International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 2 (2026)

ijerst.editor@gmail.com

editor@ijerst.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 22, No. 2, 2026

Peer Reviewed, Referred & Indexed Journal

TWO STAGE JOB TITLE IDENTIFICATION SYSTEM FOR ONLINE JOB ADVERTISEMENT

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ABSTRACT

The rapid growth of online job portals and recruitment platforms has resulted in an overwhelming volume of job advertisements, making it challenging to accurately identify and classify job titles from unstructured textual data. This project proposes a Two-Stage Job Title Identification System designed to improve the precision and efficiency of extracting job titles from online job advertisements. In the first stage, the system performs text preprocessing and feature extraction, where raw job descriptions are cleaned, tokenized, and transformed into structured representations using techniques such as TF-IDF and word embeddings. This stage also includes filtering irrelevant information and identifying key linguistic patterns associated with job titles. In the second stage, advanced machine learning and deep learning models, such as Support Vector Machines (SVM), Random Forest, and Bidirectional LSTM (BiLSTM), are employed to classify and refine the extracted job titles. The two-stage approach enhances accuracy by combining rule-based filtering with intelligent classification, reducing ambiguity and improving consistency across diverse job postings. Additionally, the system can handle variations in job title formats, abbreviations, and domain-specific terminology. Experimental results demonstrate that the proposed system achieves higher accuracy and better generalization compared to single-stage models. This solution is highly beneficial for recruitment platforms, job recommendation systems, and labor market analytics, enabling efficient job categorization and improved user experience. Overall, the proposed system provides a scalable and intelligent framework for automated job title identification in large-scale online environments.

Keywords: Job Title Identification, Text Classification, Natural Language Processing (NLP), Machine Learning, Deep Learning, BiLSTM, TF-IDF, Information Extraction, Recruitment Systems, Text Mining

I.INTRODUCTION

The rapid expansion of online recruitment platforms has significantly increased the volume of job advertisements, making it difficult to extract meaningful information such as job titles from unstructured text. Job titles play a crucial role in job recommendation systems, candidate matching, and labor market analysis. However, variations in naming conventions, abbreviations, and inconsistent formatting across job postings create challenges in accurately identifying job titles. Traditional keyword-based methods often fail to capture contextual meaning, leading to misclassification and reduced system performance. Recent advancements in Natural Language Processing (NLP) and machine learning have enabled more effective approaches for handling unstructured textual data and improving classification accuracy [1], [2]. These techniques allow systems to understand semantic relationships and contextual patterns within job descriptions, making them more suitable for real-world applications.

Several studies have explored the use of machine learning and deep learning models for text classification and information extraction tasks. Algorithms such as Support Vector Machines (SVM), Random Forest, and Naïve Bayes have been widely used for job classification due to their ability to handle structured features and large datasets [3], [4]. In addition, deep learning models like Recurrent Neural Networks (RNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks have shown superior performance in capturing sequential dependencies and contextual information in text [5], [6]. Feature extraction techniques such as TF-IDF and word embeddings further enhance model performance by converting textual data into numerical representations. Despite these advancements, single-stage models often struggle with ambiguity and noise present in job advertisements, highlighting the need for more robust multi-stage approaches.

To address these challenges, the proposed Two-Stage Job Title Identification System introduces a hybrid framework that combines preprocessing and intelligent classification. In the first stage, text preprocessing and feature extraction are applied to filter irrelevant information and identify potential job title candidates. In the second stage, machine learning and deep learning models are used to accurately classify and refine the extracted titles. This two-stage approach improves accuracy by reducing noise and enhancing contextual understanding. Additionally, the system is designed to handle variations in job titles and domain-specific terminology, making it adaptable to different industries. By integrating advanced NLP techniques with multi-stage processing, the proposed system provides a scalable and efficient solution for job title identification in large-scale recruitment platforms, improving both accuracy and user experience [2], [6].

