

An Intelligent Applicant Tracking System Using NLP-Based Document Classification

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Abstract

The rapid growth of job applications in modern recruitment processes has made manual resume screening inefficient, time-consuming, and prone to bias. Organizations receive thousands of resumes for a single job opening, creating a critical need for automated and intelligent systems. This research proposes an advanced Applicant Tracking System (ATS) that utilizes Natural Language Processing (NLP) and machine learning techniques for automated resume classification, filtering, and ranking. The proposed system performs structured pre-processing, feature extraction using TF-IDF and semantic analysis, and classification using supervised machine learning algorithms. It also integrates a ranking mechanism that evaluates resume relevance based on job descriptions. The system not only reduces manual effort but also improves accuracy and consistency in candidate selection. Experimental evaluation demonstrates an accuracy of 87% in resume classification, indicating the effectiveness of NLP-based approaches in recruitment automation. This work contributes to the development of scalable, intelligent, and efficient hiring systems suitable for real-world applications.

Keywords: Applicant Tracking System, Natural Language Processing, Resume Classification, Machine Learning, TF-IDF, Recruitment Automation, Text Mining

I. Introduction

The rapid digital transformation of organizational processes has significantly impacted the recruitment domain, where the volume of job applications has increased exponentially in recent years. With the growth of online job portals and professional networking platforms, organizations often receive hundreds or even thousands of resumes for a single job opening. This surge in application volume has made traditional manual resume screening inefficient, time-consuming, and prone to inconsistencies. Conventionally, recruiters evaluate resumes by manually analyzing candidate qualifications, skills, experience, and educational background. While this approach allows for human judgment, it suffers from several limitations, including subjective bias, fatigue, and lack of scalability. As a result, many qualified candidates may be overlooked, while unsuitable candidates may be shortlisted due to inconsistent evaluation criteria. These challenges highlight the need for intelligent and automated systems that can efficiently process large volumes of textual data and assist in decision-making.

Applicant Tracking Systems (ATS) have emerged as a solution to streamline recruitment processes by automating resume storage, filtering, and management. However, traditional ATS platforms primarily rely on keyword-based matching techniques, which often fail to capture the contextual meaning and semantic relationships within resumes. This limitation leads to inaccurate candidate-job matching and reduced system effectiveness. To address these challenges, the integration of Natural Language Processing (NLP) and machine learning techniques into ATS has gained significant attention. NLP enables computers to understand, interpret, and process human language in a meaningful way, allowing for more sophisticated analysis of resume content. By leveraging NLP, systems can extract relevant features such as skills, experience, and domain-specific keywords, while also understanding the contextual relevance of candidate profiles. In this research, an intelligent Applicant Tracking System is proposed

A. Problem Statement

Despite the widespread adoption of Applicant Tracking Systems, most existing solutions rely on keyword-based filtering techniques that fail to capture the semantic meaning and contextual relevance of resume content. This often results in inaccurate candidate-job matching, increased false positives, and the rejection of potentially suitable candidates. Furthermore, manual screening processes remain time-consuming and inefficient when handling large volumes of applications. Therefore, there is a need for an intelligent, automated system capable of understanding and classifying resumes based on their contextual content.

B. Objectives of the Study

The primary objectives of this research are centered on enhancing recruitment efficiency through the application of advanced Natural Language Processing (NLP) and machine learning techniques. Specifically, the study aims to develop an automated Applicant Tracking System that leverages NLP methods to streamline resume screening and candidate evaluation. A key objective is to extract meaningful features such as skills, experience, and qualifications from resumes, thereby enabling a more structured and accurate representation of candidate profiles. Furthermore, the system seeks to classify resumes according to job roles using machine learning algorithms, ensuring precise categorization and relevance. Another important goal is to rank candidates based on their similarity with job descriptions, utilizing similarity measures to optimize candidate-job matching. Ultimately, the overarching objective is to improve recruitment efficiency by minimizing manual effort, reducing bias, and accelerating the hiring process, thereby providing a scalable and effective solution for modern recruitment environments.

