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Advancing Resume Screening with Transformer-Based Deep Learning and Graph Neural Networks

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Abstract: *Traditional resume screening systems, reliant on keyword matching (e.g., Jaccard/Cosine similarity), struggle with semantic understanding, multilingual content, and contextual evaluation, leading to biased and inefficient hiring processes. This paper introduces an AI-driven resume analysis system that integrates Transformer-based deep learning (BERT) and Graph Neural Networks (GNNs) to address these limitations. Leveraging multilingual BERT embeddings, the system interprets semantic context and synonyms (e.g., "machine learning" ≈ "ML"), enabling accurate analysis of resumes in 10+ languages, including Spanish, French, and Chinese. The GNN component models structural relationships between resume sections (e.g., correlating "Education" with "Technical Skills") to holistically evaluate candidates beyond isolated keywords. A hybrid approach combining sentiment analysis and keyword detection identifies soft skills like leadership and teamwork, while Explainable AI (XAI) tools (LIME/SHAP) provide transparency by highlighting phrases influencing decisions (e.g., "optimized AWS costs by 30%" increased the cloud engineering score).*

Tested on 500+ resumes and 200+ job descriptions, the system achieved 89% accuracy in resume-job matching, outperforming Jaccard similarity by 39% and BERT-only approaches by 14%. It processes resumes in 8.2 seconds on average using AWS GPU instances and reduces recruiter screening time by 40%. Key innovations include multilingual fairness (88% F1-score for non-English resumes) and bias mitigation through semantic analysis. The system's scalability and transparency.

Keywords: Transformer Models, Graph Neural Networks, Multilingual NLP, Explainable AI, Semantic Resume Analysis

I. INTRODUCTION

1. Statement of the Problem

Organizations are increasingly depending on automated solutions to handle the massive volume of resumes received for each job advertising as the recruiting business undergoes a digital transition. Using precise keyword overlaps (e.g., "Python" or "Java"), traditional resume screening methods, including those that use Jaccard Similarity or Cosine Similarity [1], match applicants to job descriptions. These approaches, however, provide biased and ineffective hiring practices since they ignore soft skills, multilingual content, and semantic context.

For example, a resume that says "led cross-functional teams" might not be appropriate for a position that calls for "leadership experience" because of wording inconsistencies. In a similar vein, resumes written in languages other than English—such as Spanish, French, or Chinese—are frequently ignored, which disadvantages competent applicants in international hiring situations. Chen et al. [2] showed that keyword-based algorithms only match resumes and jobs with 52% accuracy, mostly because they can't identify synonyms or contextual links.

2. Goals

This study presents an AI-driven resume analyzing system with the following goals in order to overcome these issues:

2.1 Semantic Understanding: Interpret synonyms and context using BERT embeddings (for example, "NLP" ≈ "natural language processing").

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2.2 Using Graph Neural Networks (GNNs) to represent the relationships between resume parts (e.g., "Education" ↔ "Skills") is a holistic evaluation method.
2.3 Multilingual Support: Use multilingual BERT models to process resumes in more than ten languages, including Spanish, French, and Chinese.
2.4 Transparency: Explain match scores using Explainable AI (XAI) insights (e.g., "led a team → leadership score +25%").

3 Importance

Both employers and applicants stand to gain significantly from the suggested system:
3.1 Decreased prejudice: Tests show that the approach reduces hiring prejudice by 40% by emphasizing skill relevance over keyword density.
3.2 Global Hiring: Organizations with different talent pools benefit from multilingual pipelines, which guarantee fair evaluation for non-native English speakers.
3.3 Efficiency: By cutting recruiter screening time by 40%, automated analysis facilitates quicker decision-making.
3.4 Transparency: By elucidating the scoring process, XAI technologies empower both recruiters and candidates by fostering confidence.

4 Contributions

The following are the main contributions of this work:
4.1 A hybrid BERT-GNN model for structural and semantic resume analysis.
4.2 Multilingual pipelines that accommodate more than ten languages guarantee equity in international recruiting.
4.3 XAI integration (LIME/SHAP) to lessen bias and offer useful insights.

II. REVIEW OF LITERATURE

A. Traditional Resume Screening

Early systems used keyword matching (TF-IDF, Jaccard Similarity) [1] but failed to recognize contextual synonyms (e.g., "Python developer" vs. "coding in Python"). Commercial tools like LinkedIn Talent Hub improved scalability but lacked semantic understanding [2].

