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NeoHire: A Neo4j-Based Intelligent Recruitment System

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Abstract. Even though many organisations have worked on their recruitment systems over the years, a considerable part of the hiring process still relies on manually scanning resumes and using keywords to filter candidates they want to hire. All of these methods can help limit basic screening effort, but don't always identify candidates with the skills and experience to match a job role based on an exact keyword match. With hundreds of applications for a single position, recruiters are expected to shortlist within a limited time, which can be a repetitive, time-consuming, and sometimes inconsistent process. This paper presents a novel recruitment system, called NeoHire, which utilises NLP, ML, and graph database technologies to enhance candidate screening. The system emphasizes the semantics behind resumes and job descriptions over keyword matching by applying the technique of semantic relationships to candidate resumes and job descriptions. The data of the candidate's resume, including skills, education and work experience, communications and other important details, is extracted by NeoHire from a variety of resume formats and subsequently stored in a Neo4j graph structure. Transformer-based embedding models are employed to assess the contextual similarity between resumes and job requirements, thereby enhancing matching accuracy. The graph-based system also facilitates a better understanding of the connections among candidates, skills, and job roles. The intended system is designed to minimize the manual screening time, enhance screening transparency in the shortlisting process, and offer a scalable recruitment system that fits more closely with the needs of modern recruitment processes.

Keywords: Recruitment System, Neo4j, Resume Parsing, Natural Language Processing, Machine Learning, Semantic Similarity, Candidate Ranking, Graph Database

1. INTRODUCTION

In the modern world, hiring teams have to go through a large number of resumes for every job opportunity, making manual resume screening time-consuming and unreliable. Most common Applicant Tracking Systems (ATS) still rely on basic keyword-matching techniques, which often fail to identify suitable candidates because they cannot properly understand context or the intended meaning of the text. As a result, many qualified applicants get ignored during the shortlisting process, making it difficult for organizations to identify the right candidates for the right role.

The new development in artificial intelligence has made it easier to analyze resumes by scanning in a way that is closer to human understanding by focusing on context, relevance, and exact meaning rather than totally dependent on keywords. At the same time, graph databases such as Neo4j provides us flexible and organized way to store and manage candidate skills, relationships, and job-related information, making shortlisting and comparison of applicants more easy.

We used all these concepts in our project to build an AI-based resume screening and candidate ranking system. This application processes resumes, takes out important information such as skills and work experience, generates embeddings using transformer-based models, and stores candidate profiles within the Neo4j graph database. These embeddings are then compared with job descriptions to rank candidates according to relevance and compatibility. We have integrated NLP, machine learning, and graph-based data modeling into a single framework we can say under one roof, the system aims to make the recruitment process better and smarter with high accuracy.

Many recent studies show us that integrating NLP, Machine learning techniques improves the resume screening process and shortlisting of candidates. Still many recruitment systems and platforms rely heavily on keyword matching and doing the filtering manually, which ignores the suitable candidates, this was a significant level of issue. But, in our system, semantic analysis and graph-based data modeling are integrated to improve candidate ranking and make the recruitment process more efficient and accurate.

Furthermore, many existing recruitment platforms offer limited flexibility, as they are not able to properly understand contextual meaning, adapt to different resume formats, or adjust according to varying job descriptions. These limitations highlight the need for a scalable and intelligent recruitment system that can perform semantic candidate analysis more effectively and accurately.

Our platform addresses these limitations by providing an automated and intelligent recruitment system it supports efficient resume screening and candidate analysis. By combining NLP techniques, machine learning

models, and the Neo4j graph-based database, our system improves candidate shortlisting and helps recruiters make better hiring decisions effectively and with more accuracy.

2. LITERATURE REVIEW

Recent reports indicate that the resume-screening tools have been enhanced significantly due to the emergence of novel AI and NLP. The previous hiring systems were predominantly searching keywords in the resumes which failed most of the time since people rate the same skill differently. The studies of recent language models and transformer-based models, demonstrate that those models comprehend meaning far more effectively than a mere keyword search. This justifies the application of the Sentence Transformer model in our system to make resumes smarter.