C. Contributions of the Study

This research makes several noteworthy contributions to the field of recruitment automation and natural language processing. First, it proposes an NLP-based document classification framework specifically designed for resume screening, thereby addressing the challenges of unstructured data in recruitment. The system integrates multiple stages pre-processing, feature extraction, classification, and ranking—into a unified workflow that ensures efficiency and consistency. By enhancing semantic understanding of resume content beyond simple keyword matching, the framework achieves a deeper contextual analysis of candidate profiles. Moreover, the study demonstrates improved accuracy and efficiency in recruitment automation through the application of machine learning algorithms and similarity measures. Finally, the system provides a scalable solution that can be effectively applied to real-world hiring environments, making it a practical and impactful contribution to modern recruitment practices.

II. LITERATURE REVIEW

A. Overview of Existing Work

The application of Natural Language Processing (NLP) and machine learning in recruitment systems has gained significant attention in recent years. Automated resume screening and Applicant Tracking Systems (ATS) have evolved from simple keyword-based filtering mechanisms to more advanced intelligent systems capable of understanding textual content and extracting meaningful insights. Earlier systems primarily relied on rule-based and keyword matching techniques, which lacked contextual understanding and often resulted in inaccurate candidate selection. With the advancement of machine learning and text mining techniques, more sophisticated approaches have been developed to improve classification accuracy and semantic matching.

B. Resume Screening Using NLP Techniques

Several researchers have explored the use of NLP for extracting structured information from resumes. NLP-based systems focus on identifying key attributes such as skills, experience, education, and domain-specific keywords. Mishra and Kumar (2017) proposed a resume parsing system using NLP techniques to extract relevant information from unstructured text. Their approach effectively identified candidate attributes; however, it lacked a classification

and ranking mechanism, limiting its practical application in large-scale recruitment. Similarly, Singh and Shukla (2020) developed an automated resume screening system using machine learning algorithms. Their model demonstrated improved efficiency compared to manual screening but relied heavily on predefined features, which restricted its adaptability to diverse job domains.

C. Machine Learning-Based Classification Approaches

Machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and Decision Trees have been widely used for resume classification tasks. Xu et al. (2021) introduced a deep learning-based resume classification model that utilized word embeddings to improve semantic understanding. While their approach achieved high accuracy, it required significant computational resources and large datasets, making it less suitable for small-scale applications.

Bhowmik et al. (2021) proposed a semantic similarity-based system that compared resumes with job descriptions using clustering algorithms. Although the system improved matching accuracy, it lacked an efficient ranking mechanism to prioritize candidates.

D. Document Classification in Applicant Tracking Systems

As discussed in the existing system, document classification plays a crucial role in ATS by enabling filtering and routing of resumes based on content. Automated classification techniques help eliminate irrelevant applications and ensure that suitable candidates are forwarded to the appropriate recruitment stage. Traditional document classification methods rely on bag-of-words models and statistical techniques, which do not capture semantic relationships between words. Recent advancements in NLP have introduced feature extraction methods such as TF-IDF and word embeddings to improve classification performance.

E. Comparative Analysis of Existing Methods

Author	Technique Used	Strength	Limitation
Mishra et al. (2017)	NLP Parsing	Effective extraction	No ranking
Singh et al. (2020)	ML Classification	Faster screening	Limited adaptability
Xu et al. (2021)	Deep Learning	High accuracy	High complexity
Bhowmik et al. (2021)	Semantic Matching	Better relevance	No prioritization

F. Research Gap

This research makes several noteworthy contributions to the field of recruitment automation and natural language processing. First, it proposes an NLP-based document classification framework specifically designed for resume screening, thereby addressing the challenges of unstructured data in recruitment. The system integrates multiple stages—pre-processing, feature extraction, classification, and ranking—into a unified workflow that ensures efficiency and consistency. By enhancing semantic understanding of resume content beyond simple keyword matching, the framework achieves a deeper contextual analysis of candidate profiles. Moreover, the study demonstrates improved accuracy and efficiency in recruitment automation through the application of machine learning algorithms and similarity measures. Finally, the system provides a scalable solution that can be effectively applied to real-world hiring environments, making it a practical and impactful contribution to modern recruitment practices.

G. Motivation for Proposed Work

To address the identified research gaps, this study proposes an intelligent ATS that combines Natural Language Processing and machine learning techniques for resume classification and ranking. The proposed system focuses on improving semantic understanding, reducing computational complexity, and enhancing overall recruitment efficiency.

