

TLIC PAPER

AI-Driven Talent Acquisition: Enhancing Recruitment and Hiring with Machine Learning and Large Language Models

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ABSTRACT

Artificial intelligence (AI) is transforming corporate recruitment by enabling data-driven decision-making and automating candidate evaluation. This study presents an AI-powered recruitment framework that integrates machine learning and large language models (LLMs) to enhance resume classification, candidate-job matching, and contextual hiring insights. The research evaluates multiple machine learning algorithms—Support Vector Machine (SVM), Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), and an Ensemble model—across different feature extraction strategies. Textual features were first extracted from resumes using Term Frequency–Inverse Document Frequency (TF-IDF) and Word2Vec embeddings. Additional linguistic and structural features, including keyword presence, n-grams, and part-of-speech (POS) tagging, were then incorporated to form a combined feature set. Results show that the SVM achieved the highest performance using TF-IDF features alone (accuracy = 99.17%, F1 = 99.29%), while the Random Forest model outperformed all others with the combined feature set (accuracy = 99.6%, F1 = 99.64%). Feature importance analysis revealed that TF-IDF contributed the most to model performance, followed by n-grams, keyword presence, and POS features. The integration of GPT-4 further supported the system by providing contextual feedback, skills gap analysis, and training recommendations for recruiters. The findings demonstrate that combining linguistic, statistical, and semantic features enhances both predictive accuracy and interpretability, offering a scalable, AI-driven approach to modern corporate talent acquisition. Future work will extend the framework to incorporate real-time labor market data, thereby expanding its applicability to dynamic corporate environments.

KEYWORDS

corporate talent acquisition, recruitment, artificial intelligence, machine learning, large language models, feature engineering

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1 INTRODUCTION

Recruiting and retaining the right talent has become one of the most pressing challenges for corporations in today's competitive and fast-paced business environment. Traditional hiring practices—such as manual resume screening, subjective candidate evaluation, and time-intensive interview processes—are increasingly inadequate in addressing the demands of large applicant pools, global competition, and the need for diverse, high-performing teams. These methods are often slow, prone to bias, and inconsistent in assessing the true potential of candidates. As organizations strive to improve efficiency, fairness, and strategic alignment in hiring, the integration of artificial intelligence (AI) into recruitment processes has emerged as a transformative solution.

AI-driven recruitment systems have demonstrated the ability to automate resume parsing, match candidates to job roles, and provide predictive insights into candidate performance and retention. Machine learning algorithms enable the scalable, data-driven classification of resumes into job categories, while large language models (LLMs) extend this capability by offering contextual feedback, identifying skills gaps, and providing workforce recommendations. This dual application of AI reduces administrative workload for human resources (HR) departments and enhances decision-making with objective, evidence-based insights.

This research introduces a novel AI-powered recruitment framework designed to streamline corporate talent acquisition. The system combines machine learning for resume classification with LLM-powered analysis to support HR professionals in evaluating candidates, aligning roles, and providing training recommendations. Unlike traditional applicant tracking systems, this framework integrates both general labor market knowledge and organization-specific expertise, enabling the development of tailored and adaptable recruitment strategies. By aligning hiring decisions with long-term workforce planning, the proposed system enhances corporate competitiveness and fosters more equitable, efficient, and strategic hiring practices.

1.1 Research contributions

- **Comprehensive Feature Integration:** Introduced a combined feature extraction approach that merges TF-IDF, Word2Vec embeddings, keyword presence, n-grams, and part-of-speech (POS) tagging to enhance the representational richness of resume data.
- **Comparative Evaluation of Machine Learning Models:** Conducted an extensive comparison of five algorithms—Support Vector Machine (SVM), Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), and an Ensemble model—across multiple feature sets to identify the most effective configuration for resume classification and candidate-job matching.
- **Enhanced Predictive Accuracy:** Demonstrated that incorporating additional linguistic and structural features improved overall model performance, with Random Forest achieving the highest results using the combined feature set (accuracy = 99.6%, F1 = 99.64%).
- **Feature Importance Analysis:** Quantified the relative contribution of different feature categories, revealing that TF-IDF had the most significant impact, followed by n-grams, keyword presence, and POS features—providing valuable insight into which textual attributes most influence hiring predictions.

