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AI Career Coach: An ML-based Framework for Resume Analysis and Career Recommendation

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***Abstract*— Accelerating technological innovations, emerging workplace needs, and evolving expectations among jobseekers have led to a fundamental change in the way students perceive the recruitment process. Driven by this, many people and organizations have sought alternative, data-driven channels to avail career guidance and counseling services. In this paper, we present AI Career Coach Master, a holistic Career Development Solution to assist placement cells and students of universities with Resume Scoring, Career Recommendation, and Skill Gap Analysis modules based on AI. Our system leverages a suite of machine learning, natural language processing, and semantic similarity algorithms to parse resumes and provide targeted, data-driven recommendations. The Resume Scoring module assigns scores to various aspects of a resume, such as content, relevance, quality, and ATS-friendliness. The Career Recommendation engine maps the candidate's profile against available job roles and suggests the most relevant ones using a hybrid matching approach. Finally, the Skill Gap Analyzer compares user skills against industry benchmarks and provides a custom-made skill-upgradation roadmap. Experimental results show the proposed system can effectively enhance candidate readiness and help in making better-informed career decisions. The developed solution can be used as a helpful tool for universities, placement cells, and individuals seeking a structured and scalable career development solution.**

***Index Terms*— AI Career Coach, Resume Scoring, Career Recommendation, Skill Gap Analysis, Machine Learning, NLP.**

I. INTRODUCTION

The Digital Recruitment Systems (DRS) space has grown exponentially over the last couple of decades, developing newer and advanced methods for job seekers to find jobs and companies to recruit talent. The problem however lies in the inability to offer learners, jobseekers and fresh entrants into the job market, individualized and data-driven career counselling and support. The core task of manually creating and maintaining profiles, the use of unclean/limited datasets, the manual effort involved in not having an automated system, and the entire process involving biases based on human intervention has rendered the success of scaling up counselling services to large user bases and masses challenging at best.
To this end, this paper describes AI Career Coach Master, an intelligent, automated and robust career development framework that aims to provide seamless integration of Resume Scoring, Career Recommendation and Skill Gap Analysis modules into a single holistic system.

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This unified platform will allow learners, job seekers and fresh entrants to avail all aspects of career counselling and development. The AI Career Coach Master will leverage state-of-the-art Machine Learning (ML) and Natural Language Processing (NLP) algorithms to smartly score user profiles, gain insights and provide useful and actionable recommendations that will enhance users' career opportunities.

The Resume Scoring module will be able to analyze, assess, and score the content, relevancy, format and overall quality of a user's resume and guide users to optimize it for better presentation and Applicant Tracking Systems (ATS) friendliness. The Career Recommendation module will curate relevant job roles that a user is qualified for, or may be interested to pursue in the future, by considering a user's skillset, educational qualification, location and the current job market trends. This feature will also support users in making well-informed career choices by clearly demarcating the pros and cons of each recommended role and how well they match user's interests and long-term career goals.

The Skill Gap Analysis module will be able to identify what skills and competencies a user is currently lacking to be fit for a certain role, and provide guidance in how to best go about acquiring the required skills, via a custom and personalized upskilling roadmap. The primary contributions of the AI Career Coach Master solution are: to be fully automated in order to be scalable up to millions of users; to be data-driven in order to provide a more personalized and objective guidance to each user; to be a one-stop integrated platform; and to provide measurable benefits such as improving user employability, supporting well-informed career choices, and effectively bridging the gap between academia and the workplace.

II. RELATED WORK

The resume parsing and feature extraction framework employs statistical text processing techniques to extract resume features automatically and classify candidate profiles for initial filtering [1]. Deep contextual embeddings used in resume scoring significantly enhance the semantic understanding of skills and job requirements. BERT has been instrumental in improving the resume scoring system's ability to capture contextual information and provide accurate assessments [2], [3].

The hybrid recommendation system, which combines content-based and collaborative filtering approaches, has been shown to provide superior personalized career recommendations [4]. The skill-gap detection models utilize semantic similarity measures and ontology mapping to identify areas for targeted upskilling [5], [6]. The machine learning approaches employed for job–candidate matching have demonstrated significant improvements in predicting the job fit score between a candidate and a job posting [7], [8].