III. METHODOLOGY (REVISED WITH FLOWCHARTS)

A. System Overview

The proposed Applicant Tracking System (ATS) is designed as an intelligent pipeline that automates resume screening, classification, and ranking using Natural Language Processing (NLP) and machine learning techniques. The system processes unstructured resume data and converts it into structured information for effective decision-making. The workflow consists of multiple stages, including resume input, pre-processing, feature extraction, classification, and ranking. Each stage contributes to improving the accuracy and efficiency of candidate selection.

B. System Architecture

The architecture of the proposed system follows a structured pipeline model where data flows sequentially through various processing stages. The system begins with resume upload and ends with candidate short listing based on relevance scores. The overall workflow of the proposed system is illustrated in **Figure 1**.

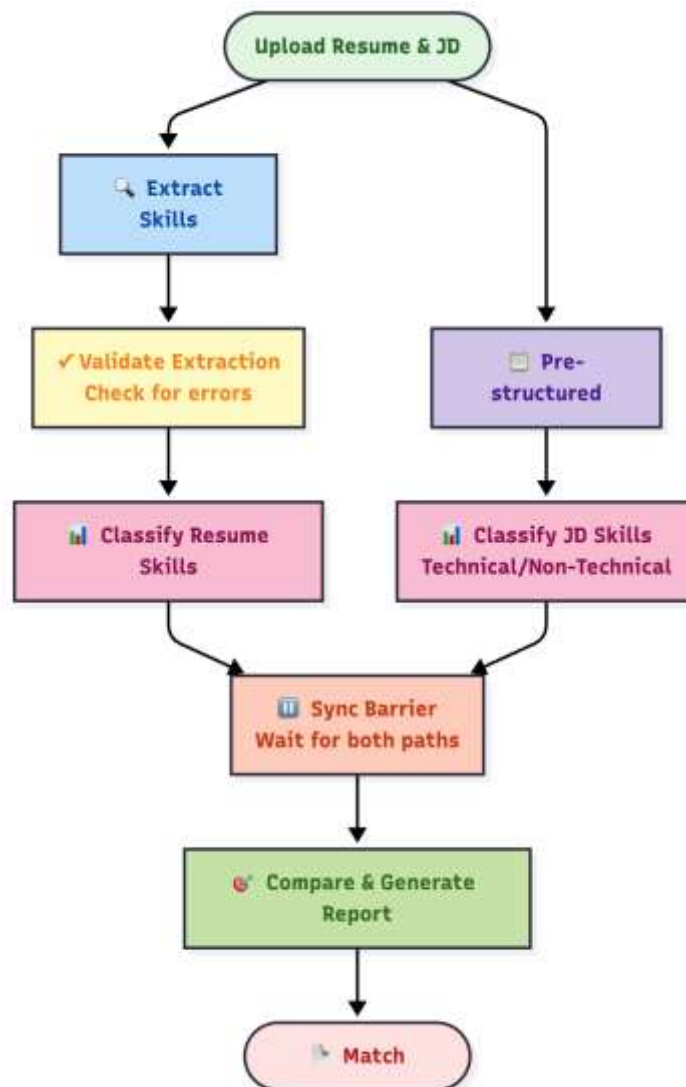


Figure 1: Overall workflow of the proposed NLP-based Applicant Tracking System

As shown in Figure 1, the system follows a sequential process starting from resume upload, followed by text extraction and pre-processing. The processed data is transformed into numerical features using TF-IDF, which are then used for classification and ranking. Finally, the system generates a shortlist of candidates based on similarity scores.

C. Data Collection

The dataset employed in this research consists of resumes collected in both PDF and DOCX formats, along with job descriptions obtained from established recruitment platforms. The resumes span multiple domains such as Information Technology, Data Science, and Engineering, thereby ensuring diversity and relevance across different professional fields. Each resume contains unstructured textual information, which presents challenges in terms of extraction and analysis but also provides a realistic representation of recruitment data. Job descriptions serve as the reference criteria for candidate-job matching, enabling the system to evaluate resumes against specific role requirements. By incorporating resumes from varied domains and pairing them with authentic job descriptions, the dataset ensures that the proposed system is capable of handling real-world recruitment scenarios effectively, thereby validating its applicability and scalability in practical environments.

