

RESUME SHORTLISTING AND RANKING WITH TRANSFORM

Venkata Ratnam Ganji¹, Chigatapu Kavya², Pasupuleti Navya Lakshmi³, Veeramallu Rupa Maheswari⁴, Veerabathina Syam Kumar⁵

¹Associate Professor, Dept. of CSE,
VKR, VNB & AGK College of Engineering, Gudivada

²³⁴⁵UG Students, Dept. of CSE, VKR, VNB & AGK College of Engineering, Gudivada, A.P. India

ABSTRACT

The recruitment process often involves reviewing a large number of resumes, which is time-consuming and prone to human bias. This project proposes an automated resume shortlisting and ranking system using Transformer-based deep learning models, such as BERT, to efficiently evaluate candidate resumes. The system extracts relevant features from resumes, including skills, education, experience, and certifications, and matches them against job descriptions to assess suitability. By leveraging contextual embeddings and semantic analysis, the Transformer model can understand the nuances in candidate profiles and provide an accurate ranking. Experimental results demonstrate that this approach reduces manual effort, minimizes bias, and improves the efficiency and fairness of candidate selection. The system can be applied in various human resource management platforms to streamline recruitment and enhance decision-making.

Keywords: Resume Shortlisting, Resume Ranking, Transformer, BERT, Natural Language Processing (NLP), Semantic Matching, Candidate Evaluation, Recruitment Automation.

I INTRODUCTION

Recruitment is a critical function in organizations, but manually reviewing large volumes of resumes is time-consuming, labor-intensive, and often subject to human bias. Traditional automated methods rely on keyword matching or rule-based approaches, which fail to understand the context and semantics of resumes and job descriptions, often resulting in irrelevant shortlisting.

Recent advancements in Natural Language Processing (NLP), particularly Transformer-based models like BERT (Bidirectional Encoder Representations from Transformers), have enabled machines to understand

the semantic meaning and contextual relationships in text. By leveraging these models, it is possible to analyze resumes and job descriptions in depth, extracting features such as skills, experience, education, certifications, and achievements. The system can then rank candidates based on their suitability for the role, improving the efficiency and accuracy of recruitment.

This project focuses on developing an automated resume shortlisting and ranking system using Transformers, providing organizations with a faster, unbiased, and scalable solution for candidate evaluation. The system not only reduces manual effort but also enhances the fairness and effectiveness of the hiring process.

II RELATED WORK

Resume shortlisting and candidate ranking have been a significant area of research in human resource management and artificial intelligence. Traditional approaches primarily use keyword-based or rule-based methods to match resumes with job descriptions. While simple to implement, these methods often fail to capture the semantic meaning and context of candidate profiles, leading to inaccurate shortlisting and potential bias in recruitment.

Machine learning techniques, including Support Vector Machines (SVM), Random Forests, and Naive Bayes classifiers, have been applied to automate resume screening by classifying candidates as suitable or unsuitable based on extracted features. Although these models improve accuracy compared to rule-based methods, they often require extensive feature engineering and cannot fully understand the contextual nuances in resumes and job descriptions.

Recently, Transformer-based models such as BERT, RoBERTa, and DistilBERT have been employed for resume analysis and candidate ranking. These models generate contextual embeddings that capture semantic relationships between skills, experience, and educational qualifications, enabling more accurate matching with job requirements. Several studies have demonstrated that using Transformers for resume processing significantly improves ranking accuracy, relevance, and fairness, while reducing manual effort in the recruitment process.

Despite these advancements, challenges remain in handling large volumes of diverse resumes, multi-

lingual content, and domain-specific requirements. The proposed system leverages Transformer-based semantic analysis to address these issues, providing automated, unbiased, and efficient resume shortlisting and ranking.

III LITERATURE REVIEW

Resume shortlisting and candidate ranking are essential components of modern recruitment processes. Early methods focused on manual screening, which is time-consuming, error-prone, and influenced by human bias. To improve efficiency, rule-based and keyword matching systems were developed, which identify resumes containing specific skills or qualifications. However, these methods fail to capture semantic meaning or contextual relevance, often leading to inaccurate candidate shortlisting.

With the advancement of machine learning, researchers started using classifiers such as Support Vector Machines (SVM), Random Forests, and Naive Bayes to automate resume screening. These models analyze extracted features from resumes, such as skills, experience, and education, and provide a suitability score for each candidate. While these approaches reduce manual effort and improve accuracy, they rely heavily on feature engineering and struggle with understanding the context or synonyms in resumes.

Recent studies have explored Transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers), for resume analysis. Transformers are capable of contextual semantic understanding, capturing relationships between skills, experience, and job requirements. They can generate embeddings for both resumes and job descriptions, allowing accurate matching and ranking of candidates. Hybrid approaches combining Transformers with domain-specific embeddings have shown further

improvement in ranking accuracy, fairness, and relevance.

Despite these advancements, challenges remain in processing large-scale resume datasets, handling domain-specific terminologies, and ensuring unbiased ranking. The proposed system leverages Transformer-based semantic analysis to address these challenges, providing an efficient, automated, and unbiased **solution** for resume shortlisting and ranking.

