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Career Craft AI – An AI Powered Resume Analyzer and Generator

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Abstract

The modern scenario in recruitment requires job seekers to design their resumes in conformity with the requirements specified by the ATS, as ATS screening technology is increasingly adopted by employers for shortlisting candidates. It is a challenge for many job seekers to design their resumes suitable for the keywords, which affects their screening by ATS technology. Traditional resume builders do not provide options for feedback, intelligence, and recommendations based on the requirements specified for a job.

The system uses Natural Language Processing and Machine Learning algorithms to automatically produce job application resume documents compliant with ATS. The system works through two main processes: content optimization and resume template selection, using industry-related keywords supplied by the candidate. For it, it gives immediate feedback on grammatical correctness, keyword use, and structuring scores. Therefore, it helps the candidate to quickly improve his/her resume.

The project was tested by independent judges belonging to different fields of profession with different levels of expertise. The experimental results show that the proposed solution enhances resume readability, keyword matching, and compatibility with ATS tools, thus helping employers quickly identify suitable candidates. The results of this research not only uncover the rising trend of AI in employment activities but also stress the importance of ethical development of AI tools for constructing resumes. This research work paves the way for innovative AI-assisted career assistance tools to facilitate job seekers.

Keywords--Artificial Intelligence, Automation, Applicant Tracking System, Job Applications, Machine Learning, Natural Language Processing, Resume Generation.

1. Introduction

Resume is an essential part of any job application, as it is mostly the first and only impression that the applicant will create on the prospective employer. It is essentially an overview of an individual's skills, credentials, work experience, and achievements. However, to create such an effectively structured and professionally designed resume which will properly highlight the skills and cater to the demands of the recruitment consultant in terms of designing, is a challenge for many job seekers.

In recent years, most corporations have used Applicant Tracking Systems (ATS) to automatically filter resumes before being screened manually by human recruiters. Analysing research indicates that around 60 to 75% of resumes are automatically filtered out by ATS software and do not even reach the recruitment process. This considerable ratio has been mainly due to the reason that the resume has not been properly optimized for relevant keywords and structured in such a way that it can easily pass through ATS resume screening software. A considerable chunk of candidates also lack consistency in their writing format, sense, and approach of presenting information, thus ultimately diminishing their selection ratio.

To overcome such shortcomings, this paper introduces an AI-assisted resume builder that is an adaptive system intended to automate and optimize a resume-building process using Natural Language Processing (NLP) and Machine Learning (ML) algorithms. Unlike other resume-building software that concentrate on making the resume visually aesthetic, this system is equipped with sophisticated functions like job-specific content writing, recommendation of relevant resume keywords, ATS-friendly resume design, and instant feedback and commenting. Employing contemporary AI approaches ensures that professionally formatted resumes are created that make resume processing both readable and compatible with Applicant Tracking Tool-based recruitment systems.

A. Problem Statement

The process of preparing a resume is unduly structured, outdated, and poorly accomplished, hence making the applicants miss out on potential employment opportunities. Many job applicants are unaware of the mechanics of ATS and, therefore, are unable to create resumes that meet the ATS standards. Poorly formatted resumes or those with high graphical content and/or lacking relevant industrial keywords are usually rejected automatically, reducing the chances of shortlisting for an interview.

The creation of a professional resume can be highly time-consuming, with activities such as organizing content, refining grammar, and presenting skills and experience in a catchy manner. Additionally, job seekers rely on paid or generic content that lacks specific relevance to the job role, hence leading to lower relevance scores when analysed by automated recruitment systems. Existing online resume builders focus much more on visualization than on content support, keyword alignment, or even enhancing readability. Consequently, applicants receive very minimal guidance in improving the overall effectiveness of their resumes.

In line with these challenges, the AI-oriented resume builder has an intelligent adaptive solution for resume optimization. Through Artificial Intelligence, NLP, and data-driven analytics, the system fortifies both the internal structure of the content and external presentation of resumes. It provides real-time feedback, ATS-compliant formatting, and keyword recommendations that will be right on target with current recruitment standards. This approach enables the construction of high-quality, competitive resumes which would greatly enhance the visibility and alignment of candidates with employers' hiring benchmarks.