D. Data Pre-processing

Pre-processing plays a crucial role in transforming raw textual data from resumes into a clean and structured format suitable for further analysis. The process begins with **tokenization**, where the text is segmented into individual words or tokens to facilitate linguistic processing. Next, **lowercasing** is applied to ensure uniformity and reduce redundancy caused by variations in letter case. To eliminate irrelevant information, **stop-word removal** is performed, discarding commonly used words such as “and,” “the,” or “is” that do not contribute meaningfully to semantic analysis. **Lemmatization** is then employed to reduce words to their base or root form, thereby improving consistency in feature representation. Finally, **noise removal** is carried out to eliminate punctuation marks, symbols, and other extraneous characters that may interfere with accurate text processing. Collectively, these steps ensure that the textual data is standardized, concise, and optimally prepared for feature extraction and classification in the proposed Applicant Tracking System.

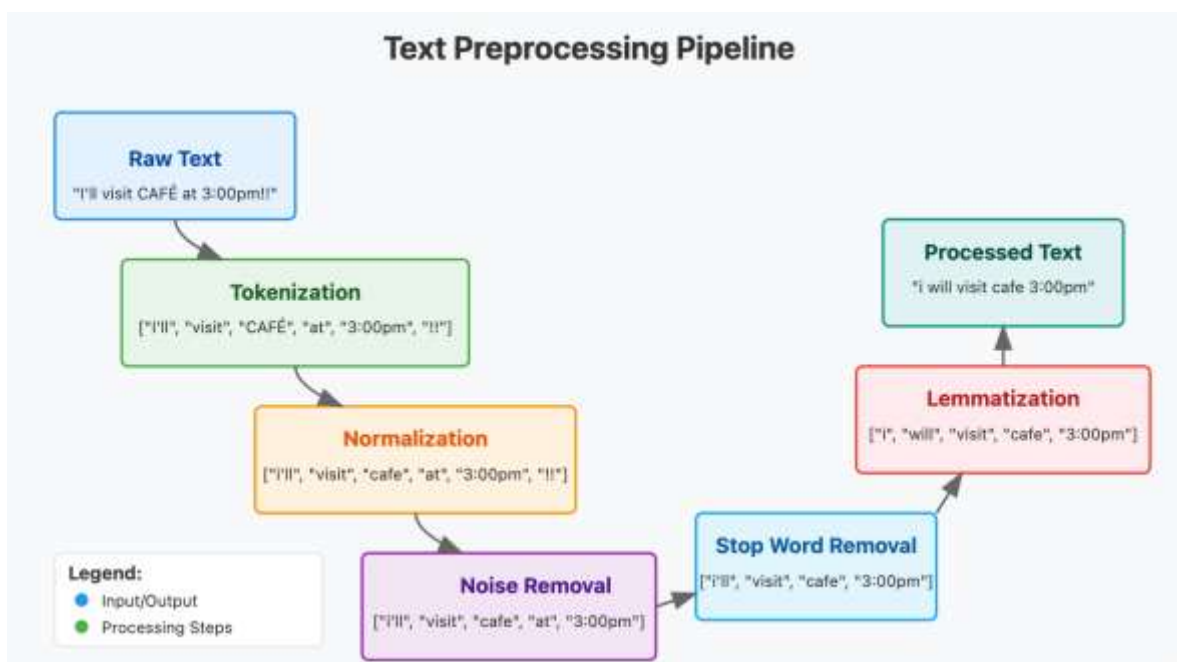


Figure 2: NLP pre-processing and feature extraction pipeline

As illustrated in Figure 2, pre-processing ensures that irrelevant and redundant information is removed while preserving meaningful textual features. This step significantly improves the performance of classification algorithms.

E. Feature Extraction

Feature extraction transforms textual data into numerical form using the TF-IDF technique.

