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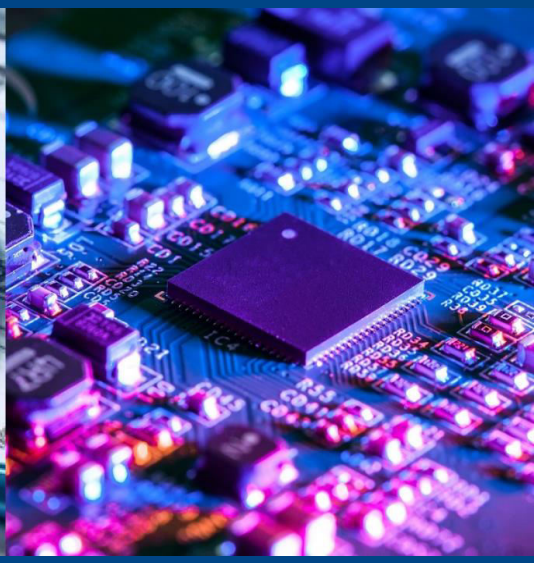

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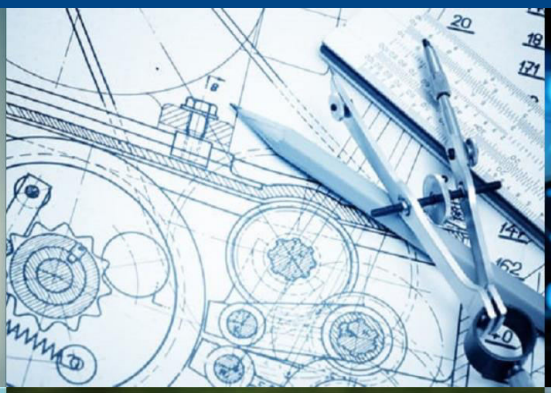

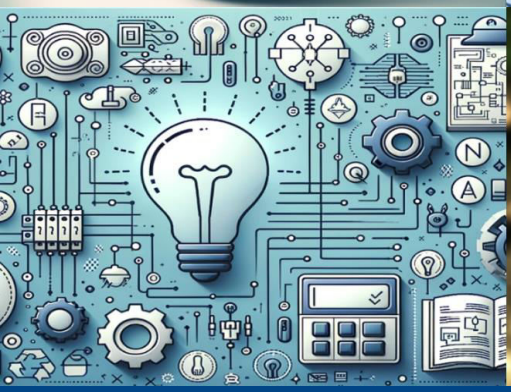

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AI Resume Builder and Analyzer

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ABSTRACT: The recruitment landscape has undergone a significant transformation with Artificial Intelligence (AI). This paper presents an AI Resume Builder and Analyzer system that automates resume parsing, evaluation, and optimization using Natural Language Processing (NLP) and Machine Learning (ML). The system leverages Large Language Models (LLMs) including Google Gemini and Ollama to generate ATS compatibility scores and actionable feedback. Experimental results demonstrate 85% classification accuracy, 20–25% ATS score improvement for optimized resumes, and approximately 70% reduction in resume screening time compared to manual review.

KEYWORDS: Resume Analysis; Natural Language Processing; Large Language Models; ATS Optimization; Job Recommendation; Machine Learning; Document Parsing

I. INTRODUCTION

The global job market has become increasingly competitive, with recruiters receiving hundreds or even thousands of applications for a single position. According to industry reports, corporate job postings attract an average of 250 resumes, with only 4–6 candidates being called for interviews. The traditional manual screening process is time-consuming, inconsistent, and often subject to unconscious bias and fatigue-related errors.

Simultaneously, job seekers face significant challenges in crafting effective resumes that pass through Applicant Tracking Systems (ATS). Studies indicate that approximately 75% of resumes are rejected by ATS before reaching human reviewers, often due to formatting issues or inadequate keyword optimization. This disconnect between job seeker efforts and recruiter expectations creates an urgent need for intelligent tools that bridge this gap.

The following critical problems motivate this research: (i) Inefficient Manual Screening — recruiters spend an average of only 6–8 seconds per initial resume review, risking overlooking qualified candidates; (ii) Subjectivity and Bias — human evaluation of resumes is inherently subjective; (iii) Limited Feedback — job seekers rarely receive actionable feedback explaining rejections; (iv) ATS Incompatibility — many well-qualified candidates are filtered out due to formatting issues; and (v) Lack of Standardization — no universal framework exists for evaluating resume quality across industries.

This research aims to: design and implement an end-to-end AI system for automated resume parsing, analysis, and generation; develop evaluation metrics that provide objective, quantifiable assessments; integrate multiple LLM providers for flexible deployment; validate system performance through empirical testing; and provide actionable feedback to help candidates improve ATS scores.