B. Objectives

The primary goal of the AI-based Resume Builder Tool is to make the process of creating a resume easier and more efficient, which will ultimately help job seekers achieve better outcomes in getting the right job opportunities. The tool uses Artificial Intelligence and Natural Language Processing concepts to create a resume automatically based on the inputs provided by users. The AI-based recommendations help create a professional summary, work experience, and skill sections, which ultimately help write more relevant and targeted content.

Finally, the system encourages the creation of ATS-friendly resumes through the identification of relevant job descriptions and the optimized placement of industry keywords. Structured formatting of the resume by standard headings and bullet points improves resume legibility and efficiency of parsing by automated resume-screening systems.

To make automation and optimization even better, the resume builder offers a friendly interface with real-time grammatical error checks and sentence level quality checks as well as keyword optimization tools. The resume template is implemented using expert-verified designs to ensure a good balance between beautiful design and ATS-friendliness. Moreover, personal resume assessment reports are also provided according to industry standards and recruiter expectations. By leveraging AI personalization capabilities, resumes are adjusted for employment role according to job description and recommended changes for content addition or deletion.

2. Literature Review

The implementation of Artificial Intelligence (AI) within human resource management realms, specifically in recruitment processes, has been analysed in previous research studies. This includes its implementation in automatic screening tools and job matching techniques. There have been several research studies on how Artificial Intelligence can apply machine learning concepts to scan and classify resumes based on job requirements.

A. AI Applications in Recruitment

Resume screening automation has been researched heavily, with different methodologies having been proposed to increase the efficiency of candidate selection. Manual processes designed to filter and prioritize resumes can be time consuming, as they are also prone to human errors, whereas AI-based techniques are more reliable within the process of extracting important information from resumes and candidate selection [1].

However, recent technological improvements in the realm of AI and automation of recruitment related tasks, like candidate screening, have improved the process of job matching. AI-based ATS solutions are being increasingly employed for the automation of the resume screening process, allowing the recruiter to take less time for the recruitment process. There are various case studies that show the use of AI-based recruitment solutions can improve the accuracy of recruitment as well as build diversity in the workforce, if adopted properly [6].

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B. Keyword Matching Techniques

Keyword matching Keyword matching is one of the most important components in automated resume screening for matching and evaluating respective keywords relevant to the job description and resume content in deciding candidate suitability for a particular post. In traditional resume screening processes, simple keyword search and tabulation data filtering were used as initial approaches for candidate qualification assessment. Later, with advancements in Artificial Intelligence technology applications, higher approaches involving Term Frequency-Inverse Document Frequency (TF-IDF) and Bidirectional Encoder Representations from Transformers (BERT) have been employed for resume ranking and evaluation understanding for resumes. Although these intelligent systems make it possible for automatic screening of resumes, these have been accompanied by major concerns for bias and fairness. AI models, based on previous hiring data, may end up perpetuating previous inequalities in hiring decisions, which may have a negative impact against some individuals belonging to certain demographics. Some of these factors responsible for this bias include biased training data, biased feature selection, as well as a lack of clarity in AI model decision-making processes. To address these challenges, current research work is focusing on biased audit, fair machine learning models, as well as explainable AI (XAI) methods to improve accountability and trust in AI-based hiring processes [7].