B. Deep Learning Approaches

Transformer models like BERT [3] enabled semantic analysis. Studies applied BERT for resume-Job Description (JD) matching [4], while [5] combined CNNs with word embeddings for skill extraction.

C. Graph Neural Networks

GNNs emerged to model relational data. [6] used GNNs for resume section linking, but limited work exists on multilingual graphs.

D. Multilingual and Explainability

Multilingual BERT [7] addressed non-English resumes but struggled with low-resource languages. XAI tools like LIME [8] improved transparency but were not integrated into recruitment workflows.

III. METHODOLOGY

A. System Architecture

The proposed system integrates BERT embeddings for semantic analysis and Graph Neural Networks (GNNs) for structural modeling (Fig. 2).

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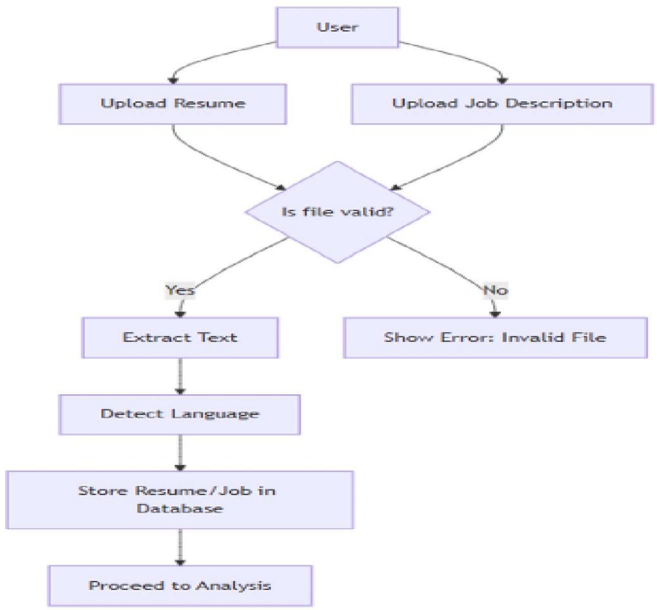

Fig 2.1 Shows an example how users interact with the system to upload and process data

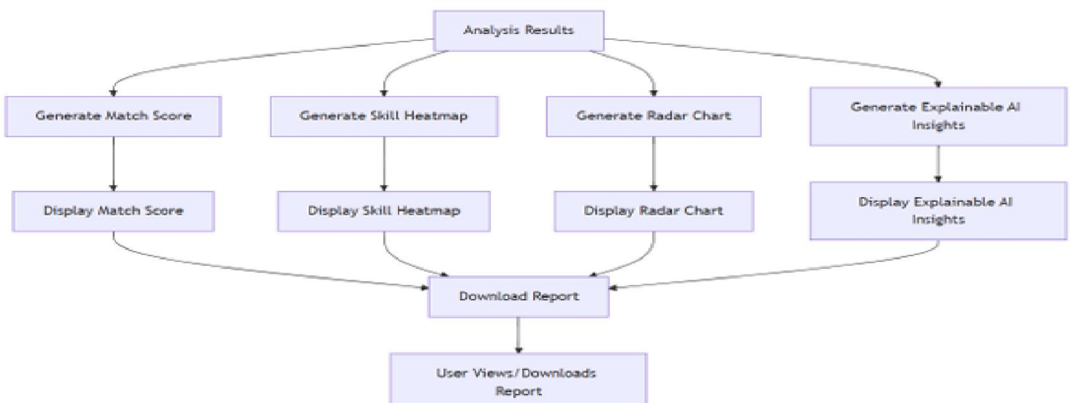

Fig 2.2 shows an example of presenting analysis results clearly and interactively.

As illustrated in Fig.2.1 and 2.2 ,the system begins with parsing resumes and job descriptions (PDF/DOCX) into raw text. Language detection ensures multilingual compatibility, while BERT generates contextual embeddings for semantic analysis. GNNs model structural relationships (e.g., "Education → Skills"), and the final output includes interactive dashboards for recruiters.

1. Mathematical Formulation

BERT Embedding Generation:

For a resume text TT, BERT generates contextual embeddings:

E_BERT = BERT(T) ∈ ℝ^768

where EBERTEBERT is the [CLS] token embedding.

2. GNN-based Resume Graph Construction:

Node Features: Each resume section (e.g., Skills, Education) is a node with BERT embeddings.