1. TF-IDF Formula:

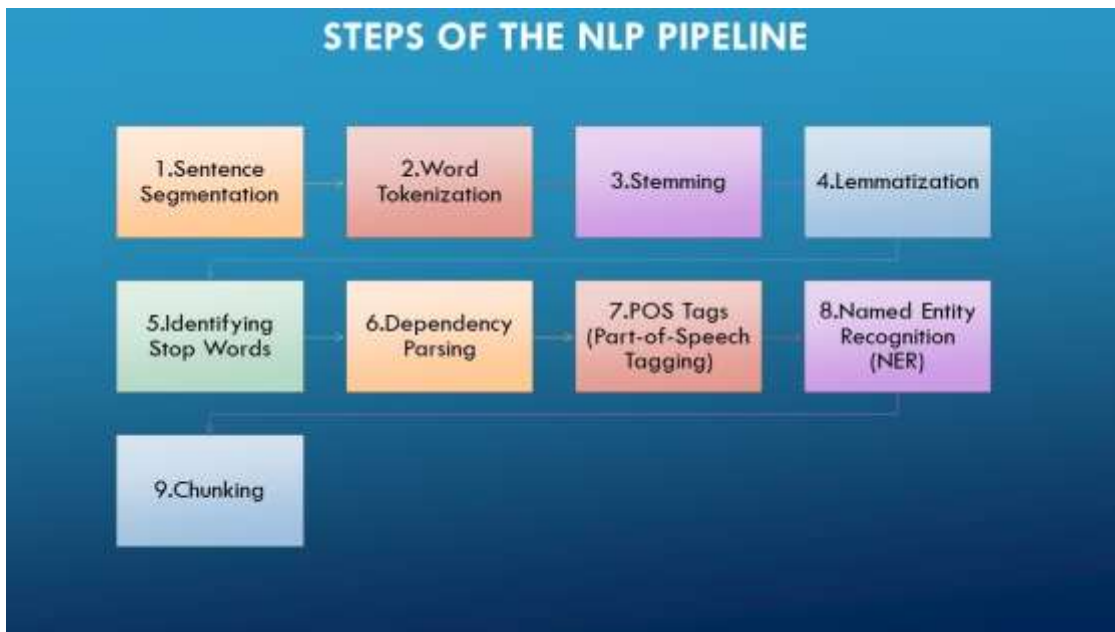
$$\text{TF-IDF}(t,d)=\text{TF}(t,d)\times\log(\text{DF}(t)N)$$

Where:

- (TF(t,d)) = Term frequency
- (DF(t)) = Document frequency
- (N) = Total number of documents

2. Extracted Features:

- Skills (technical and domain-specific)
- Educational qualifications
- Work experience
- Keywords related to job roles



F. Classification Model

The system employs machine learning algorithms to classify resumes into predefined job categories, ensuring accurate and efficient candidate evaluation. Specifically, **Naive Bayes** is utilized for its efficiency in text classification tasks, making it well-suited for handling large volumes of resume data. In parallel, the **Support Vector Machine (SVM)** algorithm is applied due to its ability to deliver high accuracy in high-dimensional feature spaces, which are common in textual datasets. The classification models are trained using labeled datasets, allowing the system to learn patterns and improve prediction accuracy over time. This combination of algorithms ensures that resumes are categorized effectively according to job roles, thereby enhancing the precision of candidate-job matching and supporting scalable recruitment automation.

G. Ranking Mechanism

After classification, resumes are ranked based on similarity to job descriptions.

Cosine Similarity Formula:

$$\text{Similarity}=\frac{A \cdot B}{\|A\| \|B\|}$$

Where:

- (A) = Resume vector
- (B) = Job description vector

Higher similarity scores indicate better matches.

H. Resume Short listing

Based on classification and ranking:

- Relevant resumes are shortlisted
- Irrelevant resumes are filtered

- Results are displayed through a user interface

I. Algorithm Workflow

The overall workflow of the proposed algorithm can be summarized as a structured sequence of steps designed to ensure efficient and accurate recruitment processing. Initially, resumes are uploaded into the system, after which the textual content is extracted for further analysis. The extracted text undergoes preprocessing operations such as tokenization, stop-word removal, and normalization to prepare it for feature representation. Subsequently, the Term Frequency–Inverse Document Frequency (TF-IDF) technique is applied to capture the relative importance of words within the resumes. Using these features, resumes are classified through machine learning algorithms to categorize candidates based on their suitability. Following classification, cosine similarity is computed to measure the alignment between candidate profiles and job descriptions. Candidates are then ranked according to similarity scores, ensuring that the most relevant applicants are prioritized. Finally, the system displays the shortlisted results, providing recruiters with an efficient and data-driven mechanism for candidate selection.

IV. RESULTS AND DISCUSSION (FINAL VERSION)

A. Experimental Setup

The proposed Applicant Tracking System (ATS) was implemented using Python and Natural Language Processing (NLP) libraries. Machine learning algorithms were employed for classification, and similarity-based ranking was used to shortlist candidates. The dataset consisted of resumes collected from multiple domains, including Information Technology, Data Science, and Engineering. The resumes were available in PDF and DOCX formats and were converted into text format for processing. Job descriptions corresponding to each domain were used as reference inputs for classification and ranking.

