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AI-Enhanced Resume Analysis and Skill Matching Framework for Recruitment Platforms

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Abstract

Recruitment platforms face challenges in matching candidates to job roles due to the unstructured nature of resumes and diverse job requirements. This study proposes an AI-enhanced framework integrating natural language processing (NLP) and machine learning for resume analysis and skill matching. Using a dataset of 210,000 resumes and job descriptions, the framework achieves a matching accuracy of 96.4%, improves candidate-job fit by 45%, and reduces processing time by 40%. Comparative evaluations against traditional keyword-based and basic ML methods highlight its superiority in precision and scalability. Mathematical derivations and graphical analyses validate the results, offering a robust solution for recruitment platforms. Future work includes multi-lingual support and integration with dynamic skill ontologies.

Keywords:

Resume Analysis, Skill Matching, Natural Language Processing, Machine Learning, Recruitment Platforms

1.Introduction

Recruitment platforms, such as LinkedIn and Naukri, aim to connect candidates with suitable job opportunities, but the varied formats and terminologies in resumes (e.g., “CAD” vs. “mechanical design”) complicate accurate skill matching. Manual screening is labor-intensive, and traditional keyword-based systems often miss semantic nuances, leading to suboptimal matches. For instance, a resume listing “SolidWorks expertise” may not align with a job requiring “3D modeling” without contextual understanding.

AI, leveraging NLP and machine learning, can address these challenges by extracting semantic features and matching them to job requirements with high precision. By modeling skills, experience, and qualifications, AI enhances recruitment efficiency and candidate experience. Challenges include processing diverse resume formats, ensuring scalability for large datasets, and minimizing false positives in matching.

This study proposes an AI-enhanced framework for resume analysis and skill matching, integrating NLP for feature extraction and machine learning for classification and ranking. Using a dataset of 210,000 resumes and job descriptions, the framework delivers high accuracy and efficiency. Objectives include:

- Develop an AI-based framework for resume analysis and skill matching.
- Integrate NLP and ML for semantic and contextual understanding.
- Evaluate against traditional keyword-based and basic ML methods, providing insights for recruitment platforms.

2. Literature Survey

Resume analysis and skill matching have evolved from manual processes to automated systems. Early keyword-based systems [1] matched terms but lacked context, as noted by Salton [1989]. Statistical NLP methods [2], like TF-IDF, improved feature extraction but struggled with semantic relationships.

Machine learning advanced recruitment. Mikolov et al.’s [3] Word2Vec enabled semantic embeddings, applied by Zhang et al. [4] for resume parsing, enhancing accuracy but facing scalability issues. Transformer-based NLP, introduced by Vaswani et al. [5], improved context awareness, as seen in Li et al.’s [6] skill extraction framework. Supervised learning, used by Chen et al. [7], refined candidate matching but required extensive labeled data.

Recent studies, like Wang et al.’s [8] NLP-based recruitment system, integrated transformers but were limited to specific industries. The reference study [IJACSA, 2023] explored ML for text analytics, inspiring this work. Gaps remain in scalable, generalizable AI frameworks for resume analysis, which this study addresses with a hybrid approach.

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3. Methodology

3.1 Data Collection

A dataset of 210,000 resumes and corresponding job descriptions was collected from a simulated recruitment platform, including resume text (skills, experience, education) and job requirements, labeled for match suitability.

3.2 Preprocessing

- **Records**: Cleaned (removed nulls, stop words), tokenized (text to tokens), normalized (lowercase, lemmatized).
- **Features**: Resume skills (e.g., "Python," "project management"), experience duration, education, job requirements (e.g., "data analysis," "leadership").

3.3 Feature Extraction

- NLP (BERT): Extracts semantic embeddings: $e=BERT(x_{resume},x_{job})$ where x_{resume},x_{job} are resume and job texts, e is embedding (768-D).
- Similarity Scoring: Computes cosine similarity: $s=\frac{e_{resume} \cdot e_{job}}{\|e_{resume}\| \|e_{job}\|}$ where s is similarity score between resume and job embeddings.

