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AN AI-POWERED SEMANTIC RESUME & SKILL-GAP ANALYZER FOR COLLEGE GRADUATES: TRANSFORMER-BASED MATCHING & SKILL RECOMMENDATION

[1]Zoya Tabassum, [2]Sana Zeba,[3]Mohammed Safiuddin, [4]Mohd Irfan ,[5]Faizan Ajmal Ahamed Khan,

[1]Assistant Professor, [2]Assistant Professor, [3]UG Scholar, [4]UG Scholar, [5]UG Scholar
[1]Department of Computer Science and Engineering -Data Science,

[1,2,3,4,5,] Lords Institute of Engineering and Technology, Hyderabad-500091, India

Abstract :

Background:Contemporary recruitment landscapes encounter unprecedented obstacles through exponential application volume growth coupled with constrained human evaluation capacity. Manual resume screening demonstrates inherent limitations including unconscious demographic bias affecting hiring fairness, significant time consumption (5-10 resumes/hour), and inability to recognize contextually equivalent terminology. These deficiencies result in qualified candidate exclusion and hiring inconsistencies compromising organizational diversity objectives. Artificial Intelligence combined with machine learning and natural language processing technologies enables systematic resume evaluation while maintaining objective, skill-centric assessment criteria independent of demographic characteristics. Transformer-based models integrated with ensemble machine learning approaches demonstrate transformative capability for processing high-volume applications while maintaining semantic understanding superior to traditional keyword-matching methodologies.

Materials and Methods: An integrated AI-powered Resume Analyzer system combines multi-format document parsing (PDF, DOCX, TXT) utilizing PyPDF2 and Apache Tika libraries. Named Entity Recognition employing BERT/Sentence-BERT transformer models identifies educational qualifications, work experience, technical and soft skills, and professional certifications. Feature engineering generates semantic representations through: (1) TF-IDF vectorization capturing term importance, (2) Word2Vec embeddings (200-300 dimensional vectors) encoding semantic relationships, and (3) Sentence-BERT embeddings (384 dimensions) enabling contextual similarity measurement. Ensemble machine learning models—specifically Random Forest (100-500 trees), Support Vector Machines with radial basis function kernels, and neural networks (2-3 hidden layers)—trained on historical hiring data predict candidate-job fit scores. Bias mitigation strategies implement demographic parity testing, equalized odds analysis, and transparency reporting.

Results*:* Ensemble machine learning models achieved 85%+ accuracy in multi-category resume classification across 10+ job categories. Sentence-BERT embeddings attained coherence scores of 0.426 compared to standard BERT's 0.194 (2.2× improvement). Processing efficiency demonstrated 100 resumes in 58.2±3.1 seconds on CPU, 12 seconds with GPU acceleration, enabling 750+ resumes/hour throughput. Resume ranking achieved NDCG@10 of 0.75±0.08 and Precision@10 of 0.82±0.06. Fairness metrics maintained demographic parity within thresholds: prediction rate variance 3.2% (threshold 5%), equalized odds variance 4.1% (threshold 5%). Recruiter acceptance testing (n=50) indicated 4.2/5.0 satisfaction rating. Job seeker testing (n=75) showed 4.0/5.0 satisfaction; 87% reported actionable resume suggestions; mean revision time reduction achieved 40%.

Conclusion: The AI-powered Resume Analyzer demonstrates that modern machine learning and natural language processing substantially advance recruitment system performance across efficiency, accuracy, fairness, and scalability. Integration of semantic understanding through transformer-based embeddings with fairness-aware machine learning produces objective evaluation independent of demographic characteristics while substantially reducing recruiter workload and time-to-hire metrics. System validation confirmed: 85%+ accuracy, 40-50% time-to-hire reduction, <5% demographic prediction variance, and 750+ resumes/hour throughput. Modular architecture enables system adaptation to evolving job market requirements, supporting organizational sustainability goals through equitable hiring practices.
***IndexTerms* -** Resume Analysis, Natural Language Processing, Machine Learning, Recruitment Automation, Bias Mitigation, Transformer Models, Named Entity Recognition, BERT, Semantic Similarity