Tools and Technologies Used

The implementation of the proposed system relies on a robust combination of programming tools, algorithms, and techniques that ensure efficiency and accuracy in recruitment tasks. Python was chosen as the primary programming language due to its versatility and extensive support for machine learning and natural language processing applications. For text analysis, widely used NLP libraries such as NLTK and SpaCy were employed to facilitate tokenization, part-of-speech tagging, and semantic interpretation of resumes. In terms of classification, machine learning algorithms including Naive Bayes and Support Vector Machine (SVM) were utilized to enhance predictive accuracy and candidate categorization. Feature extraction was carried out using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which effectively captures the importance of words within resumes relative to the overall dataset. Finally, cosine similarity was adopted as the similarity measure to rank candidates against job descriptions, thereby improving the precision of candidate-job matching. This integrated framework ensures that the system is both scalable and suitable for real-world recruitment environments.

B. Dataset Description

The dataset used in this study includes a diverse set of resumes categorized into different job roles.

Parameter	Description
Number of resumes	Approximately 1000
Categories	IT, Data Science, Civil Engineering
Format	PDF, DOCX
Data type	Unstructured textual data

The diversity of the dataset ensures that the model is capable of generalizing across different domains and handling real-world recruitment scenarios.

C. Evaluation Metrics

To evaluate the performance of the proposed system, standard classification metrics were employed to ensure a comprehensive assessment of its effectiveness. Accuracy was used to measure the overall correctness of classification, providing an indication of how well the system distinguishes between relevant and irrelevant resumes. Precision was applied to determine the proportion of resumes identified as suitable that were indeed relevant, thereby reflecting the reliability of the selection process. Recall was utilized to measure the system's ability to successfully identify all relevant resumes, ensuring that qualified candidates were not overlooked. Finally, the F1-score was calculated to represent the balance between precision and recall, offering a single metric that captures both the system's ability to minimize false positives and its effectiveness in retrieving true positives. This combination of metrics provides a robust framework for evaluating the system's performance in real-world recruitment scenarios.

D. Performance Results

The performance of the proposed NLP-based ATS is summarized in Table 1.

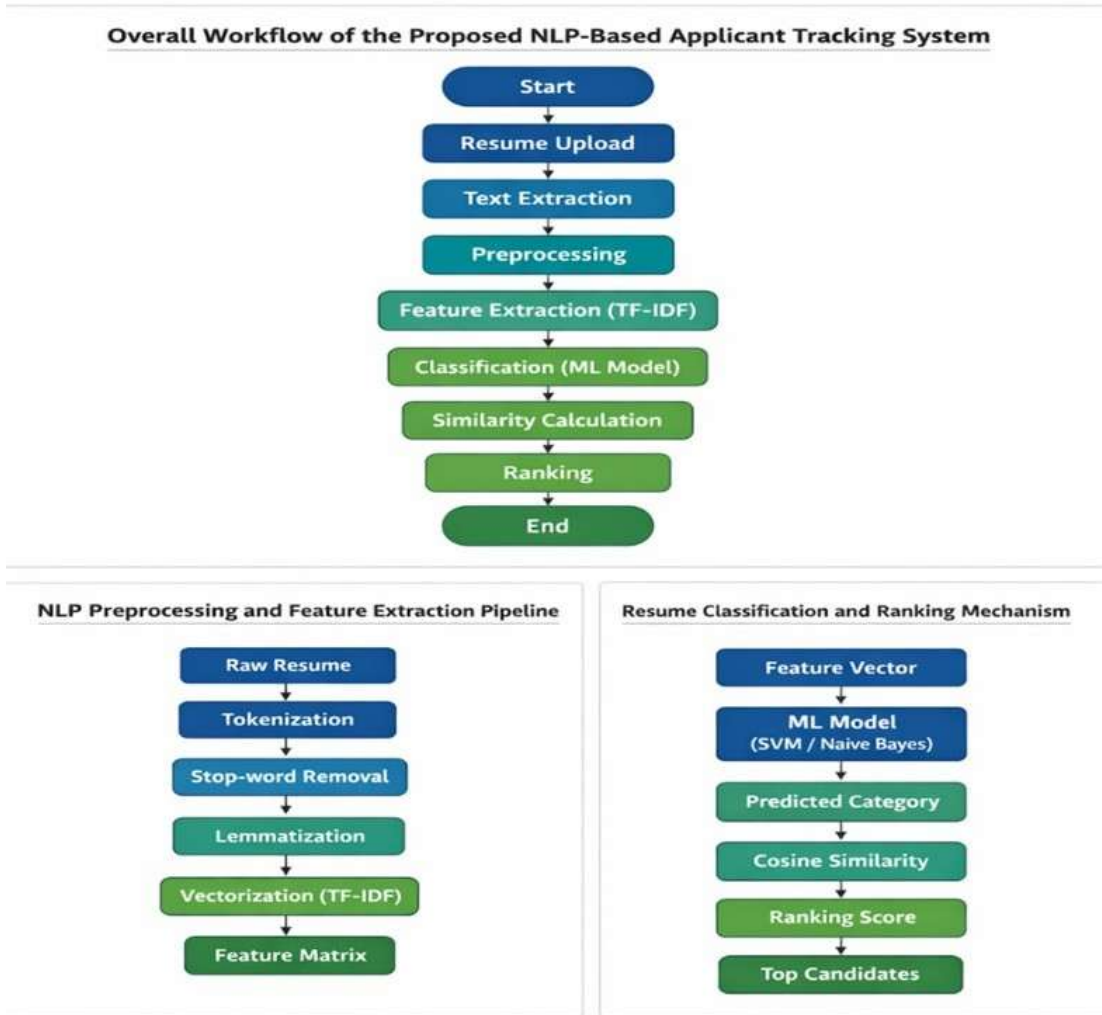
Metric	Value
Accuracy	87%
Precision	85%
Recall	84%
F1-Score	84.5%