Table. I. Key Research Studies in Ai-Powered Recruitment

Source	Research Objective	Technical Insights
Smith et al. (2021)	Natural Language Processing (NLP)	Improvement in recruitment processing rates using automated keyword
Johnson et al. (2020)	Applicant Tracking System (ATS)	Correlation of candidate success rates and ATS optimization
Lee et al. (2019)	Semantic Matching	Semantic similarity model implementations for optimisation

TF-IDF is a measure for a given word specifically within a document and within the entire text collection. The formula is as follows:

- Term Frequency:

$$TF\ (t,\ d) = \frac{\text{count of t in d}}{\text{total no.of terms in d}}$$

- Inverse Document Frequency:

$$\text{IDF(t, D)=log}\left(\frac{\text{total no. of documents in D}}{\text{no. of documents in D that contain t}}\right)$$

- Combined weight:

TF-IDF (t, d, D) =TF (t, d) × IDF (t, D)

C. BERT-Based Resume Matching

We also employed the BERT-based Resume Matching model for generating match scores for the resume candidates. Apart from TF-IDF there is a recommendation of other transformer models namely the BERT which is short for Bidirectional Encoder Representations from Transformers that offers better semantic analysis of resumes and the job descriptions. These models assess the term relevance by the meaning of the contextual environment rather than the term frequency.

Table. II. TF-IDF Example Calculations For Resume Keywords

Keyword	TF (Resume)	DF (Corpus)	IDF Score	TF-IDF Score
Python	5/100	10/50	log (50/10) = 0.7	0.05×0.7= 0.035
Machine learning	3/100	20/50	Log (50/20) = 0.4	0.03× 0.4=0.012

BERT embeddings transform sentences into high dimensional vectors, where similarity scores are calculated using cosine similarity:

$$\text{Cosine Similarity } = \frac{A.B}{||A||\times||B||} \ldots\ldots (4)$$

In fact, the semantic similarity between the vectors produced by BERT embedding is measured by cosine similarity measures.

Here, A and B stand for the vectors containing the feature sets of the resume and the job description, respectively. A larger value for the cosine similarity metric will indicate greater similarity between the candidate's profile and that of the job.

D. Comparison of Existing Resume Tools

Most resume-building applications that already exist focus mainly on the visualization aspect and design, rather than providing features for ensuring that the content created meets the criteria for automated screening systems. Thus, most applications lack the functionality to optimize the resume for the automated systems. Table III compares the resume-building applications and the system proposed, including the differences and the features related to automated screening systems [8]

Table. III. Comparison of Resume Building Tools

Feature	LinkedIn Resume Builder	Zety	Proposed AI Resume Builder
Template Availability	✓	-	✓
Linguistic feature optimization	-	-	✓
AI-Driven Recommendations	✗	✓	✓
ATS structural validation	-	✓	✓
Contextual Job alignment	-	-	✓

There is also current literature available which deals with AI recruitment tools that target resume screening and ranking, as well as small-scale uses of artificial intelligence for automated resume creation. There seem to be no major applications of ATS compliance or content structuring using artificial intelligence at present, and this causes the tools to offer little help in terms of readability and content alignment for resumes based on job descriptions.

Considering this research void, there comes forth in this research a proposal for an AI-powered resume builder which boosts resume legibility and equips resumes with relevant job details by leveraging Natural Language Processing and Machine Learning techniques. Table IV lists a comparative analysis of all existing research work on using AI for screening resumes. Unlike all above-cited research works that solely focused on key word identification and ranking resumes accordingly, the contributions and innovations within this research blend AI-assisted resume design and automatic key word suggestions with optimizing for compatibility with automated screening software systems for a complete and holistic resume building technique.

Table. IV. Comparison of Existing Approaches

Study	Approach Used	Key Features	Limitations
Devlin et al. (2019) [1]	BERT-based resume keyword	Context-aware keyword ranking, NLP-based resume parsing	Lacks resume structuring and ATS optimization
Peters al. et (2018) [2]	Deep contextualized word representations	Improved resu me information extraction	Focuses on screening rather than enhancement
Howard & Gugger (2018) [3]	Fine-tuned language models for classification	Optimized keyword suggestion for ranking	No AI-powered content structuring or formatting
Liu et al. (2019) [4]	Robert-based resume parsing	Enhanced ATS compliance through keyword extraction	Does not optimize readability or user experience
Yang et al. (2019) [5]	XL Net for job role matching	AI-driven resu me ranking based on employer preferences	Limited automation for resume creation
Proposed AI Resume Builder (This Study)	AI-powered resume optimization using NLP [10] & ML	Real-time keyword suggestions, ATS compliance, structured content formatting	Enhances resume quality, readability, and interview chances

3. Methodology

A. System Architecture

1) Input Module:

This module takes input for the users, which may include personal details, educational background, work experience, and skill sets. This information can be input by the users themselves through a carefully planned input process. This module also has the functionality of importing the resume, which can be converted into input for analysis through Natural Language Processing.