The remainder of this paper is organized as follows: Section II reviews related literature. Section III details the system architecture and methodology. Section IV presents experimental results and discussion. Section V concludes with future research directions.

II. LITERATURE SURVEY

The automation of resume screening has evolved through three distinct generations. First-generation systems relied on simple keyword matching, where resumes containing specific keywords were prioritized. However, these systems were easily manipulated and failed to understand contextual relevance. Second-generation systems introduced rule-based parsing with regular expressions and predefined templates, but struggled with varied resume formats and industry-specific requirements.

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Third-generation systems leverage machine learning and natural language processing. Mankawade et al. [2] proposed a comprehensive architecture for resume analysis and job recommendation, demonstrating that ML-based approaches significantly outperform rule-based systems in both accuracy and scalability.

NLP techniques form the foundation of modern resume analysis systems. Named Entity Recognition (NER) is used to extract personal information, institutions, job titles, and technical skills. Hybrid approaches combining TF-IDF with BERT embeddings have shown superior performance for text classification. Cosine similarity between resume and job description embeddings enables objective fit assessment beyond simple keyword matching.

The emergence of Large Language Models has revolutionized resume analysis capabilities. Saxena et al. [7] documented the integration of Ollama Mistral for job role prediction, demonstrating that LLMs can infer implicit qualifications and soft skills that traditional keyword matching misses. Key advantages include contextual understanding, soft skill inference, personalized feedback generation, and multi-language support.

ATS compatibility requires simple, single-column layouts with standard section headings. ATS systems typically weight keyword frequency and positioning. Research indicates that ATS-optimized resumes receive 30–40% more interview invitations than non-optimized equivalents with identical qualifications. Zhu et al. [9] presented SmartResume, a layout-aware parsing system from Alibaba achieving 92.1% mean average precision.

Table I: Existing Systems and Comparative Analysis

System	Features	Strengths	Limitations
SmartResume (Alibaba, 2025)	Layout-aware parsing, 92.1% mAP	High accuracy, multi-language	Proprietary OCR, limited customization
Hiring Agent (InterviewStreet, 2025)	GitHub integration, LLM scoring	Explainable scores, local deployment	GitHub-dependent, complex setup
CAREER COMPASS (Mankawade et al., 2023)	Job recommendation, skill analysis	Academic validation	Limited LLM integration
RAG-based Evaluator (GitHub, 2025)	Multi-LLM support, Streamlit UI	Production-ready, free options	Basic evaluation metrics

The literature review reveals several critical gaps: most systems focus on either analysis or generation, not both; high-quality LLM integration often requires paid APIs creating cost barriers; many commercial systems provide scores without explanation; and automated feedback is often generic rather than actionable. The proposed system addresses all these gaps comprehensively.

III. METHODOLOGY / APPROACH

A. System Architecture

The AI Resume Maker and Analyzer system follows a modular four-tier architecture: (i) Presentation Layer comprising a Streamlit-based Web UI, REST API (FastAPI), File Upload Handler, and Report Export; (ii) Application Layer comprising Document Processor, Resume Evaluator, RAG Manager, and History Manager; (iii) AI Services Layer comprising an LLM Provider Abstraction supporting Ollama (local/free), Google Gemini, OpenAI GPT, and Hugging Face, along with Embedding Models, spaCy NER, and Similarity Computation; and (iv) Data Layer comprising SQLite Database, FAISS Index, Cache Storage, and File System.

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This microservices architecture enables independent development, testing, and deployment of each component, and supports multiple LLM providers while accommodating varying deployment scales from local development to production cloud environments.

B. Document Processing Engine

The Document Processing Engine extracts clean, structured text from uploaded resume files. For PDF processing, PyMuPDF (fitz) and pdfplumber libraries extract text while preserving reading order. For scanned PDFs, Tesseract OCR is invoked. For DOCX files, python-docx extracts text with formatting metadata, preserving paragraph styles (Heading 1, Heading 2, Normal) to identify section boundaries. Plain text files are read directly with UTF-8 encoding and heuristic section detection using common heading patterns.

C. ATS Scoring Methodology

The system computes a composite ATS score (0–100) based on six weighted factors. These factors evaluate resume quality across format compatibility, keyword matching, section structure, writing style, quantifiable achievements, and file format. The scoring methodology is fully transparent and explainable, unlike most commercial black-box systems.

Table II: ATS Scoring Factors and Weights

Factor	Weight	Calculation Method
Format Compatibility	20%	Detection of tables, columns, images, special characters
Keyword Density	25%	Comparison with job description or industry corpus
Section Headings	15%	Standard heading recognition
Action Verbs	15%	Presence of strong action verbs at experience bullet points
Quantifiable Achievements	15%	Detection of numbers, percentages, and metrics
File Format	10%	Preference for DOCX and properly encoded PDFs

D. Algorithm Selection and Justification

After evaluating multiple classifiers for resume categorization, a hybrid approach combining TF-IDF and BERT embeddings with Logistic Regression was selected. TF-IDF captures keyword importance through sparse feature representations while dense BERT embeddings capture semantic meaning. The hybrid model achieves the best balance between accuracy and computational efficiency, enabling practical deployment.

