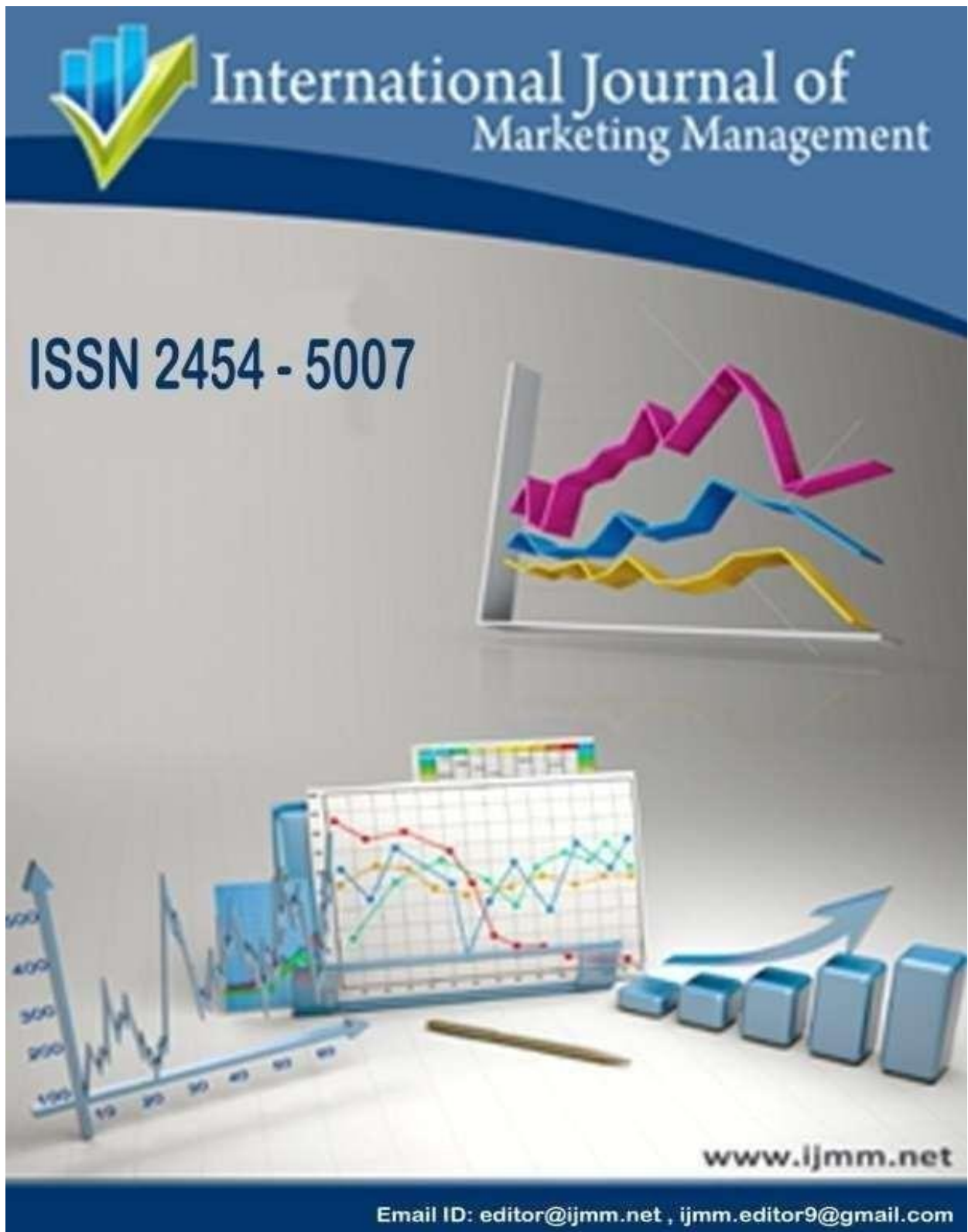




RESUME JOB MATCHER USING COSINE SIMILARITY

¹ Kotha Venkata Lakshmi Sahithi, ²Najana Varalakshmi, ³Miriyala Prudhvi Raj,
⁴Mr. N. Lakshmi Narayana

^{1,2,3}U. G Student, Dept COMPUTER SCIENCE AND ENGINEERING, St.Ann's College Of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

⁴Assistant Professor, COMPUTER SCIENCE AND ENGINEERING, St.Ann's College Of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

ABSTRACT

The Resume Job Matcher uses NLP and cosine similarity to compare resumes with job descriptions. It cleans and processes text using tokenization, stop-word removal, and TF-IDF vectorization to turn it into numerical form. This helps find how closely a candidate's skills match the job needs. Unlike simple keyword matching, it understands the meaning of words for better results. The system saves time in screening, improves hiring accuracy, and gives fair results. It can also work with web apps and databases, making it useful for real hiring situations. Overall, it makes the recruitment process smarter and more efficient. The project shows how AI can simplify hiring by matching the right candidates faster. It provides a reliable and scalable solution for modern recruitment platforms.