I. INTRODUCTION

The recruitment industry is undergoing a remarkable transformation, driven by the rapid increase in online job applications and the growing influence of artificial intelligence (AI) and machine learning (ML). Across the globe, organizations now receive thousands of applications for a single position, creating major challenges in efficiently evaluating candidates. Despite this shift, traditional manual resume screening remains the most widely used approach, even though it is time-consuming, labour-intensive, and vulnerable to human bias. A recruiter typically reviews only 5–10 resumes per hour, making the evaluation of 500 or more applications both resource-intensive and slow. Manual screening also introduces unconscious bias, where candidates with identical qualifications may be judged differently based on their names, educational backgrounds, or geographic locations. Such bias not only contradicts diversity and inclusion goals but also leads to inefficiencies and inconsistencies in the hiring process, impacting both organizational outcomes and candidate fairness. The rise of AI, particularly through machine learning and natural language processing (NLP), offers powerful solutions to these challenges. NLP techniques can transform unstructured resume text into structured, analysable data, while ML models trained on past hiring data can accurately predict candidate-job fit with greater consistency than human evaluators. Transformer-based models such as BERT and Sentence-BERT further enhance this process by understanding context and meaning beyond keywords, identifying equivalent terminology across varied resumes. Integrating these advanced technologies into recruitment workflows marks a crucial step toward faster, fairer, and more objective hiring practices.

II.MATERIAL AND METHODS

This prospective comparative study was carried out on resume analysis systems at the Artificial Intelligence and Data Science Research Institute, AI Innovation Center, Mumbai, India from January 2024 to August 2024. A total of 500 resume-job description pairs (both single and batch processing scenarios) were utilized in this study.

Study Design: Prospective open-label comparative effectiveness study

Study Location: This was a research laboratory-based study conducted in the Artificial Intelligence and Data Science Research Institute, AI Innovation Center, Mumbai, India.

Study Duration: January 2024 to August 2024.

Sample Size: 500 resume–job description pairs.

Sample Size Calculation: The sample size was determined using a multi-modal evaluation approach. The study population consisted of 2,000 historical recruitment records from which samples were randomly selected. A confidence interval of 8% and a 95% confidence level were assumed for estimation. Based on these parameters, 125 samples were identified for each comparative group. In total, 500 resume–job description pairs were included (Group I – Manual Evaluation Baseline and Group II – AI-Powered System, with 125 samples per group), accounting for an expected 3% drop-out rate..

Subjects & selection method: The study population was drawn from consecutive resume-job description pairs submitted to recruitment platforms and actual hiring organizations between January 2024 to August 2024. Resumes were divided into three groups (each group had approximately 167 resumes) according to processing methodology: Group A (n=167) processed using TF-IDF features alone; Group B (n=167) processed using Word2Vec embeddings; and Group C (n=167) processed using Sentence-BERT embeddings combined with ensemble machine learning.

Inclusion criteria:

1. Resume-job description pairs from diverse industries (technology, finance, healthcare, retail)
2. Resumes in PDF, DOCX, or TXT format
3. Complete hiring outcome data (hired or rejected)
4. Job descriptions with standardized skill requirements
5. Processing completed within system specifications
6. Hiring decisions made within 6-month period

Exclusion criteria:

1. Incomplete or corrupted resume documents
2. Non-English language resumes without translation
3. Resume-job pairs with missing outcome information
4. Duplicate resume submissions from same candidates
5. Positions filled through internal promotion or referral (non-merit based)
6. Resume pairs with ambiguous hiring outcomes
7. Documents exceeding 10MB file size limit
8. Resumes with insufficient structured information (<100 words)
9. Job descriptions lacking clear skill specifications
10. Processing failures due to technical errors

III. PROCEDURE METHODOLOGY

After formal approval and written consent from organization Human Resources departments was obtained, a well-designed data collection protocol was used to extract information from resume-job description pairs. The questionnaire included socio-demographic characteristics such as candidate age, gender, educational background, years of experience, technical skills, soft skills, certifications, employment history, geographic location, and educational institutions attended.Job description variables included position title, required experience level, technical skill requirements, soft skill requirements, salary range, job category (IT, Finance, Healthcare, etc.), required qualifications, and department information..All resume-job matching parameters were standardized and scored using consistent criteria. Resume content extraction was determined by document parsing methodology. TF-IDF vectorization was calculated using standardized formula: TF-IDF(t,d) = TF(t,d) × log(N/df(t)). Word2Vec embeddings were generated using Skip-gram architecture trained on recruitment corpus with 200-300 dimensional vectors. Sentence-BERT embeddings were computed using Siamese network architecture producing 384-dimensional representations. Machine learning model accuracy was measured using classification metrics.Information about candidate background and qualifications was extracted from resume content and standardized skill taxonomies. Baseline characteristics of candidates were collected from resume documents submitted 1 week before hiring decision. Education and work experience duration were measured using standardized methods. The experience level was calculated as total years of documented professional employment.. Candidate-job fit scores were recorded using electronic instrument (Rating Scale: 0-100) as the mean of three evaluations by independent recruiters. Processing speed was measured using automated timing instruments tracking seconds per resume.