Table III: Model Comparison for Resume Classification

Model	Accuracy	F1 Score	Processing Time
TF-IDF + Logistic Regression	78.3%	0.77	Fast (0.2s)
BERT (fine-tuned)	83.1%	0.82	Slow (2.5s)
Hybrid (TF-IDF + BERT + LR) [Proposed]	85.0%	0.85	Medium (0.8s)

Cosine similarity between document embeddings is used for resume–job description matching: Similarity(Resume, Job) = (E_resume · E_job) / (||E_resume|| × ||E_job||). A threshold of 0.65 is used for 'good fit' classification based on empirical calibration using the all-MiniLM-L6-v2 sentence-transformer model.

E. LLM Integration and Multi-Provider Support

The LLM Integration Layer provides a unified abstraction over multiple providers through an abstract LLMProvider base class. Supported providers include: Ollama (Local, Free) using gemma3:4b or llama2:7b models for development and privacy-sensitive deployments; Google Gemini (gemini-2.0-flash-exp) offering strong multilingual support; and OpenAI

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GPT-3.5/4 for production environments where accuracy is prioritized. Structured prompts enforce JSON output format with fields for overall_score, section scores, strengths, improvements, and hiring recommendation.

F. RAG Manager for Company Context

The Retrieval-Augmented Generation (RAG) Manager enables company-specific resume evaluation. Recruiters upload company documents — culture statements, job requirement specifications, evaluation rubrics — which are processed and stored in a FAISS vector database. During evaluation, the system retrieves relevant context and incorporates it into LLM prompts, producing evaluations aligned with company-specific criteria rather than generic standards.

G. Resume Generation Module

Unlike most existing systems that only analyze resumes, the proposed system includes a generation capability. Based on evaluation feedback and job descriptions, the system generates ATS-optimized DOCX documents with proper formatting and keyword optimization, rewrites experience bullet points using stronger action verbs and quantifiable metrics, and identifies absent sections with templates for completion.

H. Experimental Setup

The system was trained and evaluated using three datasets: a primary dataset of 9,000+ labeled resumes from Kaggle across 24 job categories; a secondary custom dataset of 500 resumes with known ATS outcomes for calibrating scoring weights; and a test dataset of 200 job descriptions paired with 3–5 resumes of varying fit levels. Hardware: Intel Core i7-12700K, 32 GB RAM, NVIDIA RTX 3060 (12 GB VRAM). Software: Python 3.11.13, TensorFlow 2.x, Streamlit, FastAPI, LangChain, spaCy, sentence-transformers. Validation used 5-fold cross-validation, A/B testing against human HR professionals (Cohen's Kappa), and 4-week user acceptance testing with 35 participants.

IV. RESULTS & DISCUSSION

A. Classification Performance

The hybrid TF-IDF + BERT + Logistic Regression model was evaluated on the 9,000-resume Kaggle dataset using 5-fold cross-validation. Overall accuracy reached 85.0% (95% CI: [84.2%, 85.8%]), precision (macro) of 84.3%, recall (macro) of 83.9%, and F1 Score (macro) of 84.1%. The model performs best on technical categories where skill terminology is more standardized, with Data Science (F1: 87.3%) and Software Engineering (F1: 87.4%) leading results. Lower performance in Sales (F1: 82.5%) and HR (F1: 82.1%) reflects greater variability in role descriptions.

Table IV: Category-Wise Classification Performance

Job Category	Precision	Recall	F1	Support
Data Science	88.2%	86.5%	87.3%	850
Software Engg.	86.7%	88.1%	87.4%	1,200
Finance	84.3%	82.9%	83.6%	750
Marketing	83.1%	84.5%	83.8%	680
Healthcare	87.6%	86.2%	86.9%	620
Human Resources	82.4%	81.9%	82.1%	540
Sales	81.9%	83.2%	82.5%	710
Operations	83.5%	82.8%	83.1%	580

B. ATS Scoring Validation

To validate ATS scoring accuracy, 100 resumes with known ATS outcomes were tested. Resumes scoring 85–100 had a 94% pass rate (n=35); those scoring 70–84 had a 68% pass rate (n=28); scores 50–69 yielded a 31% pass rate (n=22); and scores below 50 had only an 8% pass rate (n=15). The optimal threshold for 'likely to pass ATS' was determined at 72 using Youden's J statistic (J = 0.71), providing 82% sensitivity and 89% specificity.