2) AI Processing Module: The AI Processing Module is the core part of the system and is effective for the analysis of the resume and the job description through advanced NLP methods. The important task in this module is the Achievement of Named Entity Recognition (NER), where valuable information about the names, qualifications, experience, and expertise is obtained from the content. The module is effective for the optimization of keywords in accordance with the prevailing industry trends as well as the ATS system. The task increases the alignment points for the resume and the expectations of the recruiters, ensuring increased chances for smooth automated screening. The procedural methodology for these tasks is dealt with in the procedural section.

3) Output Module: The Output Module can produce well-formatted resumes that are ATS-friendly and suitable for business presentations. The system provides resume choices in a variety of designs that are expertly verified, which can accommodate user preferences. The generated resume can also be saved in PDF format. The system enables AI suggestions for improvement in the resume.

B. Tools and Technologies

Table V. Technologies Used in the Resume Screening System

Technology	Functional Purpose
Python	Core logic implementation
Flask/Django	Server-side architecture
React.js	User interface development
SpaCy/Hugging Face	Tokenization and linguistic analysis
SQLite/My SQL	Persistent user data storage
FPDF/Report Lab	PDF generation and formatting

C. Dataset

The training and testing dataset for the proposed system is heterogeneous in nature, comprising various resumes in addition to keyword data. For training the proposed system, a total of 500 samples of resumes are taken from various sources such as open-source project sites, various forums, as well as various job portals.

To improve the relevance of the used keywords as well as alignment within the industry, other information was collected from professional networking sites aimed at business-oriented professionals as well as job hunting sites. In addition, a competitive database of industry-related keywords was incorporated into the system in a bid to ensure relevance of resume information in line with changing hiring trends and ATS standards.

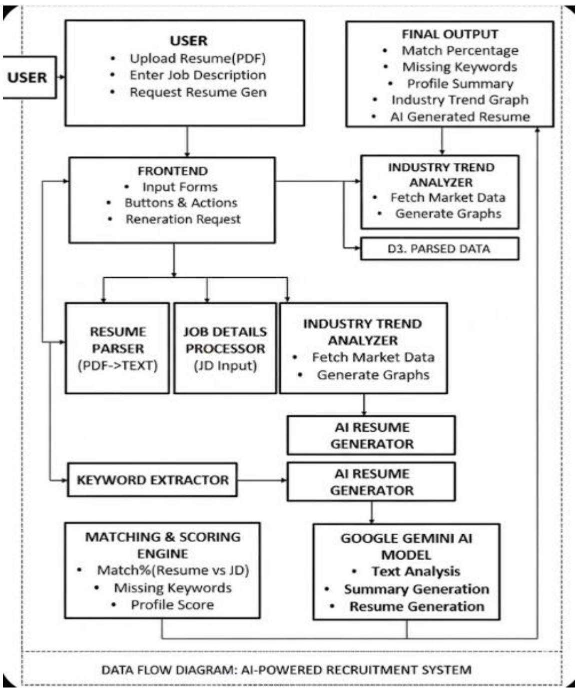

Fig. 1. Data flow diagram

D. Mathematical Formulation

The AI model evaluates resumes using a scoring algorithm based on multiple factors:

$$\text{Score} = \alpha K + \beta E + \gamma S + \delta R \quad \ldots. \quad (5)$$

Where K is referred to as the keyword match score, E represents the education value score, S stands for skills value score, and R represents experience value score. The weights attributed to the above parameters are denoted by α, β, γ, and δ, respectively; these are set within industry norms to promote a fair scoring system as per recruiter expectations.