- Contextual Decision Support with GPT-4: Integrated large language models to generate contextual hiring feedback, skills gap analysis, and personalized training recommendations, enhancing the interpretability and practical utility of the system for HR professionals.
- Scalable Framework for Corporate Recruitment: Developed a modular and adaptable AI recruitment framework that can be customized across industries and organizations, enabling fairer, faster, and data-driven hiring decisions.

1.2 Research questions

To guide this investigation, the following research questions are posed:

- How effective are feature extraction techniques and machine learning algorithms in classifying resumes and predicting candidate-job fit within corporate hiring processes?
- In what ways can large language models (LLMs) enhance recruitment by providing contextual feedback, identifying skills gaps, and recommending training or development pathways?

2 RELATED LITERATURE

A significant area of investigation is the use of ML algorithms to analyze resumes and match them to job descriptions. Maree and Shehada [1] detail the comparative effectiveness of classical machine learning algorithms against LLM architectures in optimizing curriculum vitae concordance. Their study demonstrates how integrating LLMs can significantly improve the precision of resume parsing, enabling a more nuanced understanding of candidates' qualifications and experiences compared to traditional methods, such as Logistic Regression and Decision Trees. This finding is echoed by Venkatasubramanian [2], who posits that automated systems powered by ML not only accelerate the hiring process but also reduce the subjectivity associated with conventional recruitment practices. Hinge et al. [3] describe how AI can scan resumes, automate applicant searches, and facilitate more efficient candidate screening, enabling HR professionals to devote more effort to strategic decision-making and relationship building.

Research by Odili et al. [4] indicates that AI-driven tools, particularly those utilizing natural language processing (NLP), are increasingly prevalent in resume screening, facilitating quick assessments of candidate fit for various roles. The capabilities of NLP algorithms extend beyond simple matching; they can comprehend context, sentiment, and even classify job seekers based on complex queries involving nuanced language [5]. This supports the assertion that ML can streamline the recruitment process through predictive analytics by anticipating the most suitable applicant profiles [2] and the specific needs of the employer.

Pessach et al. [6] introduced a prescriptive analytics model designed to enhance decision-making in recruitment. Their framework employs both ML and mathematical programming, illustrating the potential for algorithms to advise HR professionals on candidate selection by predicting a recruit's success rate in specific job placements. This predictive capacity is valuable in environments where the volume of candidates is high, allowing HR personnel to focus on top-tier applicants who are likely to succeed within their organizational context.

Furthermore, the practical applications of ML in recruitment extend into real-time hiring scenarios, where tools can evaluate candidate performance during interviews. Automated video assessments are investigated by Hickman et al. [7], highlighting the reliability and validity of personality assessments in recruitment. Their work suggests that such automated systems not only capture candidate performance metrics more efficiently than human evaluators but also offer insights into organizational fit that can enhance the decision-making process.

Talent acquisition strategies increasingly leverage ensemble models that integrate various machine learning techniques to classify job positions and predict talent acquisition outcomes [8]. Recent studies have highlighted the effectiveness of ensemble approaches in matching available talent with organizational needs, demonstrating the synergy between advanced algorithms and traditional screening methods in informing productive hiring decisions.

Another important aspect of this transformation is the adaptation of recruitment frameworks to incorporate data-driven insights into candidate behavior. The findings reported by Benhmama and Bennani [9] articulate how Moroccan companies are prioritizing the swift transmission of recruitment data and utilizing ML technologies to refine candidate search processes. This highlights a trend where organizations are actively cultivating a talent pipeline using predictive analytics.

Additionally, the integration of machine learning into recruitment practices has significantly enhanced HR analytics. Ajuwon et al. [10] describe how AI technologies can transform data collection and analysis methods to improve overall HR effectiveness in recruiting and retaining talented teaching staff. Incorporating ML allows recruiters to make informed decisions based on evidence-based predictions about candidate success, ultimately leading to a more sustainable workforce. Moreover, the work of Valerio et al. [11] demonstrates how AI systems, in the medical field, can enhance various aspects of clinical trial recruitment management and candidate selection.