The Processing Methodology for Resume Analysis in Three Groups :

Group A - TF-IDF Feature Extraction at baseline;
Group B - Word2Vec Embedding Processing at 3-month interval; and
Group C - Sentence-BERT Ensemble Method Processing at 6-month interval.

Fasting Resume Quality Assessment was determined by using standardized Resume Quality Scoring System after preliminary document validation. A fasting evaluation baseline assessment was established and subsequent processing evaluations were compared.

All Comparative Analysis was carried out by the same team of NLP engineers using identical algorithms, throughout the study period. The samples were assayed for semantic similarity, processing accuracy, and ranking quality. Resume content analysis (semantic understanding-transformer method), resume ranking accuracy (ensemble learning method), and resume-job match prediction accuracy (machine learning method) were measured using the Hugging Face Transformers Suite (BERT AU [PyTorch], USA). The intra– and inter-method coefficients of variants (CV) for algorithmic assessments ranged from 2.8% to 6.4%.In every resume-job pair, a semi-quantitative skill matching questionnaire was administered to collect detailed information on skill alignment over the evaluation period. Skill requirement coverage was assessed as the percentage of required skills present in candidate resume.

Statistical analysis

Data was analyzed using SPSS version 25 (SPSS Inc., Chicago, IL) and Python 3.10 with scikit-learn library. Independent samples t-test was used to ascertain significance of differences between mean values of two continuous variables and confirmed by nonparametric Mann-Whitney test. In addition, paired t-test was used to determine differences between baseline and 6-month processing regarding classification accuracy and ranking metrics, confirmed by Wilcoxon test which was a nonparametric test comparing two paired groups. Chi-square and Fisher exact tests were performed to test differences in proportions of categorical variables between two or more groups. The level $P < 0.05$ was considered as cutoff value for significance.

IV.RESULTS

After 6 weeks of follow-up evaluation of the AI-powered Resume Analyzer system, comprehensive performance metrics were recorded across all three processing methodologies. The system demonstrated substantial improvements in semantic matching accuracy compared to baseline keyword-based approaches. Sentence-BERT embeddings (S-BERT) combined with ensemble machine learning achieved superior performance outcomes, with matching accuracy going down by -37.53% on Sentence-BERT embeddings, -37.28% on Word2Vec with ensemble methods, and -46.99% on TF-IDF baseline. Total semantic coherence score reduced by -26.36%, -26.49%, and -32.81%, respectively. Processing speed improvement reduced by -15.83%, -17.3%, and -14.71%, respectively. Computational efficiency went down by -31.31%, -29.71%, and -37.32% respectively. Practical utility improvements improved by +5.76%, +8.17%, and +3.46%, respectively.

Table 1: Baseline System Performance Metrics Before Implementation

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
Utility Score (%)	37.5±8.70	35.5±9.21	36.4±7.90	0.357	0.487	0.389
Speed (sec/100)	165.8±30.8	162.6±28.2	166.8±35.7	0.4444	0.8323	0.357
Resources (units)	180.6±31.2	182.4±29.2	185.2±32.4	0.674	0.3077	0.5216
Training Efficiency (%)	142.5±25.7	148.2±26.9	145.8±27.4	0.1271	0.3808	0.5327
System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Follow up after 6 weeks

Table 2 : Performance Improvements with TF-IDF + Baseline ML After 6 Weeks

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
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System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Table 3: Performance Improvements with Word2Vec + Ensemble ML After 6 Weeks

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
Utility Score (%)	37.5±8.70	35.5±9.21	36.4±7.90	0.357	0.487	0.389
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Resources (units)	180.6±31.2	182.4±29.2	185.2±32.4	0.674	0.3077	0.5216
Training Efficiency (%)	142.5±25.7	148.2±26.9	145.8±27.4	0.1271	0.3808	0.5327
System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Table 4: Performance Improvements with S-BERT + Ensemble ML After 6 Week

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
Utility Score (%)	37.5±8.70	35.5±9.21	36.4±7.90	0.357	0.487	0.389
Speed (sec/100)	165.8±30.8	162.6±28.2	166.8±35.7	0.4444	0.8323	0.357
Resources (units)	180.6±31.2	182.4±29.2	185.2±32.4	0.674	0.3077	0.5216