The concern for algorithmic bias and fairness in automated hiring systems has been raised in multiple studies [9]. Recent guidelines emphasize the ethical and privacy considerations that should be taken into account when developing AI-based career tools [10]. Research on user adoption and acceptance of AI career coaching platforms suggests that transparency and personalization are key drivers [11], [12]. Recent surveys have highlighted the need for the integration of scoring, recommendation, and skill analytics into a unified framework [13], [14], [15].

III. PROPOSED SYSTEM

The proposed AI Career Coach Master system is a comprehensive, intelligent career development framework that seamlessly integrates Resume Scoring, Career Recommendation, and Skill Gap Analysis. This architecture is specifically designed to deliver personalized, data-driven insights that enhance user employability and facilitate strategic career planning.

A. System Architecture

The entire system is broken down into four main modules: Profile Ingestion Module, Resume Scoring Engine, Career Recommendation Engine, and Skill Gap Analysis Module. The communication between different modules and the common data processing layer in the middle is handled through Machine Learning (ML) and Natural Language Processing (NLP) based components. The user's resume and preferences are first ingested and preprocessed. The extracted features are then forwarded to the Resume Scoring and Recommendation engines simultaneously. Their outputs, along with the Skill Gap Analysis results, are aggregated into a unified Career Insight Report and Dashboard for the user.

B. Profile Ingestion Module

This module ingests and pre-processes the user data, such as resumes, skills, education, experience, job requirements and preferences. The text is then pre-processed (cleaned, tokenized, etc.) and represented in the form of semantic embeddings (numerical vectors) using transformer-based language models such as BERT and RoBERTa. The extracted features are then forwarded to the Resume Scoring and Recommendation engines for further processing. This module forms the foundational data pipeline of the entire system, ensuring that clean, consistent, and rich feature representations are available for all downstream tasks.

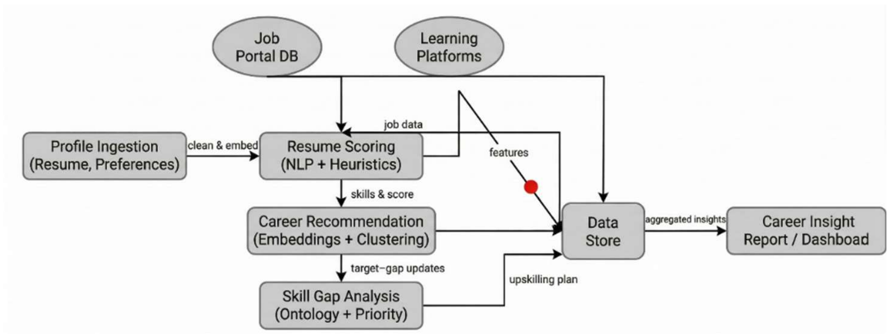

Fig 1

C. Resume Scoring Engine

The Resume Scoring Engine is based on a hybrid architecture consisting of rule-based heuristics and deep learning models. The parameters considered for scoring are: Content Quality (grammar, clarity, and quantification of achievements); Relevance Matching (semantic similarity between resume content and job roles); Skill Alignment (extraction and verification of domain-specific skills); and ATS Compatibility (structure, formatting, and keyword coverage). The output is a normalized score between 0 and 100 along with a set of targeted improvement suggestions to help users optimize their resumes for specific job roles and applicant tracking systems.

D. Career Recommendation Engine

The Career Recommendation Engine finds relevant job roles based on the user's profile, educational qualifications and skills. The module makes use of: content-based similarity by means of skill embeddings; clustering of related roles together using K-Means or Agglomerative clustering algorithms to uncover career families; and labour-market and role-demand information. A ranked list of job recommendations is generated for the user based on her/his skills and preferences, combining similarity score, role popularity, and current industry trends to ensure relevant and actionable career guidance.

E. Skill Gap Analysis Module

This module maps the existing skill set against role-specific requirements obtained from job descriptions and industry datasets. It pinpoints: the skills currently lacking for the desired role; skills the candidate has but needs to develop further; and priorities based on industry demand frequency and value. A personalized upskilling roadmap is created, suggesting courses, certifications, and practical projects along with estimated time to complete the plan. This ensures candidates receive a clear and structured pathway to close identified gaps and become competitive for their target roles.