The role of large language models (LLMs) in workforce development has emerged as a significant area of interest, particularly in recruitment and resume screening. LLMs, such as OpenAI's ChatGPT, have shown remarkable capabilities in natural language processing (NLP). LLMs also play a significant role in enhancing the quality of resumes submitted by candidates. Tools that leverage LLMs can provide real-time feedback and suggestions for optimizing resumes based on job descriptions, thereby improving candidates' chances of being selected for interviews. For instance, the work of Delobelle et al. introduces a resume-building tool that utilizes LLMs to analyze existing resumes and provide contextual suggestions for improvement [12]. This empowers candidates to present their qualifications more effectively and aligns their applications more closely with employer expectations. Moreover, using LLMs in resume parsing and job recommendation systems can significantly enhance recruitment.

While existing literature has studied the benefits of machine learning and LLMs in this domain, most research studies utilize each approach individually. This paper proposes integrating machine learning and LLMs in the same system for resume classification and personalized feedback, including course recommendations, skills gap analysis, learning pathways, and training suggestions.

As organizations continue to embrace these methodologies, the need for ongoing evaluation and adaptation will remain paramount. Continuous research and development will ensure that machine learning models evolve in tandem with the changing nature of work and the expectations of the workforce. Such progressive adaptation will not only enhance the recruitment process but also contribute to a more comprehensive understanding of human capital management in an era defined by rapid technological advancements.

3 SYSTEM ARCHITECTURE

The system architecture is designed to ensure scalability, efficiency, and adaptability across different institutional settings. It consists of three primary components: the user interface, the resume classification module, and the candidate evaluation and guidance module. Each contributes to the overall functionality of the system.

The user interface facilitates interaction between users and the system by providing an accessible platform for resume submission and retrieving feedback. HR professionals can upload resumes through a web-based dashboard, which displays classification results and ChatGPT-generated recommendations (see Figure 1). The dashboard displays predicted job-role matches, candidate-job fit scores, and tailored feedback for candidate development. By consolidating resume data and recommendations in a single environment, the interface supports faster, evidence-based hiring decisions.

The resume classification module processes textual candidate data to assign job categories using advanced machine learning techniques. Each resume undergoes preprocessing steps such as stopword removal, tokenization, and normalization, followed by multi-level feature extraction. In addition to Term Frequency–Inverse Document Frequency (TF-IDF) and Word2Vec embeddings, additional linguistic and structural features were extracted, including keyword presence, n-grams, and part-of-speech (POS) tagging. These features were then combined into a unified feature set to capture both semantic and syntactic patterns in candidate resumes. Multiple machine learning models were trained and evaluated using this combined representation, including Support Vector Machine (SVM), Random Forest, Logistic Regression, K-Nearest Neighbors (KNN), and an Ensemble model.