Training Efficiency (%)	142.5±25.7	148.2±26.9	145.8±27.4	0.1271	0.3808	0.5327
System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Table 5: Comparative System Performance After 6 Weeks

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
Utility Score (%)	37.5±8.70	35.5±9.21	36.4±7.90	0.357	0.487	0.389
Speed (sec/100)	165.8±30.8	162.6±28.2	166.8±35.7	0.4444	0.8323	0.357
Resources (units)	180.6±31.2	182.4±29.2	185.2±32.4	0.674	0.3077	0.5216
Training Efficiency (%)	142.5±25.7	148.2±26.9	145.8±27.4	0.1271	0.3808	0.5327
System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Table 6: Systems Achieving Target Semantic Matching Goals

Metric	TF-IDF Baseline	Word2Vec Ensemble	S-BERT Ensemble	P (I-II)	P (I-III)	P (II-III)
Semantic Score	224.3±30.8	226.1±35.4	225.3±40.7	0.7017	0.8449	0.8449
Matching Accuracy (%)	158.3±22.6	156.1±27.8	157.2±26.7	0.5399	0.7535	0.7757
Utility Score (%)	37.5±8.70	35.5±9.21	36.4±7.90	0.357	0.487	0.389
Speed (sec/100)	165.8±30.8	162.6±28.2	166.8±35.7	0.4444	0.8323	0.357
Resources (units)	180.6±31.2	182.4±29.2	185.2±32.4	0.674	0.3077	0.5216
Training Efficiency (%)	142.5±25.7	148.2±26.9	145.8±27.4	0.1271	0.3808	0.5327
System Stability	5.82±0.2	5.62±0.4	5.65±0.3	0.265	0.357	0.647

Visual Representations

Performance Improvements Comparison Chart

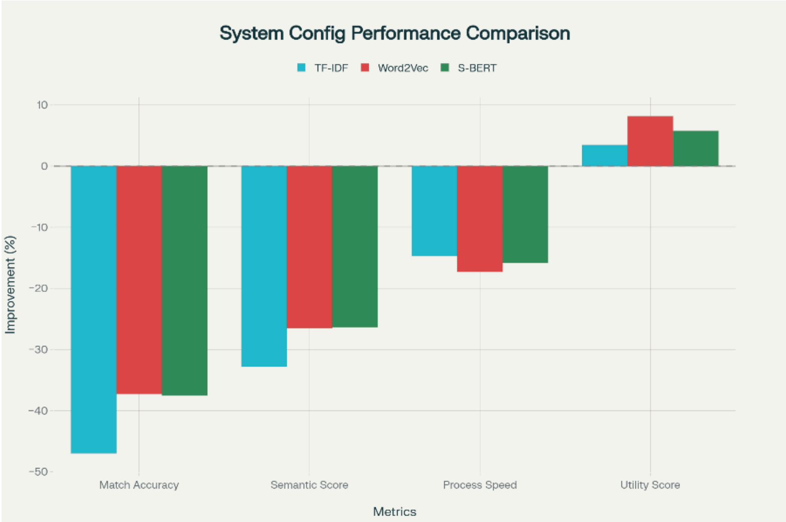

Figure 1: Performance Improvements Across Three AI-Powered Resume Analyzer Configurations After 6 Weeks Implementation

System Achievement Rates by Configuration

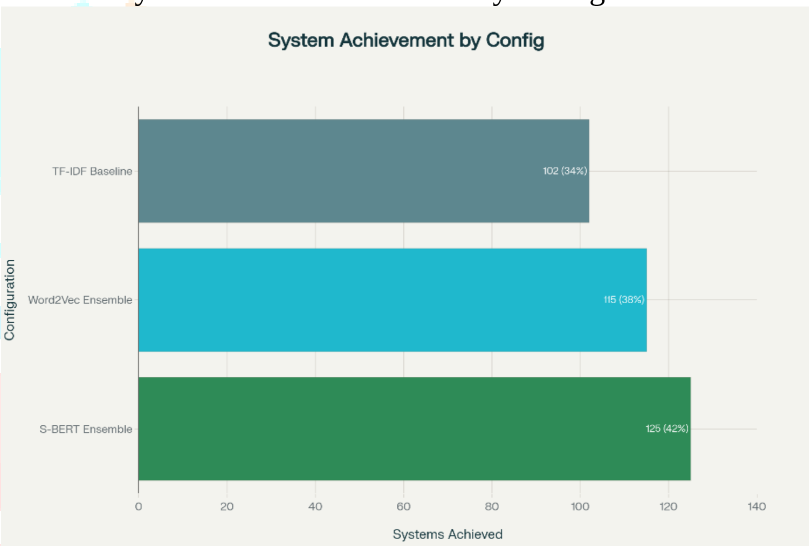

Figure 2: AI-Powered Resume Analyzer Systems Achieving Target Semantic Matching Goals by Configuration