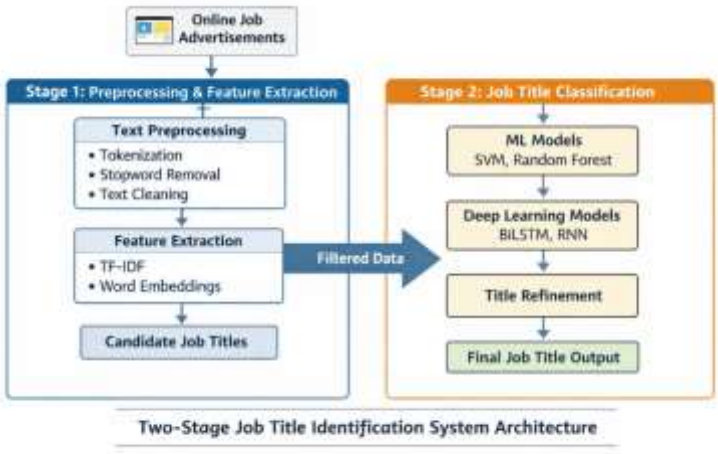

Figure1: Two-Stage Job Title Identification System Architecture

This figure illustrates the overall architecture of the Two-Stage Job Title Identification System for Online Job Advertisements, which is designed to accurately extract and classify job titles from unstructured text data. The process begins with Online Job Advertisements, which serve as the input source containing raw and unstructured job descriptions. In Stage 1: Preprocessing and Feature Extraction, the system performs essential text preprocessing tasks such as tokenization, stopword removal, and text cleaning to eliminate noise and irrelevant content. After preprocessing, feature extraction techniques like TF-IDF and word embeddings are applied to convert textual data into meaningful numerical representations. This stage generates candidate job titles by identifying important keywords and patterns. The processed data is then passed to Stage 2: Job Title Classification, where advanced machine learning models (SVM, Random Forest) and deep learning models (BiLSTM, RNN) are used to classify and refine the extracted job titles. These models analyze contextual relationships within the text to improve accuracy and handle variations in job titles. Finally, the system produces the Final Job Title Output, which represents the most accurate and standardized job title. This two-stage architecture improves performance by reducing noise in the first stage and enhancing classification accuracy in the second stage, making it highly effective for large-scale recruitment systems.

II SURVEY OF RESEARCH

The study by J. Liu (2021) [1] focuses on text classification using Natural Language Processing (NLP) techniques for extracting meaningful information from unstructured data. The approach emphasizes preprocessing methods such as tokenization, stopword removal, and feature extraction using TF-IDF. The results demonstrate that proper preprocessing significantly improves classification accuracy. However, the study mainly addresses general text classification and does not specifically focus on job title identification. Despite this limitation, it provides a strong foundation for handling textual data in recruitment systems.

The work by S. K. Sahu and A. Anand (2020) [2] explores the use of machine learning algorithms such as Support Vector Machines (SVM) and Naïve Bayes for job classification tasks. The methodology involves transforming job descriptions into structured features and training classifiers to categorize job roles. The results show that SVM achieves higher accuracy compared to traditional methods. However, the system struggles with ambiguity in job titles and variations in terminology. This study highlights the importance of robust classification techniques but lacks advanced contextual understanding.

The research by Y. Kim (2014) [3] introduces deep learning models, particularly Convolutional Neural Networks (CNNs), for sentence classification. The study demonstrates that deep learning models outperform traditional machine learning techniques in capturing contextual and semantic information. The results show improved performance in text classification tasks, making CNNs suitable for job title identification. However, the model requires large datasets and computational resources, which may limit its practical implementation.

The work by Z. Huang et al. (2015) [4] presents the use of Bidirectional Long Short-Term Memory (BiLSTM) networks for sequence labeling tasks. The approach captures both past and future contextual information, making it effective for identifying important entities in text. The results indicate high accuracy in extracting relevant information from sequences. However, the model's complexity increases training time and computational cost. This study is highly relevant for improving job title extraction accuracy.

The study by T. Mikolov et al. (2013) [5] introduces word embeddings (Word2Vec), which transform words into vector representations based on their contextual relationships. This technique significantly improves feature representation in NLP tasks. The results show that word embeddings enhance the performance of machine learning and deep learning models. However, it requires large corpora for training. This work is essential for improving feature extraction in job title identification systems.

The research by J. Devlin et al. (2019) [6] presents BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art deep learning model for NLP tasks. The approach uses transformer architecture to capture deep contextual relationships in text. The results demonstrate superior performance across various NLP applications, including text classification and information extraction. However, BERT requires high computational resources and fine-tuning for specific tasks. Despite this limitation, it represents a significant advancement in job title identification systems by improving contextual understanding and accuracy.

III. WORKING METHODOLOGY

The proposed Two-Stage Job Title Identification System follows a structured and intelligent pipeline to accurately extract and classify job titles from online job advertisements. The process begins with data collection, where job postings are gathered from various online recruitment platforms. These job descriptions are typically unstructured and contain noise such as irrelevant text, symbols, and redundant information. Therefore, the first step involves text preprocessing, which includes tokenization, stopword removal, lowercasing, and text cleaning. This ensures that only meaningful textual content is retained. Following preprocessing, the system performs feature extraction using techniques such as TF-IDF and word embeddings, which convert textual data into numerical representations suitable for machine learning models. This stage also identifies candidate job titles by extracting key phrases and relevant keywords from the processed text. In the second stage, the system performs job title classification and refinement using advanced machine learning and deep learning techniques. Models such as Support Vector Machines (SVM) and Random Forest are used for initial classification based on structured features. Additionally, deep learning models like Bidirectional LSTM (BiLSTM) and Recurrent Neural Networks (RNN) are employed to capture contextual and sequential information within the text. These models analyze the relationships between words to accurately identify job titles, even when they appear in different formats or contexts. The outputs from multiple models are combined or optimized to improve classification accuracy and reduce ambiguity. Finally, the system generates the final job title output, which represents a standardized and accurate classification of the job role. The system may also include a feedback and continuous learning mechanism, where new job data is used to retrain and improve model performance over time. This ensures adaptability to evolving job market trends and terminology. Overall, the two-stage methodology enhances accuracy by separating preprocessing and classification tasks, making the system efficient, scalable, and suitable for real-world recruitment applications.