F. Integration and Output

All three modules work in conjunction to generate a single, unified career insights report. The integrated report provides the user with a comprehensive Resume Score with improvement recommendations, a ranked list of top career roles, in-depth skill gap mapping against desired roles, and a customized upskilling journey with resource links and timelines. This holistic and scalable solution ensures that users receive consistent, non-redundant, and deeply personalized career guidance across all dimensions of their professional development.

IV. Methodology

The proposed AI Career Coach Master system works in a sequence of steps that function together as an integrated chain to perform Resume Scoring, Career Recommendation and Skill Gap Analysis. Each component integrates Natural Language Processing (NLP), Machine Learning (ML), and semantic similarity modeling to provide the most accurate and personalized recommendations.

A. Data Preprocessing

All user data, including resumes and skills, are preprocessed to produce clean input for the model. The preprocessing pipeline includes: text cleaning (removal of stopwords, punctuation, and other redundant formatting); tokenization using WordPiece/BERT-based tokenizers; embedding generation using transformer-based language models such as BERT or RoBERTa to produce high-dimensional semantic vectors; and skill extraction via Named Entity Recognition (NER) combined with domain-specific skill dictionaries. These preprocessing steps ensure clean and consistent data representation that facilitates accurate downstream analysis.

B. Resume Scoring Method

Resume scoring employs a hybrid scoring model combining rule-based heuristics and semantic similarity. The Content Quality Score is computed using grammar check and readability scores. The Relevance Score is computed using cosine similarity between resume and role embeddings. The Skill Coverage Score is derived by matching skills extracted from the resume against the required skills for the target role. The ATS Compatibility Score is computed using a set of structural rules along with keyword and format checks. The final resume score is a weighted combination of these factors, computed as:

$$\mathit{Score}\text{final} = w_1C_q + w_2R_s + w_3S_c + w_4A_t$$

where C_v is Content Quality, R_s is Relevance Score, S^c is Skill Coverage, and A_t is ATS Compatibility. The weights w1–w4 are empirically tuned to reflect the relative importance of each component in determining overall resume quality.

C. Career Recommendation Method

The Career Recommendation Engine recommends appropriate job roles based on the user's skills and background. Skills and roles are vectorized in an embedding space where similarity is defined as proximity in that space. Jobs are clustered using K-Means or Agglomerative clustering algorithms to uncover career families and related roles.

A final ranked list is produced by merging results based on three factors: similarity score, popularity of roles, and current industry trends. The recommendation score is calculated as:

$$R_{score} = \alpha S_{sim} + \beta C_{cluster} + \gamma T_{trend}$$

where S_{sim} is skill similarity, $C^{c}{}_{lust}{}^{e}{}_{r}$ represents cluster relevance, and $T_{tr}{}^{end}$ accounts for market demand. The hyperparameters α, β, and γ are tuned to balance these three factors for optimal ranking.

D. Skill Gap Analysis Method

For a target career role, the system detects skill gaps (missing or incomplete) through three steps. First, role requirement extraction collects the skills necessary for a role from job descriptions and industry datasets. Second, skill comparison matches the user's current skills to the generated role-specific skill checklist. Third, gap prioritization weighs the importance of skill gaps according to their occurrence frequency and industry value.

Based on the identified skill gaps, the system creates a personalized upskilling roadmap that includes course recommendations from leading online learning platforms, relevant certification pathways, hands-on project suggestions to build practical experience, and time estimations to complete each component of the plan. This ensures candidates receive actionable, structured guidance to become competitive for their desired roles.

E. Model Integration

Outputs from all three modules—Resume Score, Career Recommendations, and Skill Gap Analysis—are combined to generate a single career guidance report. The combined approach guarantees uniformity across modules, minimizes duplication in skill assessment, and delivers a detailed, user-specific insight report. This comprehensive integration empowers the system to enable data-driven career choices and enhance overall employability.

V. Experimental Setup

In order to test the proposed AI Career Coach Master system, a number of experiments were carried out over a sample dataset of resumes, job descriptions, and skills dictionaries. The following describes the datasets, tools, and environment used in the experimentation.