KEYWORDS

Natural Language Processing (NLP), Cosine Similarity, TF-IDF Vectorization, Resume Parsing, Job Description Analysis, Semantic Matching, AI-driven Recruitment, Machine Learning, Information Retrieval, Human Resource Management (HRM).

INTRODUCTION

Through resume analysis and job description comparison, the Resume Job Matcher initiative aims to match job seekers with suitable prospects. While recruiters spend a lot of time going through resumes, candidates frequently struggle to locate positions that actually match their skills in the competitive job market of today. By employing Natural Language Processing (NLP) techniques, this system seeks to address these issues and improve the speed and accuracy of the matching process. Cosine similarity, which gauges how well a resume's content meets job description criteria, is the main tool used in this study. The system may suggest the best positions for a candidate by displaying text in a vector space and computing the similarity score. This guarantees that resumes are matched based on the general relevance of abilities and experience rather than simply keywords. In addition to position matching, the system gives candidates suggestions on how they may improve. It draws attention to areas where the CV might be strengthened to better match the job description, such as missing skills or keywords. Because of this, the project is helpful not just in suggesting positions but also in assisting applicants in

crafting more compelling resumes, which raises the likelihood that they will be shortlisted.

LITERATURE SURVEY

A literature survey helps review earlier work in automated resume screening and understand how the proposed system improves on them. Patel et al. (2021) used a keyword-based filtering method that often missed relevant candidates because it could not understand the meaning behind words. Singh and Mehta (2022) built a machine learning model that depended on manual feature selection, which made it harder to apply across different job domains. Zhao et al. (2023) developed a deep learning approach using word embeddings, but it needed large datasets and high computing power. In comparison, the proposed Resume Job Matcher uses NLP techniques, TF-IDF, and cosine similarity to compare resumes and job descriptions more effectively. It reduces manual work, runs efficiently, and adapts easily to different job roles, making it a practical tool for improving the recruitment process.

RELATED WORK

Several studies have explored the use of artificial intelligence and natural language processing (NLP) in automating the recruitment process. Traditional resume screening systems often rely on keyword-based searches, which fail to capture contextual or semantic similarities between resumes and job descriptions. Recent research has shifted toward NLP-driven techniques to extract, analyze and compare textual data more effectively. Models using TF-IDF and word embeddings have shown improved accuracy in matching candidate

profiles with job requirements. However, many of these systems either focus on specific domains or require large labelled datasets, limiting their general usability. Some approaches use deep learning to enhance semantic understanding but are computationally expensive and not easily deployable. Other models struggle to integrate with existing HR systems or web applications. The proposed Resume Job Matcher builds on these advancements by combining TF-IDF vectorization and cosine similarity for efficient and interpretable text comparison. It offers a lightweight yet powerful approach that balances accuracy, scalability, and real-world applicability in modern recruitment systems.

EXISTING METHOD

In existing resume screening systems, most recruitment platforms use basic keyword matching or rule-based filters to compare resumes with job descriptions. These systems primarily search for exact word overlaps between candidate profiles and job requirements, often missing candidates who use different terminology for similar skills. Some advanced models use machine learning with manually defined features, but they require frequent updates and lack flexibility across domains. Deep learning-based systems have been introduced to improve semantic understanding; however, they demand large amounts of labelled data and high computational resources, making them difficult to deploy in small or medium-scale organizations. Many of these systems also face challenges in integrating with web-based hiring platforms and maintaining real-time performance. As a result, existing methods often produce inaccurate matches, require manual

intervention, and fail to provide fair or efficient screening.

PROPOSED METHOD

The proposed Resume Job Matcher improves existing resume screening methods by using NLP-based techniques for better and more accurate matching. While traditional systems depend on simple keyword searches or manual filters, this method focuses on understanding the actual meaning of the text. It starts by cleaning and processing the data using tokenization and stop-word removal to prepare it for analysis. Then, TF-IDF vectorization is used to convert resumes and job descriptions into numerical form. Cosine similarity is applied to measure how closely a candidate's resume matches the job requirements. This approach helps identify suitable candidates even when different words are used to describe similar skills. The system can also be linked with web applications and databases for easier real-world use. Overall, the proposed method provides a more efficient, fair, and adaptable solution for improving the hiring process compared to older systems.