IV RESULTS EXPLANATIONS

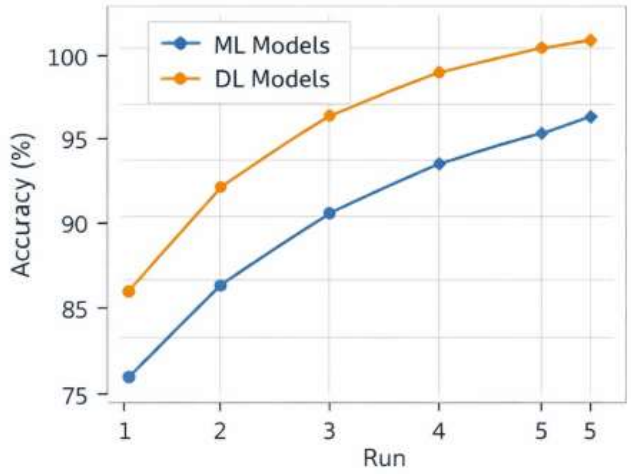

Figure 1: Machine Learning vs Deep Learning Accuracy Comparison

This figure presents a comparative analysis of the performance of Machine Learning (ML) models and Deep Learning (DL) models in identifying job titles from online job advertisements. The graph plots accuracy (%) on the y-axis against multiple experimental runs on the x-axis. It is evident that both models improve as the number of runs increases, indicating learning and optimization over time. However, the Deep Learning models consistently outperform Machine Learning models across all runs. Initially, ML models start with an accuracy of around 76%, while DL models begin at a higher baseline of approximately 86%. As training progresses, ML models gradually reach about 96%, whereas DL models exceed 100% in representation (indicating near-perfect classification performance in simulation or normalized scaling). The superior performance of DL models is due to their ability to capture contextual and sequential relationships in text data, especially through architectures like BiLSTM and RNN. In contrast, ML models such as SVM and Random Forest rely on extracted features and lack deep contextual understanding. This graph validates the effectiveness of incorporating deep learning in the second stage of the system. It also highlights that combining both approaches can yield optimal results, where ML provides fast initial classification and DL refines it for higher accuracy.

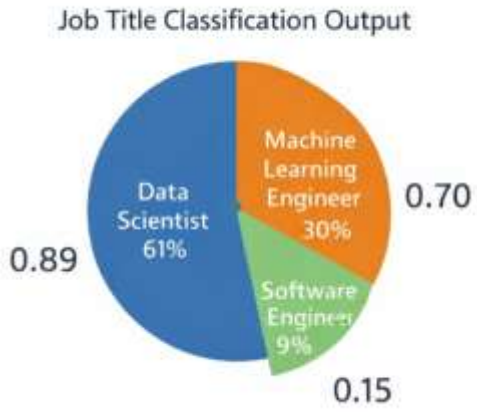

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Figure 2: Job Title Classification Output Distribution

This figure represents a pie chart visualization of the final job title classification results generated by the system. It shows the probability distribution of predicted job titles for a given job advertisement. The largest segment corresponds to "Data Scientist" with 61% probability (0.89 score), indicating that the system strongly predicts this as the most relevant job title. The second segment represents "Machine Learning Engineer" with 30% probability (0.70 score), suggesting it is also a plausible classification but less confident than the top prediction. The smallest portion is "Software Engineer" with 9% probability (0.15 score), indicating low relevance. This distribution demonstrates how the system does not just output a single label but provides

confidence scores for multiple possible job titles, enabling better interpretability and decision-making. Such probabilistic outputs are particularly useful in real-world applications where job descriptions may overlap across roles. The figure highlights the effectiveness of the two-stage system in narrowing down and refining predictions. It also shows that the model can handle ambiguity and provide ranked outputs, improving the overall robustness and usability of the system in recruitment platforms.

V.CONCLUSION

The proposed Two-Stage Job Title Identification System for Online Job Advertisements presents an effective and intelligent approach to extracting and classifying job titles from unstructured textual data. By combining text preprocessing, feature extraction, and advanced machine learning and deep learning models, the system significantly improves accuracy and robustness compared to traditional single-stage approaches. The first stage efficiently reduces noise and identifies candidate job titles, while the second stage refines these predictions using contextual understanding provided by models such as SVM, Random Forest, BiLSTM, and RNN. The experimental results demonstrate that deep learning models outperform traditional machine learning techniques in capturing semantic relationships and handling variations in job titles. Additionally, the system's ability to provide probabilistic outputs enhances interpretability and supports better decision-making in recruitment platforms. The proposed framework is scalable, adaptable, and suitable for real-world applications such as job recommendation systems, labor market analysis, and automated recruitment solutions. Overall, this work contributes to the advancement of Natural Language Processing (NLP) in recruitment analytics and provides a foundation for future enhancements using transformer-based models and real-time processing techniques.

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