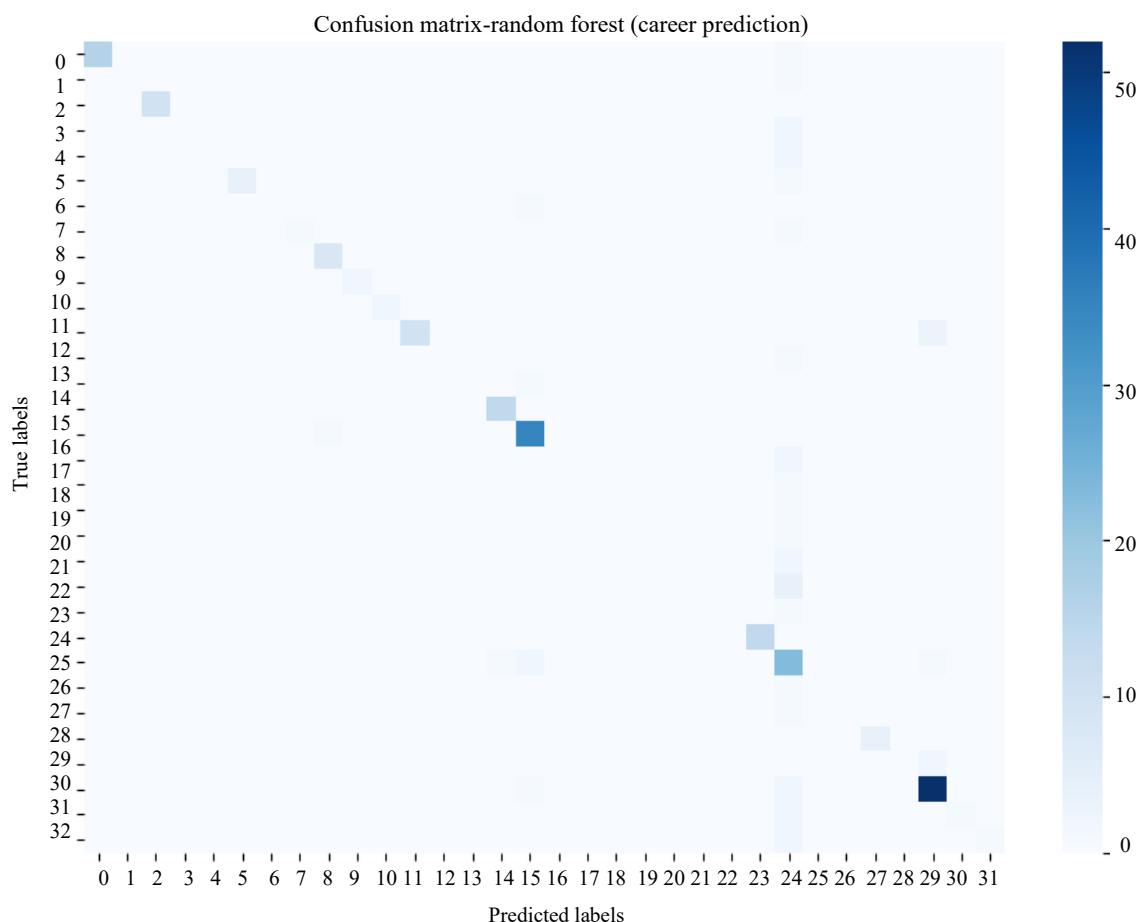


Figure 3. Confusion matrix.

Thus, the results support the fact that the Random Forest classifier can recognize the differing textual characteristics of each career category, thereby supporting the high accuracy and weighted F1-score that was also found.

Performance Analysis

In addition to evaluating the accuracy of prediction made by the system, performance and scalability of the system were also tested. We observed that the average time for prediction and roadmap generation was less than 2-seconds which is acceptable for real-time interaction with the user. This determines how efficiently the transformation of documents using TF-IDF and the Random Forest model is for deployment in an interactive web application.

Decomposing machine learning logic into Python microservices made it possible to avoid negative effects on frontend responsiveness while performing computationally intensive tasks. During testing, the dashboard was smooth and responsive, even though it handled multiple requests to the apis.

DISCUSSION

This section compares the outcomes of the proposed Elevare system with the objectives determined prior to the study period. The interpretation of the experimental results will be discussed, as well as the developmental understanding of the practical implications of the results, potential limitations of the system, and possible enhancements to the system. Instead of presenting futuristic "repeating numerical results" this section analyzes how successful the system was in providing career guidance for students in a real-world setting.

Interpretation related to Objectives

A Predictive System Based On Student's Larger Perspective

Instead of using an individual factor, such as test scores or personality type, the system uses a combination of factors, including academic history, field of study, interests, and technical skills as input to understand the student's entire picture. As shown by the Random Forest model (a total accuracy of 83.68% and a weighted F1-score of 0.8065), this approach provides a more complete and well-rounded predictive model for careers that can be applied to many different types of careers, both common and uncommon.

Identifying the Gap Between What is Needed and What Exists in a User's Skills

The second goal of the system was to help students who know what they want to do but have no idea what they need to do to get there. The system provides a direct comparison of the user's existing skill sets to the job skills required in their identified career area. This comparison gives users clarity into their strengths and weaknesses, as opposed to generic guidance [8, 4].