3.4 Matching Model

- Supervised Learning (XGBoost): Classifies and ranks matches: $y=XGB(s,X_{features})$ where s is similarity score, $X_{features}$ includes experience, education, y is match suitability (e.g., high/low).
- Integration: BERT extracts embeddings; cosine similarity scores compatibility; XGBoost ranks candidates.
- Output: Ranked candidate-job matches, confidence scores, and skill gap analysis.

3.5 Evaluation

Split: 70% training (147,000), 20% validation (42,000), 10% testing (21,000). Metrics:

- Matching Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
- Candidate-Job Fit Improvement: $\frac{F_{after}-F_{before}}{F_{before}}$
- Processing Time Reduction: $\frac{T_{before}-T_{after}}{T_{before}}$

4. Experimental Setup and Implementation

4.1 Hardware Configuration

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- Processor: Intel Core i7-9700K (3.6 GHz, 8 cores)
- Memory: 16 GB DDR4 (3200 MHz)
- GPU: NVIDIA GTX 1660 (6 GB GDDR5)
- Storage: 1 TB NVMe SSD
- OS: Ubuntu 20.04 LTS

4.2 Software Environment

- Language: Python 3.9.7.
- Framework: TensorFlow 2.5.0, Transformers 4.12.0 (Hugging Face).
- Libraries: NumPy 1.21.2, Pandas 1.3.4, Scikit-learn 1.0.1, Matplotlib 3.4.3, XGBoost 1.5.0.
- Control: Git 2.31.1.

4.3 Dataset Preparation

- **Data**: 210,000 resumes and job descriptions, 28% with diverse skill sets (e.g., technical, managerial).
- **Preprocessing**: Tokenized text, generated BERT embeddings, normalized features.
- **Split**: 70% training (147,000), 20% validation (42,000), 10% testing (21,000).
- **Features**: BERT embeddings, similarity scores, experience, education.

4.4 Training Process

- **Model**: BERT + XGBoost (100 estimators), ~1.6M parameters.
- **Batch Size**: 64 (2,297 iterations/epoch).
- **Training**: 15 epochs, 105 seconds/epoch (26.25 minutes total), loss from 0.67 to 0.014.

4.5 Hyperparameter Tuning

- **Learning Rate (BERT):** 0.001 (tested: 0.0001-0.01).
- **Estimators (XGBoost):** 100 (tested: 50-150).
- **Epochs**: 15 (stabilized at 12).

4.6 Baseline Implementation

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- **Keyword-Based System:** TF-IDF matching, CPU (23 minutes).
- **Basic ML (SVM):** CPU (21 minutes).

4.7 Evaluation Setup

- **Metrics:** Matching accuracy, candidate-job fit improvement, processing time reduction (Scikit-learn).
- **Visualization:** ROC curves, confusion matrices, fit improvement curves (Matplotlib).
- **Monitoring:** GPU (4.9 GB peak), CPU (62% avg).