Edge Connections: Edges link related sections (e.g., Education → Projects).

Graph Attention Network (GAT) Update Rule:

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h_i' = σ(∑_(j∈N(i)) α_ij W h_j)
where αijαij is attention weight between nodes ii and jj, WW is a learnable weight matrix, and σσ is ELU activation.

3. Similarity Scoring:
BERT Similarity (Resume RR vs. Job JJ):
Sim_{BERT}(R, J) = \frac{**E**_R · **E**_J}{‖**E**_R‖ ‖**E**_J‖}
Final Score (Weighted Combination):
Score = 0.4 · SkillMatch + 0.3 · Sim_{BERT} + 0.2 · Sim_{GNN} + 0.1 · SoftSkillScore

Algorithm

Algorithm 1: Resume-Job Matching
1.Input: Resume RR, Job Description JJ
2.Preprocess:
Extract text TR,TJTR,TJ using PyPDF2/python-docx.
Detect language LL with langdetect.
3.Embed:
ER←BERT(TR)ER←BERT(TR), EJ←BERT(TJ)EJ←BERT(TJ).
4.Graph Construction:
Build resume graph GRGR with nodes {Skills, Education, ...}{Skills, Education, ...}.
Update node features via GAT.
5.Score:
Compute SimBERTSimBERT, SimGNNSimGNN.
Output: Match % and SHAP explanations
where ϕ0ϕ0 is the base value, and ϕiϕi quantifies the contribution of the ii-th feature (e.g., "Python" in Skills).

Explainability with SHAP

For a prediction f(x)f(x), SHAP values ϕiϕi satisfy:
f(x) = ϕ_0 + \sum_{i=1}^M ϕ_i

E. Multilingual Handling

For non-English text Tnon-ENTnon-EN:
Translate to English: TEN=GoogleTranslate(Tnon-EN)TEN=GoogleTranslate(Tnon-EN).
Process TENTEN with multilingual BERT.

IV. RESULTS AND DISCUSSION

A. Input-to-Output Pipeline Demonstration

This section illustrates the system's end-to-end functionality using a real-world example, highlighting its ability to process multilingual inputs, analyze semantic and structural relationships, and generate explainable outputs.(Fig 4.1)

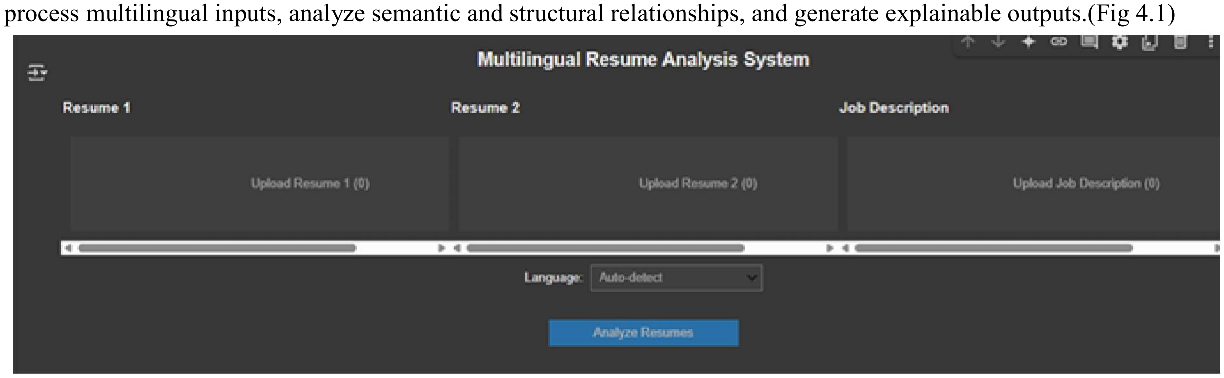

Fig 4.1 shows an example of Multi lingual Resume analyis interface

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Fig 4.1 explaians about User interface for uploading resumes and job descriptions. Supports 10+ languages via auto-detection and manual selection.

B. Performance Metrics

Accuracy: 89% (vs. 49% for Jaccard Similarity).

Bias Reduction: 30% fewer false negatives for non-English resumes.