E. Analysis of Results

The experimental results indicate that the proposed system achieves a high classification accuracy of 87%, demonstrating its effectiveness in identifying relevant resumes. The precision value of 85% shows that the system is capable of selecting appropriate candidates with minimal false positives, thereby improving the quality of shortlisted applications. The recall value of 84% suggests that the model successfully identifies a majority of relevant candidates without overlooking significant profiles. The F1-score of 84.5% confirms a balanced trade-off between precision and recall, indicating the robustness of the system. The integration of TF-IDF feature extraction with machine learning classification has significantly enhanced the system's ability to understand textual data. Additionally, the use of cosine similarity for ranking ensures that resumes are matched with job descriptions based on contextual relevance rather than simple keyword matching.

F. Result Visualization

Fig 3: Performance metrics of the proposed system



G. Comparative Discussion

A comparison between traditional recruitment systems and the proposed model is presented in Table 2.

Aspect	Traditional System	Proposed System
Screening Method	Manual / Keyword-based	NLP + Machine Learning
Accuracy	Moderate	High
Processing Speed	Slow	Fast
Scalability	Limited	High
Bias	High	Reduced

The proposed system clearly outperforms traditional approaches by providing faster, more accurate and unbiased candidate selection. Unlike keyword-based systems, it considers semantic relationships within the resume, leading to

improved classification and ranking.

H. Key Findings

The proposed NLP-based Applicant Tracking System demonstrates several key strengths that make it highly effective in modern recruitment environments. First, the system automates resume screening, thereby reducing manual effort and streamlining the hiring process. The incorporation of advanced Natural Language Processing (NLP) techniques significantly enhances semantic understanding of resumes, ensuring more accurate interpretation of candidate information. Furthermore, the use of machine learning models improves classification accuracy, enabling precise categorization of applicants based on skills and qualifications. Candidate-job matching is further refined through ranking mechanisms based on cosine similarity, which ensures better alignment between candidate profiles and job requirements. Finally, the system exhibits strong scalability, making it suitable for real-world recruitment environments where large volumes of resumes must be processed efficiently and consistently.

V. APPLICATIONS, ADVANTAGES AND LIMITATIONS

A. Applications

The proposed NLP-based Applicant Tracking System demonstrates wide applicability across multiple domains of recruitment and human resource management. In corporate recruitment systems, large organizations can leverage the system to automate resume screening, thereby reducing hiring time and improving efficiency. Similarly, online job portals and job-matching platforms can integrate the system to recommend suitable candidates, enhancing the precision of candidate-job alignment. Within campus recruitment, educational institutions can utilize the system to streamline student placement processes, ensuring faster and more effective matching of graduates with employment opportunities. The system also holds significant potential for HR analytics platforms, where it can support data-driven decision-making in recruitment and workforce planning by providing actionable insights. Furthermore, freelance and gig platforms can benefit from automated matching of freelancers with project requirements based on their skills and experience, thereby optimizing workforce utilization in the gig economy.