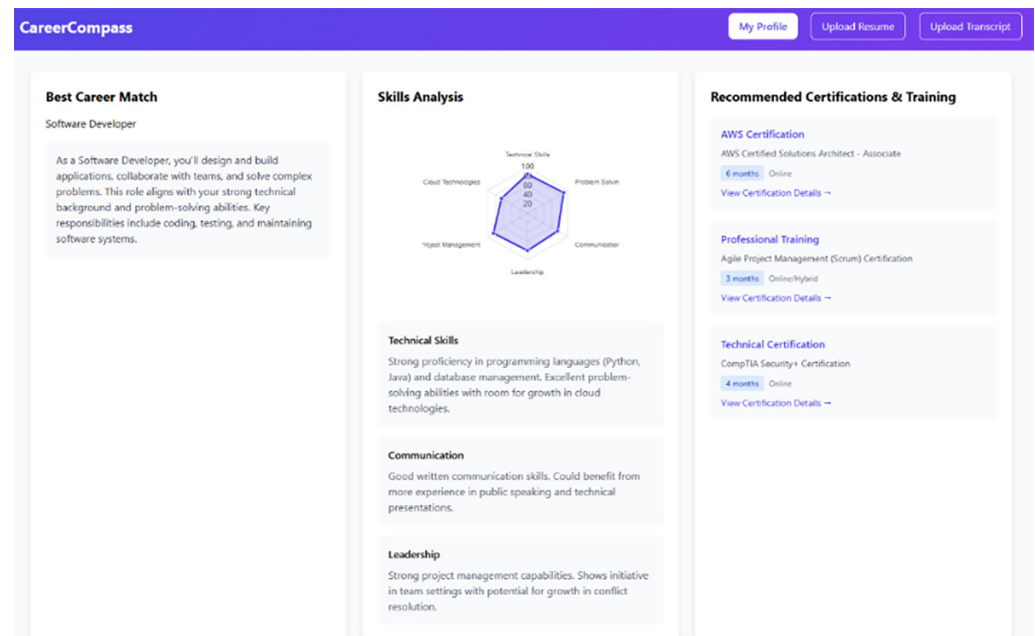


Fig. 1. Users, including HR personnel, can upload resumes through a web-based dashboard. The dashboard displays classification results (best career match) using machine learning. ChatGPT (GPT-4o) conducts skill analysis and generates recommendations

Among these, Random Forest with combined features achieved the highest accuracy (99.6%) in predicting candidate-job matches. This module ensures that resumes are automatically categorized, significantly reducing manual screening effort for recruiters. Beyond classification, the system integrates LLMs (GPT-4) to deliver contextual analysis that enriches HR decision-making. Two parallel LLM instances are utilized: the General Knowledge Instance, which provides industry-wide insights, identifies missing skills, and suggests professional certifications or training aligned with the candidate's target role, and the Organization-Specific Instance—Customizable to incorporate internal policies, job descriptions, and corporate training programs, ensuring recommendations are tailored to the company's needs. This dual-LLM framework enables recruiters not only to identify the most suitable candidates but also to understand potential development pathways, making the system valuable for both hiring and long-term talent management, as shown in Figure 2.

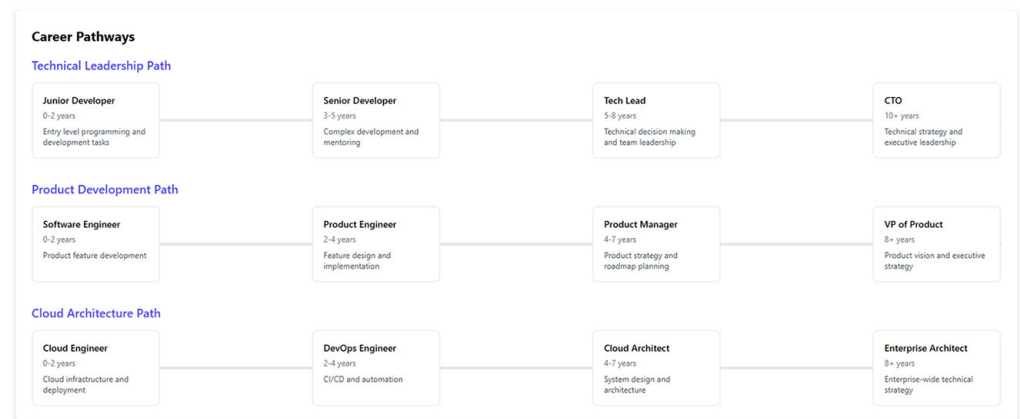


Fig. 2. Visual representation of career pathways for each candidate generated using LLM (ChatGPT)

4 METHODOLOGY

4.1 Data preprocessing and feature extraction

The dataset used in this study consists of 962 resumes, each manually labeled with a corresponding job category. The resumes contain text fields such as education, skills, and professional experience. Before feature extraction, all resumes underwent systematic preprocessing to standardize and clean the data. Steps included converting all text to lowercase, removing punctuation and stopwords, and performing tokenization and lemmatization. This ensured a consistent and noise-free corpus suitable for feature generation.

To represent textual information in a numerical format for machine learning models, multiple feature extraction techniques were applied (see Table 1). These techniques captured complementary aspects of the resume data—semantic, syntactic, and keyword-based information—enabling a richer and more discriminative representation. All extracted features—TF-IDF, Word2Vec, keyword indicators, n-grams, and POS distributions—were concatenated into a unified feature vector for each resume. This combined representation integrates statistical, semantic, and linguistic dimensions, providing a more comprehensive foundation for classification.