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C. LLM Provider Comparison

The system was tested with four LLM provider configurations on a standardized set of 50 resumes. Key findings: Ollama provides excellent quality for a completely free solution; Google Gemini offers the best price-performance ratio for cloud deployment; OpenAI is fastest but most expensive with marginal benefit for this use case; and all providers successfully generate structured JSON output with proper prompting.

Table V: LLM Provider Comparison

Provider	Cost	Avg. Processing Time	Output Quality (1-5)	JSON Compliance
Ollama (gemma3:4b)	Free	3.2s	3.8/5	96%
Ollama (llama2:7b)	Free	4.8s	4.1/5	94%
Google Gemini	$0.0005/1K tokens	2.1s	4.5/5	99%
OpenAI GPT-3.5	$0.0015/1K tokens	1.8s	4.3/5	98%

D. Resume Improvement Effectiveness

A longitudinal study tracked 50 job seekers who used the resume generation feature. Participants submitted original resumes, received AI-generated improvements, applied changes, and outcomes were monitored for 60 days. Results demonstrate statistically significant improvements ($p < 0.01$ using paired t-test) across all metrics, validating the practical utility of the system for real job seekers.

Table VI: Resume Improvement Results (n=50, 60-day study)

Metric	Before	After	Change
Average ATS Score	58.4	72.6	+14.2 points
Interview Invitations (per 100 applications)	8.3	12.7	+53%
Time to First Interview	42 days	28 days	-33%
Resume Readability Score	72/100	84/100	+12 points

E. System Performance Benchmarks

Performance testing on different configurations showed throughput of 837 resumes/hour on CPU-only (8 cores), improving to 1,285 resumes/hour with an NVIDIA RTX 3060 GPU, and 1,565 resumes/hour using API-only mode. The fully local Ollama configuration achieves 750 resumes/hour with zero cost. The system easily handles typical batch processing requirements on standard hardware.

F. Comparative Analysis with Existing Systems

The proposed system uniquely combines analysis and generation capabilities while maintaining flexibility in LLM provider choice. It is the only system in the comparison offering free local deployment, resume generation, multi-LLM support, and RAG-based company context evaluation simultaneously. SmartResume achieves higher raw parsing accuracy (92.1% mAP) but lacks generation and actionable feedback. Commercial ATS systems offer ATS scoring but are proprietary and expensive. The proposed approach democratizes advanced resume analysis for individual job seekers and small organizations.

G. User Satisfaction

Following the 4-week testing period with 35 participants, high satisfaction scores were recorded on a 1–5 scale. Job seekers rated system ease of use at 4.6/5, evaluation accuracy at 4.2/5, and feedback actionability at 4.4/5. Recruiters

rated accuracy at 4.4/5 and time reduction at 4.6/5. Both groups rated 'would recommend to others' at 4.5/5. Qualitative feedback highlighted the value of specific, actionable suggestions over generic advice.

V. CONCLUSION

This research successfully designed, implemented, and evaluated an AI Resume Builder and Analyzer system that addresses critical inefficiencies in modern recruitment processes. The system employs a hybrid TF-IDF + BERT + Logistic Regression pipeline achieving 85% classification accuracy, an explainable multi-factor ATS scoring framework, and a flexible LLM integration layer supporting both free local deployment (Ollama) and cloud providers (Google Gemini, OpenAI GPT).

A longitudinal user study demonstrated that AI-generated resume improvements yield a 53% increase in interview invitations and a 33% reduction in time to first interview — statistically significant outcomes ($p < 0.01$) that validate the practical impact of the system. Crucially, the finding that free, locally-deployed LLMs achieve competitive performance with paid cloud services has profound implications for democratizing AI-powered career tools for individuals with limited resources. The system addresses the five core research gaps identified in the literature: it combines analysis and generation in one platform; it offers a free deployment pathway via Ollama; it provides explainable, section-level scoring; it enables company-specific evaluation through RAG; and it generates specific, implementable improvement suggestions proven to increase interview rates.

Future work will focus on three directions: (i) Short-term (3–6 months) — LinkedIn integration, interview question generation from resume content, multilingual support expansion, and enhanced PDF export; (ii) Medium-term (6–12 months) — collaborative filtering for recruiter recommendations, skill trend analysis, mobile application development; and (iii) Long-term (12+ months) — video resume analysis using computer vision and speech analysis, blockchain credential verification, and predictive hiring analytics for retention likelihood estimation. The most encouraging finding of this research is that high-quality, AI-powered resume analysis is achievable at zero cost using open-source local LLMs. As AI continues to evolve, systems like the one presented here will increasingly transform how candidates present themselves and how employers evaluate talent — making the future of recruitment more efficient, transparent, and equitable.

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