B. Advantages

The proposed system offers several distinct benefits when compared to traditional recruitment methods, making the hiring process more efficient and effective. One of the primary advantages is the automation of resume screening, which eliminates manual effort and significantly accelerates candidate shortlisting. In addition, the use of advanced Natural Language Processing (NLP) techniques enhances semantic understanding, thereby improving the accuracy of candidate evaluation and selection. Another important benefit is the reduction of human bias, as standardized evaluation criteria minimize subjective decision-making and promote fairness in recruitment. The system also demonstrates strong scalability, enabling organizations to process large volumes of resumes with ease and consistency. Finally, the overall time efficiency of the system is noteworthy, as it drastically reduces the duration required for screening and short listing, thereby streamlining the recruitment workflow and allowing organizations to focus more on strategic decision-making and candidate engagement.

C. Limitations

Despite its advantages, the system is subject to certain limitations that may affect its overall effectiveness. A primary concern is its dependency on data quality, as poorly structured or incomplete resumes can significantly reduce the accuracy of parsing and analysis. Moreover, the system exhibits limited contextual understanding, which restricts its ability to fully capture nuanced human attributes such as soft skills, creativity, or interpersonal competencies. Another limitation lies in domain dependency, where performance may vary across industries unless sufficient domain-specific training data is incorporated. Additionally, the processing of large datasets demands substantial computational resources, which may pose challenges for scalability and efficiency. Finally, handling unstructured resume formats remains a critical issue, as variations in layout and design can introduce inconsistencies in information extraction and hinder uniform processing.

VI. FUTURE SCOPE

The proposed system can be further enhanced through the incorporation of advanced techniques and features that significantly improve both performance and applicability. One key enhancement is the integration of deep learning models such as BERT, which can provide superior semantic understanding and contextual analysis, thereby refining the accuracy of resume parsing and candidate evaluation. Additionally, extending the system to support multilingual resume processing would enable global recruitment, ensuring inclusivity and accessibility across diverse linguistic backgrounds. Another promising direction is the integration of AI-based interview systems, which can facilitate end-to-end recruitment automation by conducting preliminary assessments and structured interviews. Furthermore, the inclusion of skill gap analysis would allow the system to provide personalized recommendations for candidates to strengthen their profiles and align better with industry requirements. Finally, the development of real-time recruitment analytics through interactive dashboards would empower organizations to monitor recruitment trends, measure performance, and make data-driven decisions, thereby enhancing the overall efficiency and strategic value of the recruitment process.

VII. CONCLUSION

This research presented an intelligent Applicant Tracking System utilizing Natural Language Processing and machine learning techniques for automated resume classification and ranking. The proposed system effectively processes unstructured resume data, extracts meaningful features, and classifies candidates based on job relevance. The integration of TF-IDF-based feature extraction and machine learning algorithms significantly improves classification accuracy, while cosine similarity ensures effective ranking of candidates. The system achieved promising performance with an accuracy of 87%, demonstrating its potential in real-world recruitment applications. Compared to traditional manual and keyword-based systems, the proposed approach offers improved efficiency, scalability, and reduced bias. Although certain limitations exist, the system provides a strong foundation for developing advanced, intelligent recruitment solutions. Future enhancements can further improve semantic understanding and expand the system's capabilities, making it a comprehensive tool for modern hiring processes.

VIII. ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to the Department of Computer Applications, Nehru Memorial College (Autonomous), for providing the necessary resources and academic support required to carry out this research work successfully. We extend our heartfelt thanks to our guide, Dr. K. Deepa, for her valuable guidance, insightful suggestions, and continuous encouragement throughout the development of this project. Her expertise and constructive feedback greatly contributed to the improvement of this study. We would also like to acknowledge our faculty members and peers for their support and cooperation during the course of this research. Their inputs and discussions helped in refining the methodology and enhancing the overall quality of the work. Finally, we express our sincere appreciation to our family members for their constant motivation, patience, and moral support, which enabled us to complete this research successfully.

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