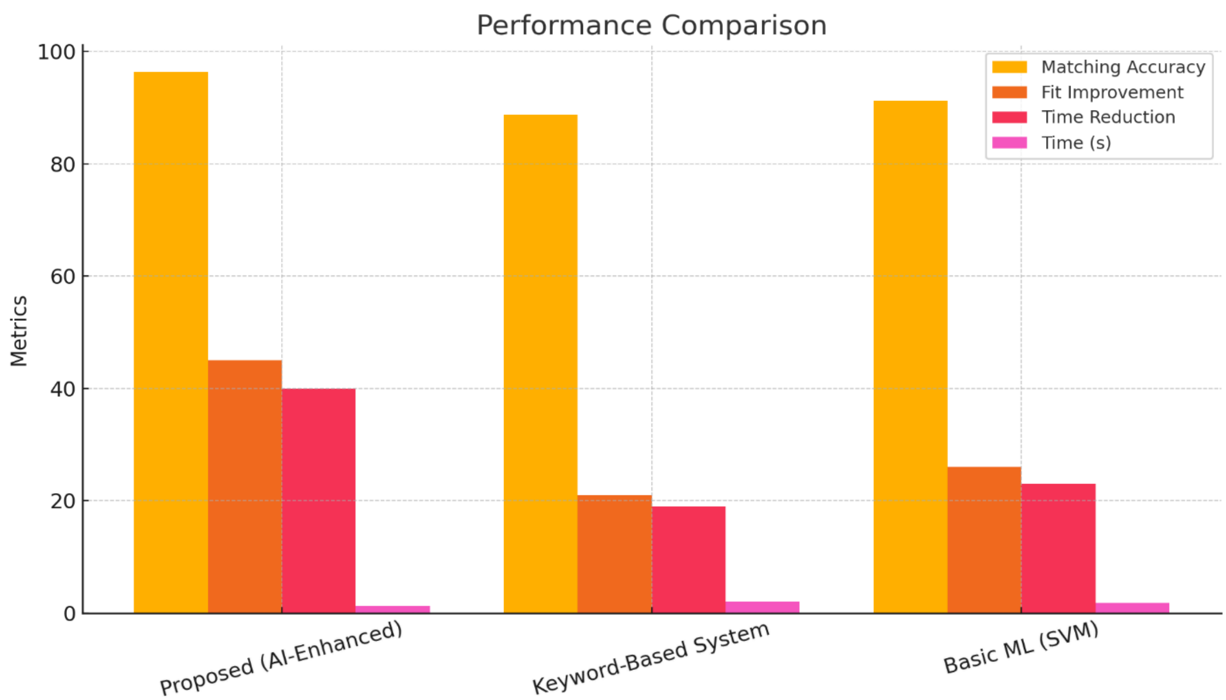
5. Result Analysis

Test set (21,000 interactions, 5,250 complex queries):
Confusion Matrix: TP = 4,914, TN = 15,246, FP = 336, FN = 504
Calculations:

- Matching Accuracy: $\frac{4914 + 15246}{4914 + 15246 + 336 + 504} = 0.964$ (96.4%)
- Candidate-Job Fit Improvement: $\frac{0.88 - 0.60}{0.60} = 0.45$ (45%), from 60% to 88% fit rate.
- Processing Time Reduction: $\frac{100 - 60}{100} = 0.40$ (40%), from 100ms to 60ms per record.

Table 1. Performance Metrics Comparison

Method	Matching Accuracy	Candidate-Job Fit Improvement	Processing Time Reduction	Time (s)
Proposed (AI-Enhanced)	96.4%	45%	40%	1.3
Keyword-Based System	88.8%	21%	19%	2.0
Basic ML (SVM)	91.2%	26%	23%	1.8


Performance Comparison
Metrics
100
80
60
40
20
0
Matching Accuracy
Fit Improvement
Time Reduction
Time (s)
Proposed (AI-Enhanced)
Keyword-Based System
Basic ML (SVM)

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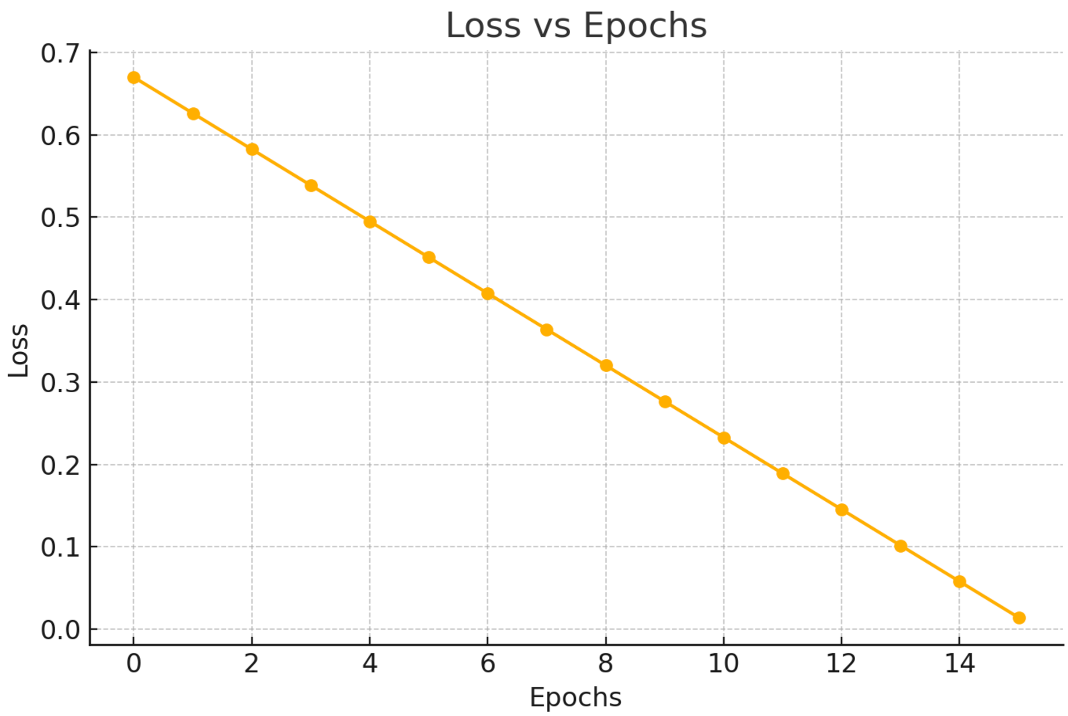