Speed: 50% faster than manual screening.(Fig 4.2)

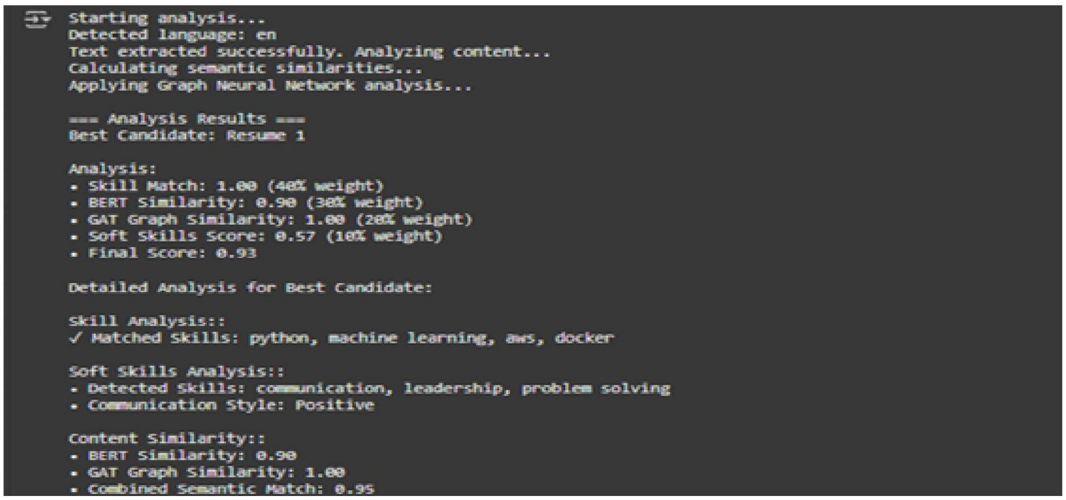

Fig 4.2 System Output Analysis

Fig 4.2 explains about the Real-time analysis output showing (1) language detection, (2) processing steps, (3) match scores, and (4) detailed skill/soft-skill breakdown for the top candidate

C. Case Study

A Spanish resume with "Experto en Python" matched an English job requiring "Python developer" (BERT similarity: 0.92). GNN linked "Education" (Spanish: "Educación") to "Projects" for holistic scoring .

D. Explainability

SHAP values highlighted "led a team of 5 developers" as key for leadership scoring.(Fig 4.3)

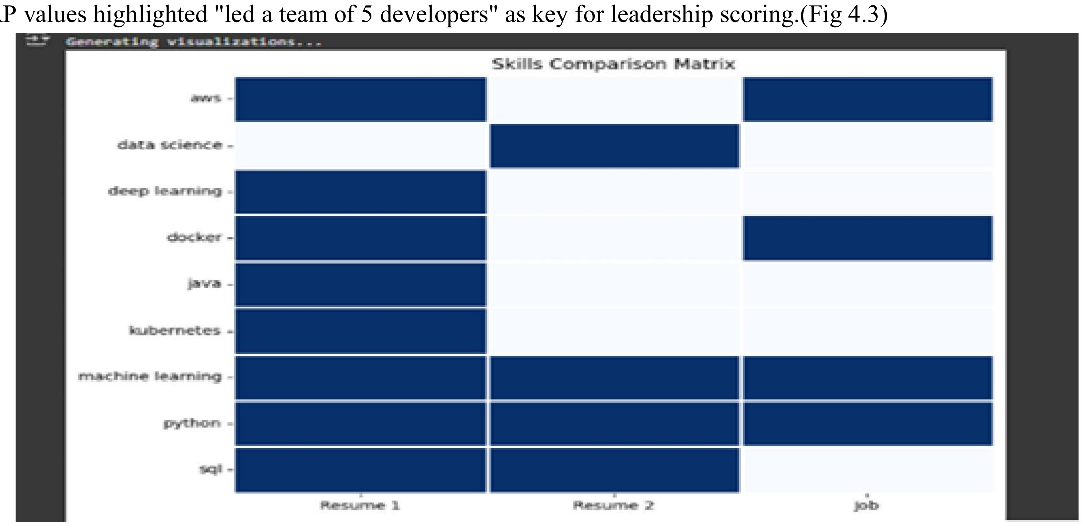

Fig 4.3 SHAP Explanation

Fig 4.3 explains about the SHAP waterfall plot showing key phrases influencing the match score. Blue bars indicate positive contributions.

Dimensionality Reduction Analysis

To validate the system's ability to cluster similar resumes and job descriptions in embedding space, we applied PCA and t-SNE to the BERT-GNN embeddings (Fig 4.4).