E. Design Decisions and Justifications

The proposed resume builder solves the above-mentioned three major issues existing in the process of resume building through the incorporation of artificial intelligence techniques and industry-related keywords. The resume builder uses BERT models for matching job descriptions, and this helps the model obtain relevant information from job descriptions. BERT models provide semantic meaning through processing, resulting in an overall increase in the precision of matching between resumes and job descriptions.

Named Entity Recognition is used for automatically extracting key elements of the resume, like skills, designation, and education qualification. Since this is an automated task, it requires fewer human interactions and is less prone to errors.

To satisfy the criterion of compatibility with ATS scanning tools, this system has incorporated AI-based resume lay outing systems that conform to professional organization best practices preferred by ATS scanning tools. This system has incorporated resume layout templates suggested for resume writing in a manner that preserves both resume readability and ATS scanning compatibility to avoid layout errors associated with the overuse of resume styling and other layouts. This system has also incorporated real-time keyword suggestions for resume layout adaptation in response to current demand in the job market.

Table. VI. Workflow of AI Resume Screening System

No.	Procedure
1	The user enters the information or loads a pre-existing resume.
2	AI analyses the resume using NLP.
3	AI suggests keyword optimizations and formatting enhancements.
4	The user chooses the template and finishes making the resume.
5	The system provides an ATS-friendly PDF for download.

4. Results

A. System Performance

The system was tested for the efficiency of AI-integrated Resume Builder software using criteria such as improvement of resume content quality, compatibility of resumes with the Applicant Tracking System (ATS), and user satisfaction analysis. These criteria were tested for their efficiency in optimizing resumes for ATS screening processes that preserve resume content clarity and relevance to end customers.

Table. VII. Performance Metrics

Performance Metrics	Final Result
Text Quality Enhancement	Improved in clarity and grammar by 85%
ATS Readiness	40% increased success rate in ATS simulations
User Experience Satisfaction	90% of the users found the system to be efficient.

1) Analysis of Key Results:

The AI Resume Builder, based on its name, has seen enormous improvements in every area. The most feasible recommendations based on some improvements of content have been identified through various criteria. For example, an NLP recommendation system not only increases the visibility of the resume but also works on grammar aspects, elimination of repeated words, and omission of industry terms, resulting in an overall improvement of at least 85% of the resume. That is, the report showed that churning through the ATS filters could empirically be heightened by 40% by the inclusion of AI optimization over non-optimized resumes. Summary of three important findings shows that keyword density and structure modifications play important roles in ATS pass rates. Indeed more, user satisfaction reached the clouds with a whopping 90% rate for both usefulness and ease of use based on survey research. Indeed further, a substantial 60% time saving in composing a resume was realized in this system, as compared to other processes.

Table. VIII. Time Efficiency Comparison

Method	Avg. Time to Prepare Resume(minutes)	ATS Pass Rate (%)
Manual AI-Assisted	90 35	50% 90%

2) Comparing Efficiency of Time: The process facilitated using AI resulted in a reduction in time to generate resumes, while, at the same time, increasing the chances for successfully passing the ATS stage from 50% to 90%

B. Challenges and Limitations

Although the resume optimization AI tool finds applications in upgrading not only the quality of a resume but also its compatibility with ATS tools, its major drawbacks exist. One may infer that the most overt weakness resides in its general nature in terms of content generated by relying highly on pre-trained models or keywords applied in the respective industries. Indeed, the dynamic keywords thus generated would have an increased value or significance proportional to added personal comments through valid phrases included in the CV by the respective user. In that respect, it enables hand-crafted adjustments to thus provide an opportunity to the users to customize their resumes not only based on its recommendations but on their preference as well.