SYSTEM ARCHITECTURE

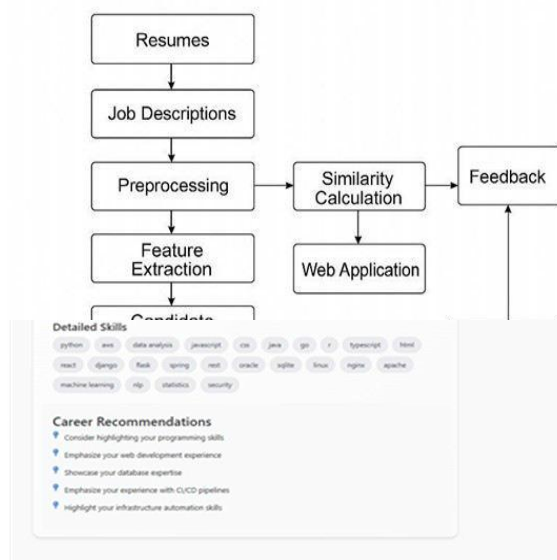


Fig.1: Architecture of Resume Job Matcher using Cosine Similarity

METHODOLOGY DESCRIPTION

Input Collection: Resumes and job descriptions are collected from users or connected databases for analysis.

Preprocessing: The text data is cleaned by removing unwanted symbols, numbers, and stop- words, and then tokenized to make it easier to process.

Feature Extraction: The cleaned text is transformed into numerical form using TF-IDF (Term Frequency–Inverse Document Frequency) to identify the most important words in each document.

Similarity Calculation: Cosine similarity is applied to compare resumes and job descriptions, measuring how closely they match based on context rather than exact words.

Candidate Ranking: Candidates are ranked according to their similarity scores, from the most suitable to the least suitable match for a given job.

Database Storage: All processed data, including candidate profiles, job descriptions, and match scores, are stored securely in a database for easy retrieval.

Web Application Interface: A simple and user- friendly web interface allows recruiters to view, sort, and analyze ranked candidates conveniently.

Feedback System: Recruiters can provide feedback on the match accuracy, which helps refine the model and improve results in future searches.

Outcome: This structured approach makes the recruitment process faster, fairer, and more reliable compared to manual resume screening.

RESULTS AND DISCUSSION

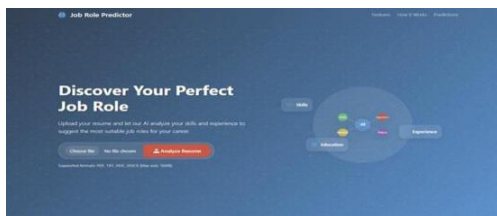


Fig.2: Application Home Page

This figure shows the landing page of the Resume Job Matcher, where users can easily upload their resumes. The page provides a simple and clear interface with an option to analyze the resume and find matching job roles.

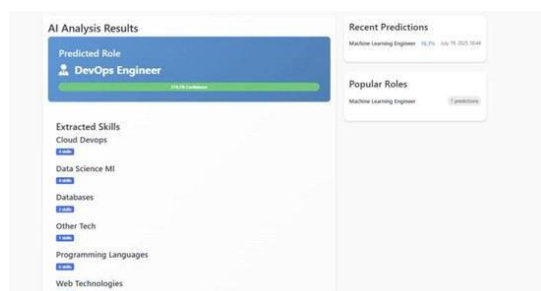


Fig.3: Predicted Role and Extracted Skills

This screenshot shows the AI analysis result, where the system suggests the most relevant job role with a confidence score. It also lists key skills identified from the resume, such as Cloud DevOps, Data Science, Databases, and Programming Languages.

Fig.4: Detailed Skills and Career Recommendations

This figure shows the extracted skills, including programming languages, web technologies, and machine learning. The

system also provides career recommendations to help users improve their resumes and match job requirements more effectively.

CONCLUSION

The Resume Job Matcher simplifies hiring by using NLP and cosine similarity to accurately match resumes with job descriptions. It saves recruiters time and ensures fairer candidate selection. The use of TF-IDF makes it efficient and adaptable across domains.

FUTURE SCOPE

In the future, it can be improved using deep learning models like BERT and integration with job portals. A feedback-based module could further enhance its accuracy and intelligence over time.

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