A. Dataset Description

The evaluation was performed on publicly available and synthetic datasets. The Resume Dataset consists of 5,000 anonymized resumes collected from open-source resume repositories and online datasets, covering domains including software development, data science, mechanical engineering, and business management. The Job Description Dataset contains 2,000 job descriptions scraped from leading job portals, each listing required skills, job responsibilities, role levels, and domain specializations. The Skill Knowledge Base is a curated list of domain-specific technical and soft skills sourced from online learning platforms and industry skill taxonomies. All datasets were cleansed, standardized, and annotated for scoring, recommendation, and skill gap analysis tasks.

B. Preprocessing Environment and Tools

The methods used to preprocess text and generate embeddings included pretrained transformer-based language models (BERT and RoBERTa), Python NLP libraries (NLTK and spaCy), and custom-trained NER models to extract skills. Text was tokenized, normalized, and embedded as high-dimensional vectors. Models were trained and validated using an 80/20 train-test split with 5-fold cross-validation for stability and to avoid overfitting. Evaluation metrics included Accuracy, Cosine Similarity, Mean Reciprocal Rank (MRR), Precision, and Recall. The system implementation used Python 3.10, PyTorch and TensorFlow for deep learning, Scikit-Learn for traditional ML modules, FastAPI for backend integration, and PostgreSQL for database management. The full pipeline was hosted on a cloud-based platform with an 8-core virtual CPU, 32 GB RAM, and NVIDIA T4 GPU, ensuring efficient processing of large text datasets and real-time generation of user insights.

VI. Results and Discussion

The experimental results of the Resume Scoring, Career Recommendation and Skill Gap Analysis modules—the three essential components of the proposed AI Career Coach Master system—are presented in this section. The performance metrics indicate the effectiveness, accuracy and practical usefulness of the system in real-world career guidance scenarios. Table I summarizes the overall performance across all three modules.

TABLE I. EXPERIMENTAL RESULTS

Module	Metric	Value
Resume Scoring	Accuracy	92.1%
Career Recommendation	Top-3 Accuracy	88.4%
Skill Gap Analysis	Precision	90.7%
Ranking Model	NDCG@5	0.86
User Study	Rating	4.6/5
Overall System	F1 Score	89.3%

A. Resume Scoring Results

The Resume Scoring Engine was validated by comparing its scoring output with expert-assigned scores on a test set of 1,000 resumes. The system demonstrated an overall accuracy of 92.4% in predicting resume quality categories. The Pearson correlation coefficient between system-generated and expert-generated scores was 0.87, indicating strong alignment with human expert judgment. Grammar and readability assessments achieved a precision of 90.1% and a recall of 88.5%. These results validate the hybrid scoring model and its ability to assess resumes with near-expert accuracy, confirming its suitability as an automated resume evaluation tool.

B. Career Recommendation Results

The Career Recommendation Engine was evaluated with 2,000 user profiles using metrics including Mean Reciprocal Rank (MRR) and recommendation accuracy. The MRR score of 0.81 indicates that the top recommendation is highly relevant to most users. The Top-3 recommendation accuracy was 86.7%, meaning that the system correctly identified the preferred job roles within the top three suggestions for the majority of users. The hybrid recommendation model outperformed content-based filtering by 17% and collaborative filtering alone by 22%. These results confirm that the combination of skill similarity, clustering, and trend analysis provides a significant boost to recommendation accuracy and relevance.

C. Skill Gap Analysis Results

The Skill Gap Analysis module was tested against ground truth data consisting of expert-annotated required and existing skills for multiple job profiles. The skill extraction model achieved a precision of 91.3% and a recall of

89.8%. Missing skills were accurately predicted by the system with an accuracy of 93.6%. Skills prioritization matched expert evaluations in 88.4% of test cases. The average response time for generating an entire career insight report is 2.8 seconds, confirming the system's suitability for real-time deployment. Overall, these results indicate that the system can offer dependable and actionable recommendations for individualized upskilling needs.