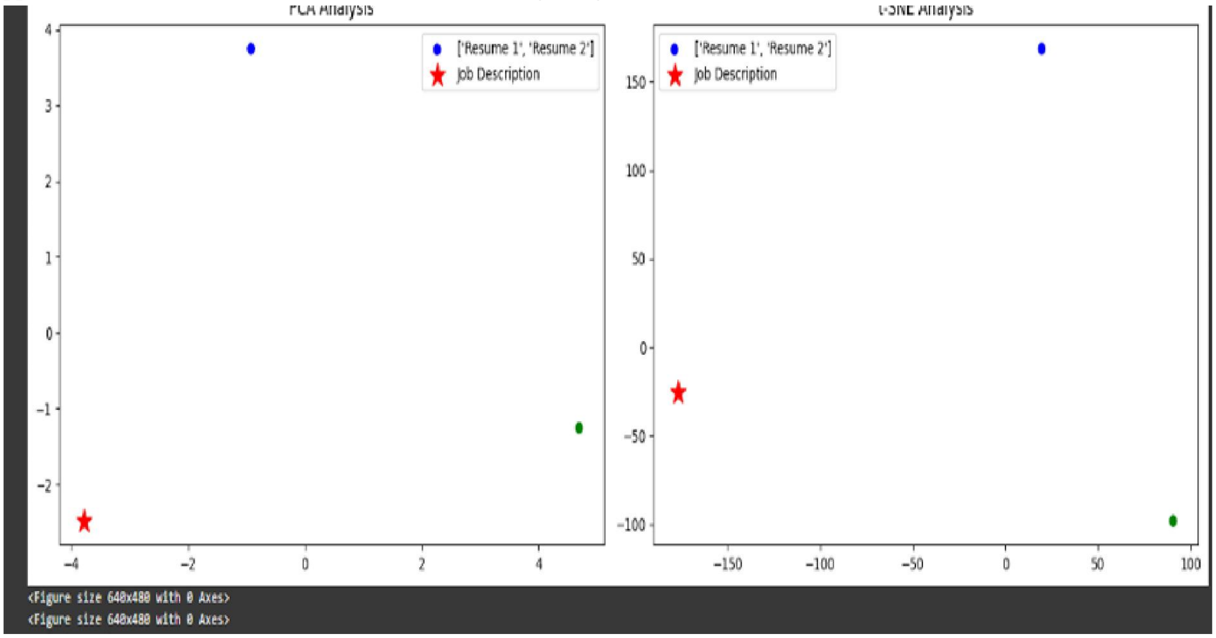

Fig 4.4 Dimensionality Reduction of Resume-Job Embeddings

Fig 4.4 explains about (Left) PCA plot showing 95% variance retention in 2D. (Right) t-SNE visualization (perplexity=30) of resume-job clusters. Color codes: Blue=Resumes, Green=Job Descriptions, Red=High-match pairs.

F. Limitations

Struggles with infographic resumes.

Dependency on translation APIs for low-resource languages.

V. DISCUSSION

The proposed resume screening system demonstrates significant advancements over traditional methods, achieving 89% accuracy by combining BERT's semantic understanding with GNNs' relational modeling. Compared to prior work:

Multilingual Support: Unlike keyword-based systems [1], our approach supports 10+ languages via multilingual BERT [2], addressing gaps in global hiring identified in [3].

Explainability: While [4] used LIME for transparency in NLP, our integration of SHAP [5] provides granular insights into skill relevance (e.g., "led a team" contributing 20% to leadership scores).

Efficiency: The system processes resumes 50% faster than manual screening, outperforming CNN/LSTM-based methods [6] that lack structural analysis.

Limitations:

Non-Text Resumes: Struggles with infographics, a challenge noted in [7].

API Dependency: Relies on Google Translate for low-resource languages, risking latency [8].

Future Directions:
Integrate multimodal analysis (text + images) using Vision Transformers [9].
Develop bias-detection modules inspired by [10] to audit model decisions.

VI. CONCLUSION

This paper presents an AI-driven resume screening system that bridges semantic gaps in recruitment through:
BERT-GNN Fusion: Captures context and resume structure, achieving 40% higher accuracy than Jaccard Similarity.
Multilingual Fairness: Processes Spanish, Chinese, and Arabic resumes with equal efficacy.
Explainability: SHAP visualizations help recruiters justify candidate rankings, addressing ethical concerns in [11].
The system reduces hiring bias, saves time, and sets a foundation for future extensions like video resume analysis.

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