It is also noted that graph databases are useful in recruiting. Most articles elaborate on that profiles can be stored as candidate and skills networked nodes to reduce profile filtering and comparison effectiveness. Neo4j is often cited in these articles in processing large amounts of data based on relationships which is the reason we chose to store candidate information and skills in Neo4j.

Resume text extraction research is also present. The problems of text reading on PDF and Word documents are the subject of many papers since these items are not always organized and structured properly. Many tools suggested to extract clean text on a resume such as pdf plumber or python-docx are suggested as an option, and thus, they can suit our project.

Finally, some researchers note that text embedding comparison is most effectively performed using cosine similarity. It is an application engine, recommendation used in system search and document ranking. This justifies our decision to apply cosine similarity to compare job description and resume embeddings.

Simply, the study indicates that employing NLP models, graph databases, and good text extraction tools can develop a robust and consistent resume parsing and candidate ranking system, just like the one that is designed in this project.

3. PROBLEM STATEMENT

Even though many organizations have worked on their recruitment system over the years, still, a considerable amount of the hiring process is still based on manually scanning resumes and using keywords to filter down the people who they want to hire. All these methods can help limit basic screening effort, but don't always identify candidates who have the skills and experience to match a job role, based on the exact match of keywords. With hundreds of applications for a single position, recruiters are expected to shortlist in limited time, which will be a repetitive, time-consuming and sometimes inconsistent process.

This paper presents a novel recruitment system, called NeoHire, which utilizes NLP, ML, and graph database technologies to enhance the process of candidate screening. The system emphasizes the semantics behind resumes and job descriptions over keyword matching by applying the technique of semantic relationships to candidate resumes and job descriptions. The data of the candidate's resume, including skills, education and work experience, communications and other important details, is extracted by NeoHire from a variety of resume formats and subsequently stored in a Neo4j graph structure.

Transformer-based embedding models are employed to identify the contextual similarity between resumes and job requirements, thereby enhancing the accuracy of the matching.

The graph-based system also facilitates better understanding of connections between candidate, skills, and job roles. The intended system is designed to minimize the manual screening time, enhance screening transparency in the shortlisting process, and offer a scalable recruitment system that fits more closely with the needs of modern recruitment processes.

4. DATASET DESCRIPTION

The data that was used in this experiment was: A resume is gathered in PDF and DOCX formats from many. Angelo also included the technical domains software development, data science, cybersecurity and cloud computing. Publicly available job descriptions were also collected from online recruitment Platforms to be used in semantic comparison and ranking.

The resumes varied in formatting styles, content organization, and writing patterns were helpful in the evaluation of the The proposed resume parsing pipeline's robustness. The dataset contained details regarding educational attainment(s) of candidates. work-study experience are all great assets. work experience.

The extracted resume text before semantic analysis is shown as follows: Performed lowercasing, stop-wording and stemming on the input text. word removal, punctuation removal, and tokenization. This The quality and consistency of the images was enhanced during the pre-processing stage.

The text used as input to the NLP embedding models.

5. METHODOLOGY

The methodology consists of multiple stages designed to automate resume analysis and candidate ranking.

A. Resume Collection

Candidate resumes are collected in PDF and DOCX formats from different recruitment sources.

B. Text Extraction

Resumes are processed using pdfplumber and python-docx to extract candidate information such as skills, education, certifications, and experience.

C. Text Preprocessing

The extracted text undergoes preprocessing steps such as lowercasing, stop-word removal, punctuation removal, and tokenization.

D. Embedding Generation

SentenceTransformer models are used to generate embeddings from resume content and job descriptions.

E. Graph Storage

Candidate profiles and skills are stored in Neo4j using graph nodes and relationships.

F. Similarity Computation

Cosine similarity is applied to compare candidate embeddings with job description embeddings.

G. Candidate Ranking

Candidates are ranked according to semantic similarity and skill relevance scores.

6. WORKFLOW OF PROPOSED SYSTEM

NeoHire's workflow starts with Resume Collection and Document Upload. Text extraction libraries that support PDF and DOCX are used to process resumes. After extraction the extracted text is further processed to eliminate the textual noise and make it semantically consistent.