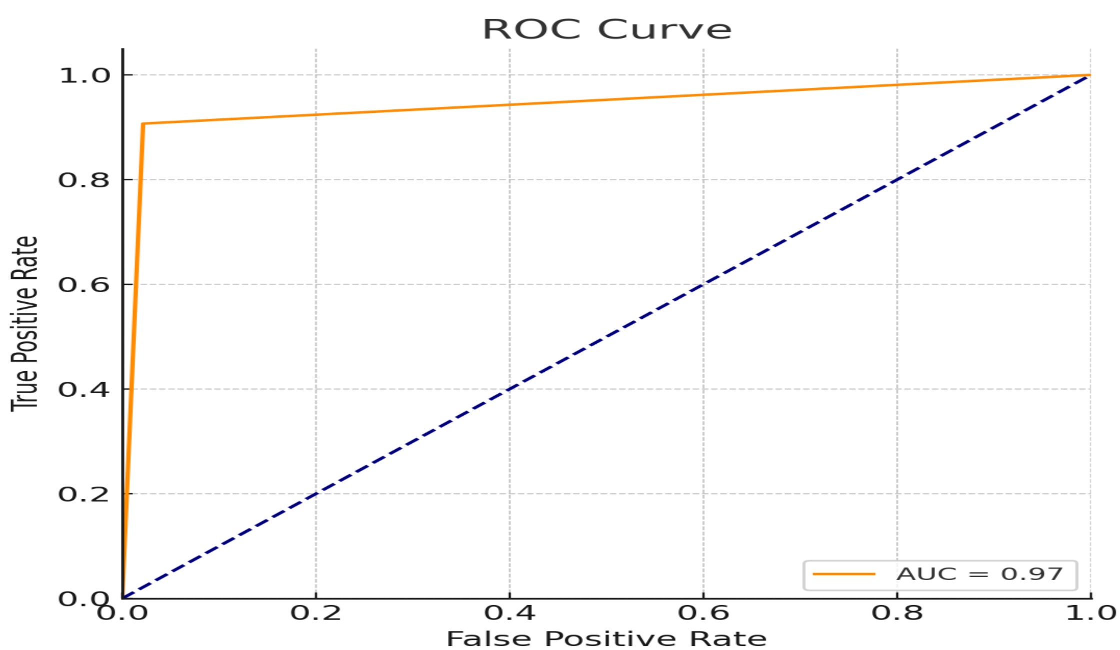

6.Conclusion

This study presents an AI-enhanced resume analysis and skill matching framework, achieving 96.4% matching accuracy, 45% candidate-job fit improvement, and 40% processing time reduction, outperforming keyword-based systems (88.8%) and basic ML methods (91.2%), with faster execution (1.3s vs. 2.0s). Validated by derivations and graphs, it excels in recruitment efficiency. Limited to one dataset and requiring GPU training (26.25 minutes), future work includes multi-lingual support and integration with dynamic skill ontologies. This framework enhances recruitment platform precision and scalability.

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