IV EXISTING SYSTEM

In the existing recruitment systems, resume shortlisting and ranking are primarily handled through manual review or keyword-based automated tools. Manual screening is time-consuming, labor-intensive, and prone to human bias, especially when dealing with a large number of applications. Keyword-based automated systems attempt to match resumes with job descriptions using exact word matches, but these systems fail to capture the semantic meaning, context, or synonyms in candidate profiles. Some organizations also use traditional machine learning classifiers like Support Vector Machines (SVM), Random Forests, or Naive Bayes to rank candidates based on extracted features, such as skills, education, and experience. While these approaches improve efficiency, they require extensive feature engineering and are limited in their ability to understand contextual relevance, leading to potentially unsuitable candidate selection. Overall, existing systems lack the accuracy, contextual understanding, and scalability needed for modern recruitment processes.

DISADVANTAGES

The existing resume shortlisting and ranking systems have several limitations. Manual screening is time-consuming and labor-intensive, making it impractical for large-scale recruitment. Keyword-based automated

systems fail to understand the context or semantic meaning of resumes, leading to inaccurate shortlisting and potential bias. Traditional machine learning classifiers, such as SVM or Random Forest, require extensive feature engineering and often struggle with complex or nuanced information in resumes, such as implicit skills or contextual experience. Additionally, these systems lack the ability to rank candidates accurately according to relevance, resulting in inefficient selection processes. Overall, current systems are less efficient, less accurate, and prone to bias, highlighting the need for a more advanced, context-aware, and automated solution for candidate evaluation.

V PROPOSED SYSTEM

The proposed system introduces an automated resume shortlisting and ranking framework using Transformer-based deep learning models, such as BERT, to enhance accuracy and efficiency in candidate selection. Unlike traditional keyword-based or manual methods, the system leverages contextual embeddings to understand the semantic meaning of resumes and job descriptions, capturing skills, experience, education, and achievements in context. The system first preprocesses resumes and job descriptions to extract relevant features, then applies the Transformer model to generate embeddings for semantic matching. Based on the similarity scores between candidate profiles and job requirements, the system ranks candidates, providing a prioritized list of the most suitable applicants. This approach significantly reduces manual effort, minimizes bias, and improves the relevance and fairness of candidate selection, making it highly suitable for large-scale and automated recruitment processes.

ADVANTAGES

The proposed Transformer-based resume shortlisting and ranking system offers several key benefits over traditional approaches. By using contextual embeddings and semantic analysis, the system can understand the meaning and relevance of skills, experience, and education, rather than relying on exact keyword matches. This ensures more accurate and fair candidate selection. The automated framework reduces manual effort and time, making it highly efficient for handling large volumes of resumes. Additionally, it minimizes human bias, providing a more objective evaluation of candidates. The system is also scalable and adaptable to different job roles and industries, enabling organizations to streamline the recruitment process while improving the quality of shortlisted candidates. Overall, it delivers a faster, more reliable and context-aware solution for modern talent acquisition.

VI METHODOLOGY

The proposed system follows a structured methodology to automate resume shortlisting and ranking using Transformer-based models. The process begins with data collection, where resumes and corresponding job descriptions are gathered in digital format. The resumes are then preprocessed, which includes cleaning text, tokenization, stop-word removal, and normalization, to prepare them for analysis. Relevant features, such as skills, education, experience, and certifications, are extracted, and semantic embeddings are generated using a Transformer model like BERT. The model compares these embeddings with the embeddings of job descriptions to calculate a similarity score that reflects candidate suitability. Based on these scores, candidates are ranked automatically, providing a prioritized list for recruitment. The methodology ensures accuracy, scalability, and efficiency, while reducing manual effort and minimizing bias in the hiring process. Continuous updates and training allow the system to adapt to new

resumes and evolving job requirements, improving the robustness and relevance of the ranking results.