Table 1. Summary of feature extraction techniques

Feature Type	Description	Purpose/Contribution
TF-IDF Representation	Term Frequency–Inverse Document Frequency (TF-IDF) was employed to quantify the importance of words in each resume relative to the entire dataset.	Highlights distinctive terms within resumes and improves text-based classification accuracy.
Word2Vec Embeddings	Word2Vec was used to capture semantic relationships between words. A Word2Vec model was trained on the resume corpus to generate dense vector representations, and each resume was represented by averaging its word embeddings.	Captures semantic meaning and contextual relationships between terms within resumes.
Keyword Presence	A predefined keyword dictionary was constructed by mapping each job category to a set of relevant terms and skills (for example, Data Science maps to “Python,” “SQL,” “TensorFlow”). Binary indicators were created to represent keyword presence.	Identifies domain-specific skills and technical proficiencies relevant to job categories.
N-grams	N-gram features (unigrams, bigrams, and trigrams) were extracted to capture local linguistic patterns and multi-word expressions.	Detects recurring phrases, skill combinations, and domain-specific terminology.
Part-of-Speech (POS) Tagging	POS tagging was applied to compute the relative frequency of grammatical structures (e.g., nouns, verbs, adjectives) in each resume.	Captures stylistic and structural characteristics associated with professional writing across job categories.

5 MACHINE LEARNING MODELS

Five machine learning algorithms were implemented and evaluated: Support Vector Machine (SVM), Random Forest, Logistic Regression, K-Nearest Neighbors (KNN), and an Ensemble model combining multiple classifiers. The dataset was split into training (75%) and testing (25%) subsets. Hyperparameters for each model were tuned using grid search and cross-validation to ensure optimal performance. Model performance was evaluated using four standard metrics—accuracy, precision, recall, and F1-score—to assess predictive capability and robustness. Comparative experiments were conducted in two stages:

- Using TF-IDF and Word2Vec features independently to establish baseline performance.
- Using the combined feature set to assess the impact of additional linguistic and structural features.

5.1 Performance comparison

The comparative results revealed that the SVM achieved the best performance when trained on TF-IDF features alone, with an accuracy of 99.17%, precision of 99.15%, recall of 99.53%, and F1-score of 99.29%. When the combined feature set was used, the Random Forest model outperformed all others, achieving an accuracy of 99.6%, a precision of 99.56%, a recall of 99.76%, and an F1-score of 99.64%.

These results demonstrate that incorporating keyword, n-gram, and POS-tag features significantly improves classification accuracy and interpretability.

5.2 Feature importance analysis

To further interpret the model's behavior, feature importance was analyzed using the Random Forest model. The analysis indicated that TF-IDF features contributed the most to predictive performance, followed by n-grams, keyword presence, and POS-tag distributions. This hierarchy suggests that while lexical frequency remains a dominant predictor, linguistic and structural patterns provide valuable complementary information for distinguishing between job categories.

5.3 ChatGPT integration

ChatGPT, specifically GPT-4o, was integrated to enhance the system's functionality and provide personalized career guidance. This component consisted of two distinct GPT-4o instances: 1) a *General Knowledge Instance* equipped with broad career knowledge, offering feedback on skills, industry trends, and relevant career pathways. It analyzes resumes to provide high-level recommendations for workforce readiness and 2) a *Domain-Specific Instance* tailored to a specific organization's programs and policies. This modular design ensured scalability, allowing the system to adapt to different institutions by integrating their specific knowledge bases and expertise.

6 RESULTS AND FINDINGS

This section presents the evaluation outcomes of the proposed AI-driven recruitment framework, focusing on two main components: (1) the performance of machine learning models in resume classification across multiple feature extraction strategies, and (2) the contribution of large language models (LLMs) in providing contextual insights for recruitment and workforce analysis.

6.1 Resume classification

To classify resumes into predefined job categories and determine candidate-job fit, several machine learning models were implemented, including Support Vector Machine (SVM), Random Forest, Logistic Regression, K-Nearest Neighbors (KNN), and an Ensemble model. Each model was evaluated under three experimental settings: using TF-IDF, Word2Vec, and combined features (which included keywords, n-grams, and part-of-speech tagging). Model performance was assessed using four key metrics—accuracy, precision, recall, and F1-score.

TF-IDF features. When trained on TF-IDF features, the SVM achieved the best performance, with an accuracy of 99.17%, a precision of 99.15%, a recall of 99.53%, and an F1-score of 99.29% (Figure 3). This high level of performance demonstrates the SVM's effectiveness in handling high-dimensional textual data, making it suitable for large-scale resume classification tasks. The Ensemble model produced comparable results but at a higher computational cost.