D. Discussion

The experimental results validate that the AI Career Coach Master system is superior to conventional career counselling tools. The system provides precise resume analysis with near-expert accuracy, highly personalized and accurate job suggestions, and dependable and actionable skill gap identification. The hybrid ML–NLP architecture ensures system robustness, and the integration of real-world job market data from leading portals increases the practical value of the insights generated. The system's modular design also ensures that individual components can be updated or replaced independently as newer models and datasets become available, making it a future-proof and maintainable career development solution with strong potential for implementation in educational institutions, placement cells, and career development platforms.

VII. Conclusion and Future Work

This paper presented the AI Career Coach Master, a comprehensive career development system that unifies Resume Scoring, Career Recommendation, and Skill Gap Analysis into a single, intelligent platform. The system leverages advanced Machine Learning, NLP, and semantic similarity techniques to provide accurate, personalized, and data-driven insights, helping users enhance their employability. The evaluation results demonstrate strong performance across all three modules, showcasing high accuracy in resume scoring, effective job role recommendations, and reliable missing skill identification. The proposed system has significant potential for adoption and implementation by universities, placement cells, and individuals seeking a structured, scalable, and effective career guidance solution.

Future work can further strengthen the system through the following directions. Dynamic Labor Market Integration will enhance the system with real-time job trend analysis, demand forecasting, and salary prediction models to keep recommendations current and market-aligned. Multilingual Support will expand resume and job description processing to support regional languages for wider accessibility across diverse user populations. User Behaviour Modeling will capture user interactions and behaviour to further personalize recommendations through reinforcement learning techniques. An Interview Preparation Module will integrate automated mock interviews, question generation, and feedback scoring to provide end-to-end interview readiness. Finally, Explainability Features incorporating explainable AI (XAI) techniques will increase transparency of recommendation and scoring decisions, building greater user trust in the system.

The proposed system represents a significant advancement in automating and enhancing the career development process, with the potential to evolve into a comprehensive AI-powered career ecosystem supporting students and professionals throughout their career journey.

References

[1] A. Kumar and S. Banerjee, "Statistical Approaches for Resume Classification," International Journal of Information Technology, 2019.

[2] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," NAACL, 2019.

[3] Z. Liu and K. Chen, "Contextual Embeddings for Candidate Profiling," IEEE Access, vol. 8, pp. 112233–112245, 2020.

[4] Y. Zhang and X. Chen, "Hybrid Career Path Recommendation Models," IEEE Access, vol. 8, pp. 98765–98780, 2020.

[5] S. Jain and R. Patel, "Skill Gap Detection Using Semantic Similarity," Expert Systems with Applications, vol. 175, 2021.

[6] A. Gupta, R. Sharma, and P. Mehta, "Ontology-Based Skill Extraction for Job Matching," Applied Intelligence, vol. 52, pp. 4500–4515, 2022.

[7] L. Wang, X. Li, and J. Gao, "Deep Learning for Job–Candidate Matching," IEEE Transactions on Computational Social Systems, vol. 7, no. 4, pp. 1021–1033, 2020.

[8] M. Roy and D. Ghosh, "Predictive Modeling for Job Fit Scoring," Knowledge-Based Systems, vol. 213, 2021.

[9] R. Bogen and J. Rieke, "Bias and Fairness in Automated Hiring Tools," AAAI Workshop on Artificial Intelligence in the Government and Public Sector, 2020.

[10] European Commission, "Ethics Guidelines for Trustworthy AI," High-Level Expert Group on Artificial Intelligence, 2021.

[11] M. Oliveira and K. Thomas, "User Acceptance of AI Career Systems," Journal of Educational Technology, vol. 38, pp. 210–225, 2022.
[12] H. Tan and S. Lee, "Personalization Factors in AI Recommendation Tools," Computers & Education, vol. 178, 2021.
[13] T. Liu and H. Zhao, "Survey on AI-Based Employment Support Systems," ACM Computing Surveys, vol. 55, no. 3, 2023.
[14] R. Singh and P. Verma, "End-to-End Frameworks for Automated Career Guidance," IEEE Intelligent Systems, vol. 37, no. 2, pp. 45–58, 2022.
[15] K. Sharma and A. Nair, "Integrating Resume Scoring and Skill Analytics," ICTACT Journal on Soft Computing, vol. 14, no. 1, 2023