Moving from Predictions to Actionable Steps

Most career guidance tools end by suggesting a career path. It was designed to go beyond this point. In addition to recommending a suitable career path, the system automatically generates structured next steps to follow, ensuring that users receive informative and actionable outputs. The transition from "what should i become?" To "what should i do next?" is a key problem that was designed to solve.

Providing Individualized Learning Paths

The system converts skill gaps into clearly defined step-by-step paths for users to learn new skills. Each missing skill has relevant learning materials associated with it, creating an organized path rather than random suggestions, making the guidance process more structured and easier to follow by the user.

Developing a Scalable and Realizable Architecture

The goal of this project was to prove that it is possible to develop an intelligent Career Guidance System that can provide both strong technical performance and practical applicability. The integration of a Python-based Machine Learning Micro-Service into a MERN-based Web Platform maintained

response times of under 2 s, while maintaining modularity and scalability. Therefore, successful Educational AI Solutions are not always dependent on the use of very complex Deep Learning Models.

Implications of the Findings

The conclusions of this study are relevant for student populations, educational organizations, and the EdTech sector. For students, the system resolves many of the unknowns related to their career paths through the use of data to guide each student individually, as opposed to generic career advice that is available online. Students are exposed to an overwhelming amount of information on the Internet; however, there is little direction.

The system also demonstrates the increasing disconnection between what is taught in schools and the skills required by employers in industry. By making the missing skills apparent and explicitly identifying them, students are encouraged to be accountable for acquiring the necessary skills to address these deficiencies.

The system demonstrates the potential of combining web full-stack applications and machine learning models to develop practical solutions for the EdTech industry. Additionally, it demonstrates the potential of intelligent career guidance systems to assist in automating and scaling the delivery of personalized counseling, particularly in developing countries or regions of the world where there is limited access to professional counselors.

LIMITATIONS

Although the proposed system is beneficial, it has limitations that should be recognized. The career prediction model is dependent on the quality and amount of the training dataset for the machine to make predictions. Since the dataset used for training the machine was pulled from a publicly available repository, the data may not be as up-to-date and/or as comprehensive regarding the ever-changing job market and new career opportunities.

Also, since the system utilizes predefined skill templates for each career path, the system will provide consistent results. Due to the lack of real-time data on the current job market, the recommendations of skills may become outdated over time.

Finally, another limitation of the system is that the generation of the roadmap is static in nature. While the roadmap will be customized based on the identified skill gaps that exist for the user, it does not currently have the ability to adjust (dynamically) based on the users' progression of skills or learning outcomes.

Future Improvements

There are several ways in which we could enhance the proposed system for better use. The first major enhancement would be to allow users to access live job postings and professional networks such as LinkedIn. This would allow recommendations to reflect today's requirements and trends in employment opportunities.

We also envision extending the machine learning module to process user information using deep learning techniques (such as neural networks) or transformer-based text models to learn additional relationships from user information [11]. We also believe that future versions will include the ability to dynamically adapt roadmaps to reflect the user's progression through the course material and provide feedback to the user [9, 3].

Additionally, we foresee that future versions will incorporate user behavioral analysis and update recommendations based on how the user interacts with the system. As a result, it will evolve from a simple recommendation tool to a living and breathing career development ecosystem.

CONCLUSION

This is a summary of all the research conducted in this research project. Here, we will discuss how our system contributes to practice, what is the contribution of the proposed system, and what are the contributions to the practice of the system. This is a combination of the methodology, results, and discussion sections to provide a clear view of how useful and relevant the system is for career guidance.

Key Findings

The primary outcome of the study was that the career prediction model utilizing machine learning combined with skill gap analysis was significantly more useful for users than the individual components alone. In addition to the higher accuracy and consistency of career recommendations generated by the Random Forest model compared to baseline models, the developed system also extended its functionality beyond providing career predictions to provide users with an outline of the skills needed to achieve their recommended careers, as well as a structured learning plan to help them develop those skills.

Another key takeaway is that considering multiple variables (academic history, technical skills, and personal interest) can lead to more personalized and relevant career suggestions for each individual. Finally, the interactive dashboard improved users' comprehension of themselves through easy-to-understand representations of complex data analysis results. These findings indicate the utility of the proposed end-to-end process in developing a career development strategy.

Contribution to the Field

This project fits into the domain of career guidance using Artificial Intelligence because this system provides a complete solution for the entire process of predicting, analyzing, and providing guidance as part of the solution itself, unlike many previous solutions that have focused solely on prediction (or only one piece of a single test, such as an aptitude or personality test). It is sensible to develop both a career prediction tool and a skill gap analysis tool together because they provide recommendations directly tied to action [1, 4].

The project also demonstrates the possibility of implementing a modular architecture based on MERN technologies in conjunction with a Python machine-learning service that can be scaled and maintained. Additionally, the project shows how simple machine learning techniques can be used effectively within education-related applications, so that the results are easy to interpret and implement by educators [12, 13].

Applications and Recommendations

The proposed system has several practical applications in several types of organizations. Educational institutions could use it as a decision support mechanism to assist students in choosing appropriate careers early in their academic experience. Likewise, training institutes and on-line learning systems could provide career and/or skills development recommendations based upon similar decision support mechanisms. Similarly, career counseling centers may also want to consider incorporating such an approach into their traditional career counseling to complement the process with data-based recommendations.

To further deploy the system in the future, it is recommended that the system be enhanced with both real-time job market data and adaptive learning components.

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