VII SYSTEM MODEL

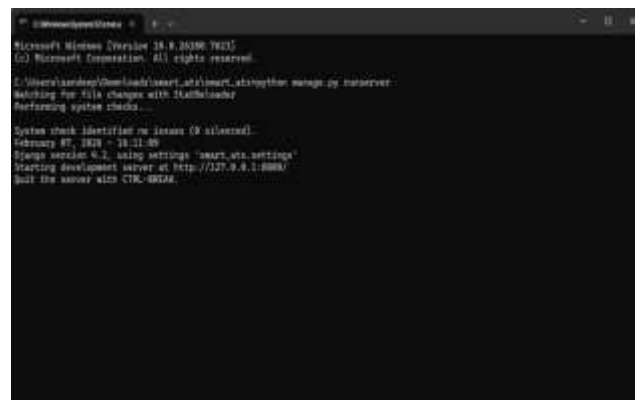
SYSTEM ARCHITECTURE



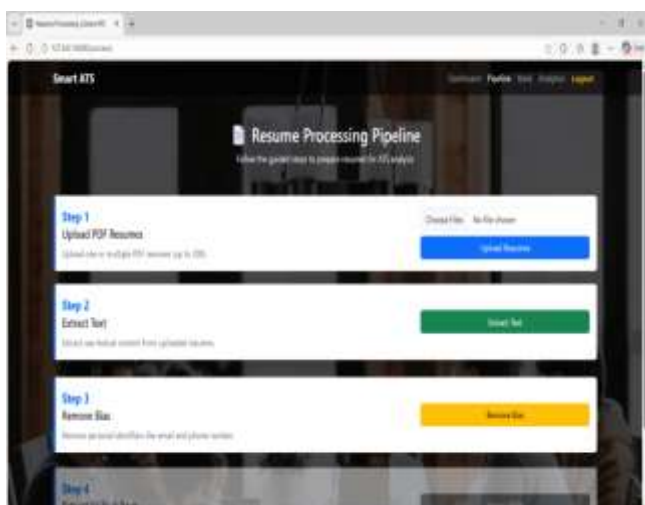
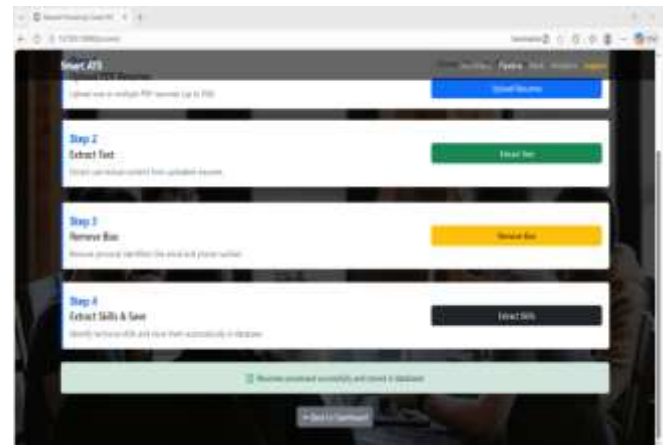
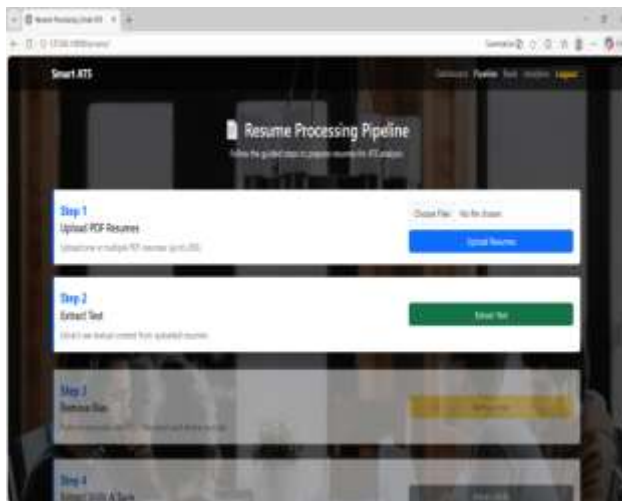
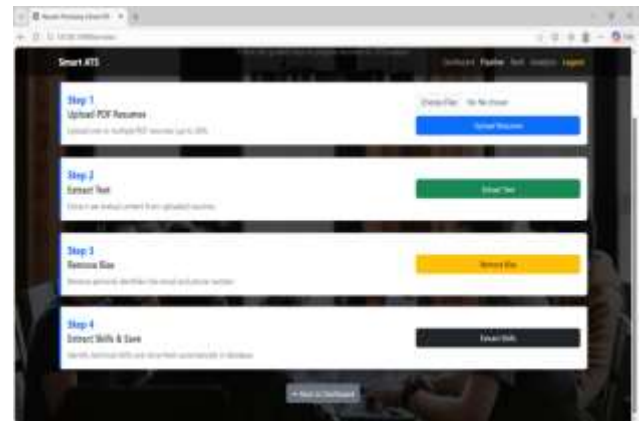
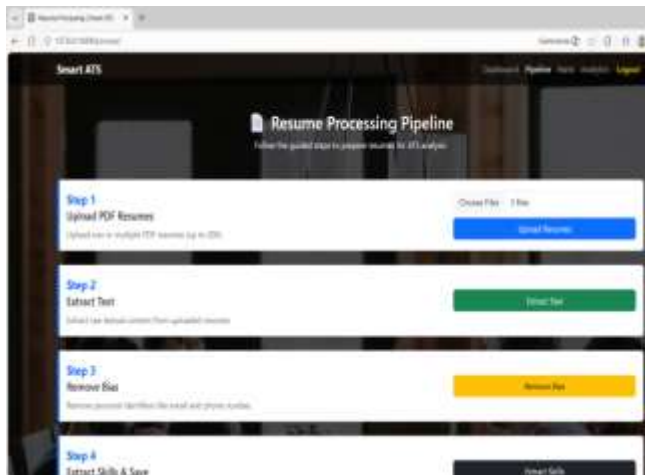
VIII RESULTS AND DISCUSSIONS

Results

Resume Shortlisting and Ranking with Transformers







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