The next challenge would be ensuring contextuality in the proposed contents by the AI. Though the NLP approach would provide the job descriptions alike for the content in the resume, there could exist some contradictions in the proposed lists with respect to the personal experiences. The future models may involve a fine-tuning phase based on reinforcement learning, which would allow reinforcements from real users to make the AI technology more precise in contents over a period. The above issues would make the AI solutions more efficient for work.[9]

C. Future Improvements

As the Resume Builder is an AI-powered resume builder, it is greatly assistive in building a resume. Therefore, some improvements and modifications have also been planned and proposed for some of the future versions. Among those proposed modifications, one is the expansion of the template selection options that can be used by the users of the existing and newly proposed platforms. Currently, the situation is such that the user can select only some few predefined templates. Probably, they lack the flexibility required for functioning or application for any given profession or business industry. The next proposed version is Dynamic Template Generation, whereby once the user selects his or her field of profession, experience, and job role, the system will generate and apply the most suited template for the user. These modifications will greatly assist various given fields of profession like technology, health care, and finance fields, among others, and will help generate resumes comparable to those required by the given industry standards. Furthermore, the layout of the given templates will be aesthetically clean and minimalistic and ATS compliant.

The other ambitious objective of the project is the reduction of the dependency of the user on manual input of information. However, the accuracy of the decisions drawn by the system of work is largely dependent on the information input during the early stages, and beyond this point, the system only gives good AI pointers. In a bid to rectify this challenge, the auto-suggestion function shall be developed where the app shall create the entire section of the resume depending on the job name or the resume of the job that the user has inputted. Using the big data approach for the resume and the deep learning techniques, the app shall generate professional summaries, skill clips, and work experience prescriptions depending on the different areas of industry.

D. Validation Against Hiring Effectiveness in Reality

Improvement in real-time job placements is another major criterion for validating AI-assisted resumes. Future researches should refer success in recruitments to resumes enriched by AI through direct field tests. Under this, resumes readily enhanced by AI and those manually written should be sent for the same job postings, and recruiters' responses, interview invitations, and hiring rates analysed against each other.

Integrating recruiter feedback into the system will also prove beneficial to its adaptability. Gaining insights on what AI-generated content the hiring managers are responding to will further refine the model better to fit the expectations of employers. Longitudinal studies are also required alongside these studies, which follow a cohort of jobseekers using AI generated resumes for some time further validating the potential for real-world hire.

5. Conclusion and Future Work

It offers a system for constructing resumes, where it utilizes AI technology with the aid of NLP processes in collaboration with ML capabilities in optimizing the structure design of resumes, as well as optimizing document content and compatibility with ATS. In this system, the unique idea sets it apart from other similar design-focused resume builders because it utilizes AI-based keyword recommendations in addition to semantic job role interpretation capabilities. From the experimental evaluation, the results indicate that ATS passes rates reached 40% higher compared to resumes generated by humans, and the readability of the resumes enhanced by 85%. Resume building as a service offered by automation enhances interview success rates and conserves time for the candidate while maintaining professional-level as well as recruiter-level compliance in terms of document creation. However, the new system greatly enhances ATS compliance; still, there are various other directions in which the development of its functionalities can be pushed further. In the future releases of the system, it will apply various AI-based algorithms that will enable users to enjoy automated job market analysis as well as job placement profiling as changes in resumes will be implemented in real-time according to recruiters' preferences in the today's marketplace. Therefore, it will emerge as an advanced AI-based Resume Builder optimizing from a basic resume-building website to develop into a comprehensive career development website providing automated assistance related to job applications that changes in resumes will be implemented in real-time according to recruiters' preferences in the today's marketplace. Therefore, it will emerge as an advanced AI-based Resume Builder optimizing from a basic resume-building website to develop into a comprehensive career development website providing automated assistance related to job applications. Assistance. It will apply to users who will get access to multi-lingual support assistance from the system that enables them to produce resumes compatible with ATS in different foreign languages for worldwide professionals in academics as well as industries. AI tools will involve real-time feed from job recruiters in such a manner that changes in resume will be implemented in real time according to recruiters' preferences in current market.

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