The system preprocesses the data and then creates contextual embeddings using the SentenceTransformer models. They are matched with job description embeddings using cosine similarity methods to assess the relevance of candidates to jobs.

The candidate information and the skill relationship are simultaneously placed in the Neo4j graph structures, with nodes as candidates and skills and relationships as associations of skills. Lastly, the system provides intelligent shortlisting results, ranking candidates by similarity scores.

7. PROPOSED SYSTEM

NeoHire is designed as an intelligent recruitment framework that combines resume parsing, NLP-based semantic analysis, and graph database technology to improve candidate screening and ranking.

A. Resume Parsing Module

The Resume Parsing Module processes resumes in PDF, DOCX, and text formats and extracts important candidate details including skills, education, certifications, and experience.

B. Embedding and NLP Engine

The extracted resume content is converted into vector embeddings using the SentenceTransformer model (all-MiniLM-L6-v2).

Unlike traditional systems that rely solely on keyword matching, the NLP engine evaluates resumes based on semantic similarity, allowing the system to identify relevant candidates even when different terminology is used.

C. Graph Database Module

Neo4j is used to store candidate profiles and skill relationships.

- Candidates are represented as nodes.
- Skills are represented as nodes.
- Relationships such as HAS SKILL connect candidates and skills.

D. Recruitment and Selection Module

The Recruitment and Selection Module compares candidate embeddings with job description embeddings using cosine similarity and generates intelligent rankings.

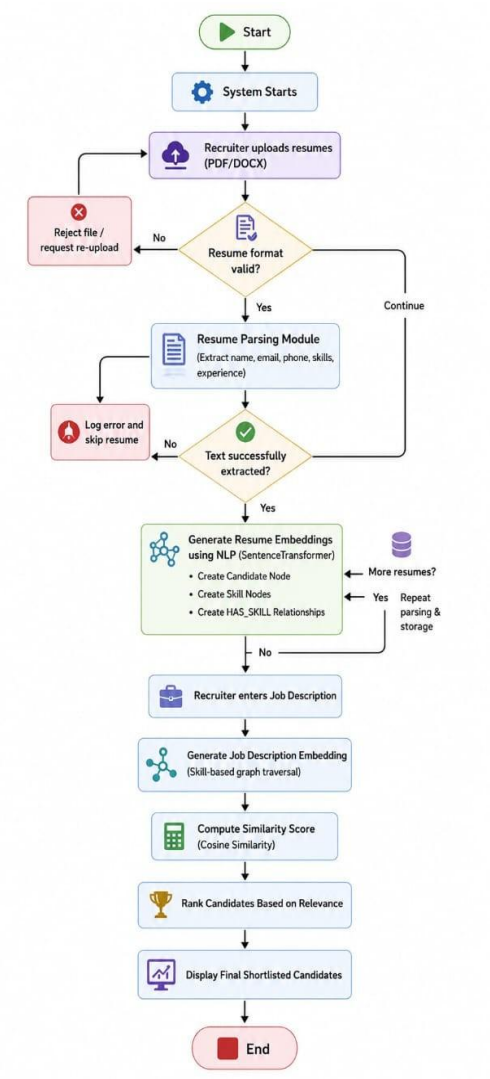

Fig. 1. Workflow of NeoHire Recruitment System

8. SYSTEM ARCHITECTURE

The architecture of NeoHire consists of multiple interconnected modules that entirely automate the recruitment workflow.