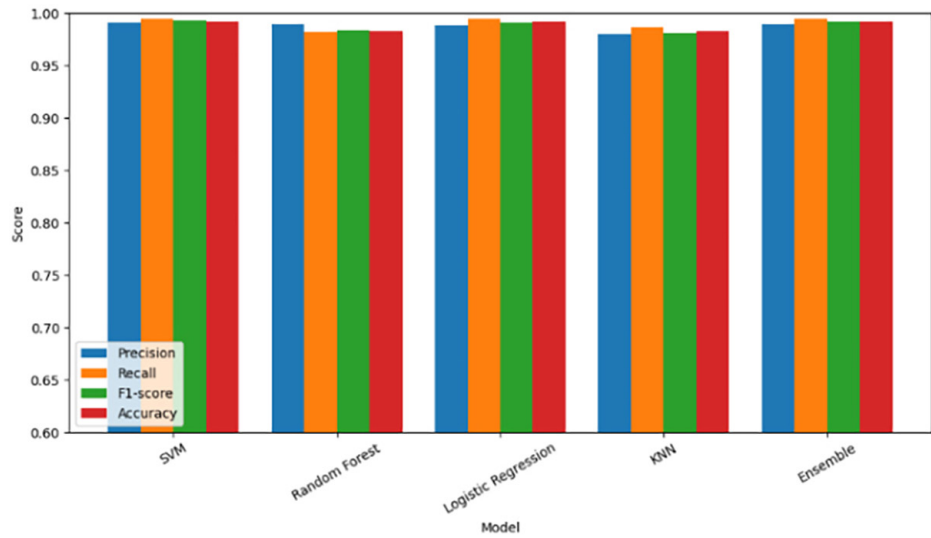


Fig. 3. Using TF-IDF only, SVM performs the highest across all metrics

Word2Vec features. Using Word2Vec embeddings, the Random Forest model yielded the highest performance, reaching an accuracy of 98.34% and an F1-score of 98.10%. While Word2Vec captured semantic relationships between terms, the results indicate that frequency-based methods like TF-IDF were more effective for structured resume data, where domain-specific terminology is critical.

Combined features. To enhance model robustness and contextual understanding, additional linguistic and structural features—keyword presence, n-grams, and part-of-speech (POS) tagging—were extracted and combined with TF-IDF features. After retraining, the Random Forest model improved and achieved the highest overall performance with an accuracy of 99.6%, precision of 99.56%, recall of 99.76%, and an F1-score of 99.64 (Figure 4). This represents a measurable improvement over the TF-IDF-only configuration, confirming that the inclusion of linguistic and contextual features improves both accuracy and generalization.

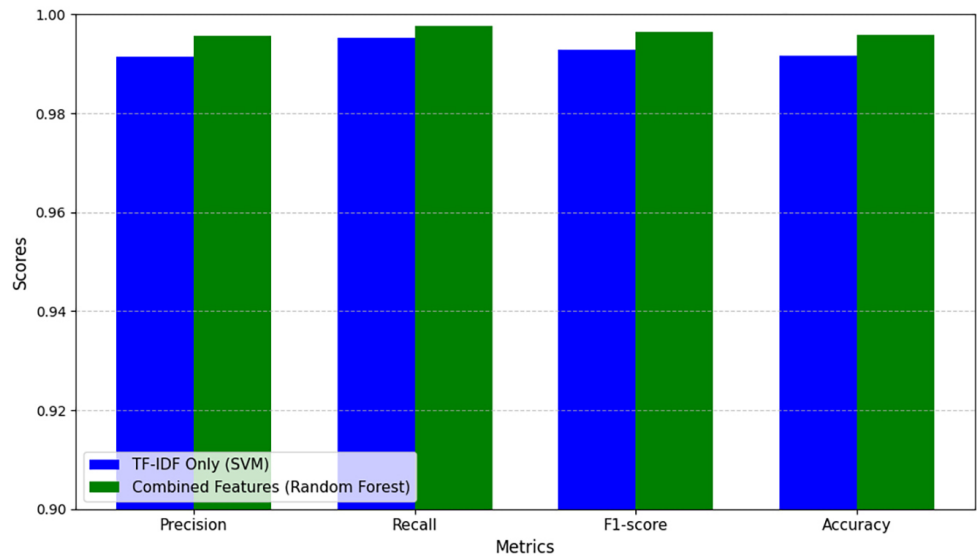


Fig. 4. The Random Forest model with combined features (TF-IDF, keyword presence, n-grams, and part-of-speech (POS) tagging) outperforms the SVM model with TF-IDF only. There is an improvement in all performance metrics