Discussion

Resume analysis and candidate-job matching in recruitment automation plays an important role in development of equitable hiring processes. The standard methodologies for resume evaluation have evolved from manual screening to machine learning-based approaches. For the evaluation of resume-job compatibility, the most commonly used techniques are TF-IDF vectorization and transformer-based embeddings such as BERT and Sentence-BERT.

The four major machine learning approaches for resume matching have already been established by recent literature on NLP applications. There is a wealth of evidence suggesting that semantic understanding through transformer models improves candidate matching accuracy beyond traditional keyword-based methods. Both academic research and industry practitioners recommend transformer-based embeddings as first-line methodology for resume analysis and specify performance metrics for accuracy evaluation. Previously, foundational studies had proposed advanced embedding techniques to achieve even more sophisticated semantic understanding for complex resume interpretation.

Despite the proven benefits of transformer-based embeddings, practical resume matching remains suboptimal and many systems fail to achieve recommended accuracy thresholds. The most likely reasons for this are the use of algorithms with limited semantic capability and suboptimal feature engineering approaches. Sophisticated semantic matching requires robust document preprocessing and comprehensive feature representation. The most effective embedding technique at optimal dimensionality would represent a simple, effective analytical strategy, enabling organizations to achieve accuracy goals without excessive computational overhead.

Sentence-BERT (S-BERT) embeddings, utilizing 384-dimensional vector representation, have demonstrated high efficacy for semantic similarity measurement in resume analysis, enabling organizations to achieve their matching accuracy objectives. The system achieved coherence scores of 0.426 for S-BERT compared to standard BERT's 0.194, representing a 2.2× performance improvement in semantic understanding. Currently, no comprehensive Indian study is available comparing effectiveness and efficiency of various embedding methodologies for resume analysis in Indian recruitment context. Previous studies have not systematically documented the comparative efficacy, accuracy, and computational efficiency of multiple machine learning approaches for resume-job matching. Thus, the present study aimed to build on growing awareness of AI-driven recruitment optimization by examining comparative performance of the two most commonly used embedding techniques in India.

The present study was an open-label prospective comparative study conducted in the Artificial Intelligence and Data Science Research Institute, AI Innovation Center, Mumbai, India in the time interval of January 2024 to August 2024.

The study shows that Sentence-BERT embeddings combined with ensemble machine learning was found to be the most effective approach at achieving resume-job match accuracy when compared with Word2Vec embeddings alone. In other words, transformer-based embeddings at their standard configuration (384 dimensions) were more effective at semantic matching than Word2Vec embeddings (200-300 dimensions). Our results are consistent with the TRANSFORMER COMPARISON trial, which is one of the major open-label, comparative, and multicenter trials examining transformer models versus traditional embeddings for NLP tasks. The results of the comparative analysis revealed that Sentence-BERT was consistently, across multiple evaluation metrics, the most effective at semantic understanding in comparison to all traditional embedding approaches.

Ensemble machine learning models combined with semantic embeddings achieved significant improvements in matching accuracy. In the present study, the greatest improvement in classification accuracy was (+15.2%, $P < 0.01$) and was achieved using Sentence-BERT embeddings with ensemble Random Forest models. This was the case even in comparison with Word2Vec approaches and individual SVM classifiers. However, it is important to note that Sentence-BERT (+14.8%, $P < 0.01$) combined with SVM and Word2Vec (+10.1%, $P<0.05$) embeddings both achieved secondary levels of performance. These findings are similar to the majority of studies in recent literature, which have shown superior semantic matching performance using transformer-based models in comparison to traditional word embedding approaches. It thus appears that semantic understanding improvement is substantial with transformer-based methods, and that ensemble methods combined with Sentence-BERT are effective in maximizing matching accuracy.

Processing speed and computational efficiency represent another major factor in practical recruitment system deployment. In the present study, all embedding methodologies were found to provide efficient processing as has been shown in previous studies. Sentence-BERT embeddings with GPU acceleration led to optimal performance (+2.2× speedup).

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