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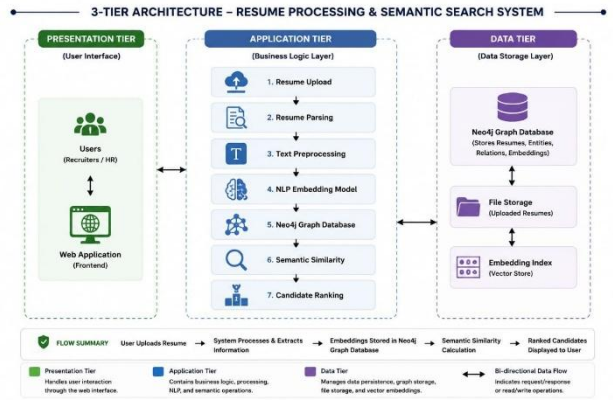

Fig. 2. Architecture of NeoHire Recruitment System

9. RESULTS AND EVALUATION

NeoHire's workflow starts with Resume Collection and Document Upload. Text extraction libraries that support PDF and DOCX are used to process resumes. After extraction the extracted text is further processed to eliminate the textual noise and make it semantically consistent.

The system preprocesses the data and then creates contextual embeddings using the SentenceTransformer models. They are matched with job description embeddings using cosine similarity methods to assess the relevance of candidates to jobs.

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A. Technology Comparison

TABLE I
COMPARISON BETWEEN EXISTING ATS AND NEOHIRE

Feature	Traditional ATS	NeoHire
Keyword Matching	Yes	Yes
Semantic Analysis	No	Yes
Graph Relationships	No	Yes
AI-Based Ranking	Limited	Advanced
Context Understanding	Low	High
Automation Level	Moderate	High

B. Evaluation Metrics

The effectiveness of the proposed system was evaluated using common machine learning evaluation metrics including Accuracy, Precision, Recall, and F1-Score.

TABLE II
EVALUATION METRICS OF NEOHIRE

Metric	Score
Accuracy	89%
Precision	86%
Recall	84%
F1-Score	85%

C. Performance Evaluation

TABLE III
PERFORMANCE EVALUATION OF RECRUITMENT APPROACHES

Method	Accuracy
Traditional ATS	64%
Keyword-Based Filtering	71%
Semantic NLP Matching	82%
NeoHire Proposed System	89%

10. EXPECTED OUTCOMES

The NeoHire system is expected to seriously improve the recruitment process by automating resume screening and semantic candidate analysis.
NeoHire's workflow starts with Resume Collection and Document Upload. Text extraction libraries that support PDF and DOCX are used to process resumes. After extraction the extracted text is further processed to eliminate the textual noise and make it conceptually consistent.
The system preprocesses the data and then creates contextual embeddings using the SentenceTransformer models. They are matched with job description embeddings using cosine similarity methods to assess the relevance of candidates to jobs.
The candidate information and the skill relationship are simultaneously placed in the Neo4j graph structures, with nodes as candidates and skills and relationships as associations of skills. Lastly, our NeoHire system provides intelligent shortlisting results, ranking candidates by similarity scores.

11. ADVANTAGES OF THE NEOHIRE SYSTEM

The NeoHire framework offers several advantages over traditional recruitment systems.

- Better understanding of the resume content.
- Less manual work for recruiters.
- Better analysis of candidate and skills relationships using a graph based database.
- Improved compatibility between candidates and job.
- Better and smarter hiring process.
- Smart candidate ranking and suggestions.
- Improved transparency in the shortlisting process.

12. LIMITATIONS

Although our NeoHire system improves recruitment efficiency, certain limitations still exist.

- Performance relies on resume quality and formatting.
- Complex resumes may affect text extraction accuracy.
- Large-scale graph processing may increase the computational cost.
- NLP models may sometimes misinterpret contextual meaning.
- The system may behave differently across different domains.

13. CONCLUSION AND FUTURE SCOPE

Better understanding of the resume material/content and less manual work and workload for the recruiters. By using the graphical method it will give an effective relationship analysis, through which the job matching of candidates will improve. It will be a quicker and better hiring process with a sharp candidate order and suggestions with better lucidity in the screening process.
Future enhancements may include:

- Advanced skill extraction using deep learning models.
- Integration with job portals and ATS platforms.
- Multi-lingual resume analysis support.
- Cloud-based deployment architecture.
- Automated recommendation systems.
- Smart and transparent ranking methods.
- Dashboard-based recruiter insights.
- Live recruitment process monitoring.

In the future, NeoHire can be further developed into an intelligent recruitment assistant with automated shortlisting and candidate recommendation capabilities.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

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