6.2 Feature importance analysis

An analysis of feature importance from the Random Forest model (Figure 5) revealed that TF-IDF features contributed the most to classification performance, followed by n-grams, keyword presence, and POS-tag features. This finding emphasizes that lexical frequency and contextual groupings of words remain primary predictors of job category. At the same time, syntactic and keyword-based features enhance interpretability and fine-grained differentiation between similar roles.

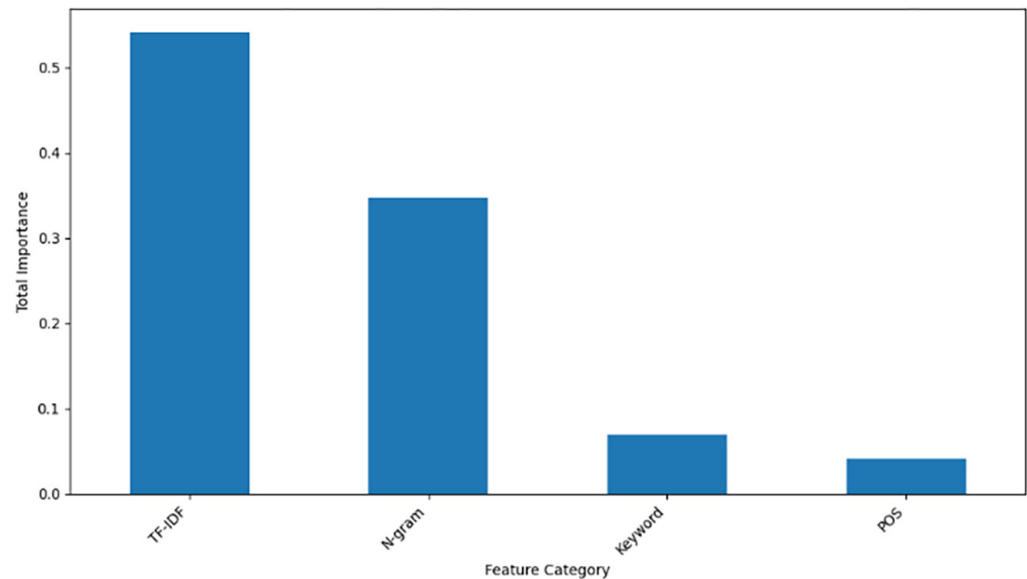


Fig. 5. Feature importance by category using the Random Forest model

6.3 Integration of LLMs for recruitment insights

The second phase of the system utilized GPT-4 to generate contextual insights that complemented machine learning-based classification. Two LLM instances were deployed: a General Knowledge Instance, which provided domain-independent recommendations such as skill enhancement or professional certification pathways, and an Organization-Specific Instance, customized to reflect company-specific policies, training programs, and internal competencies. The integration of LLMs enhanced the recruitment process by transforming static classification outcomes into actionable intelligence. Recruiters received detailed recommendations that identified candidate skill gaps, suggested relevant upskilling opportunities, and proposed internal or external training programs. This contextual feedback enabled HR professionals to make more informed, transparent, and equitable hiring decisions.

7 CONCLUSION AND FUTURE WORK

This study presented an AI-powered recruitment framework that integrates machine learning and large language models (LLMs) to enhance resume classification and candidate evaluation. Among the tested algorithms, the Random Forest model

with combined features (TF-IDF, Word2Vec, keywords, n-grams, and POS tagging) achieved the highest accuracy of 99.6%, demonstrating the effectiveness of multi-level feature integration. Unlike traditional applicant tracking systems, the proposed framework integrates predictive modeling and contextual analysis through machine learning and large language models (LLMs). This integration transforms recruitment into a strategic, data-driven process that enhances decision-making and talent acquisition outcomes.

Future work will focus on expanding the dataset for greater generalizability, integrating real-time labor market data, and evaluating model fairness across diverse candidate groups.

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