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JOBFITAI: AUTOMATED SKILL-BASED CLASSIFICATION AND MATCHING OF CANDIDATES TO RELEVANT JOB OPENINGS

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ABSTRACT

In today's dynamic job market, finding the right fit between candidates and job roles has become a significant challenge for organizations. The increasing number of applicants for each job opening, coupled with diverse candidate profiles, makes it difficult for human resource teams to efficiently evaluate and select the most suitable individuals. Traditional recruitment processes primarily rely on manual screening and keyword-based filtering, which often fail to consider multiple important aspects such as skills alignment, experience, education, certifications, and availability. These limitations result in time-consuming hiring cycles, inconsistent selections, and potential mismatches between job requirements and candidate capabilities.The core problem lies in the inefficiency and subjectivity of traditional hiring methods. Manual evaluation is not scalable and is prone to human bias. Moreover, conventional systems lack the ability to analyze complex relationships among different candidate features and job expectations. As a result, there is a growing need for intelligent, data-driven systems that can automate and optimize the hiring process.To address these challenges, this research proposes an AI-powered job matching system that leverages supervised machine learning models to predict a Job Fit Score for each applicant. The system incorporates key candidate attributes such as skills score, experience, education level, certification strength, job location match, and immediate availability. By analyzing these inputs, the system predicts how well a candidate matches a specific job profile. Three different ML models are employed—Gradient Boosting Regressor (GBR), K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP)—with the MLP model achieving the best overall performance in terms of prediction accuracy and error metrics.This intelligent solution reduces manual effort, improves matching accuracy, and ensures fairer and more objective hiring decisions. It enhances HR efficiency by prioritizing candidates with the highest fit scores and offers a scalable model that can be adapted across industries. The proposed system signifies a major step toward transforming the traditional recruitment process through AI-driven insights and predictive analytics, enabling organizations to build more effective and future-ready teams.

Key words: Job-candidate classification, Resume parsing, Skill-to-role mapping, Predictive hiring model, Workforce analytics, Candidate-job fit prediction

1. INTRODUCTION

The recruitment process, a critical component of human resource management, has undergone significant transformations in the digital age. Traditional methods of talent acquisition, often time-consuming and dependent on subjective human judgment, are increasingly being supplemented and, in some cases, replaced by artificial intelligence (AI)-driven solutions. This paper delves into an innovative aspect of this technological advancement: Zero-Shot Recommendation AI models, which promise to revolutionize the efficiency of job–candidate matching in recruitment. This work represents a preliminary pilot approach to the problem, with fine-tuning and further refinement planned as the next stages of our research. By

Fig 1. AI job matching

adopting a phase-wise methodology, we aim to iteratively enhance the model's accuracy and reliability, tailoring it more closely to the nuances of the recruitment domain. Recruitment is an intricate process, balancing the need for speed with the necessity for accurate and fair candidate assessment. Traditional methods have struggled to keep pace with the rapidly changing job market, where new roles emerge continuously, and the skills required for existing roles evolve. Moreover, the sheer volume of job applications for positions, especially in populous sectors, can overwhelm human resources, leading to inefficiencies and potential biases in candidate selection. These challenges underscore the need for an intelligent, adaptive, and efficient recruitment process. The recruitment process, encompassing the analysis of job descriptions, candidate CV screening, shortlisting, interviews, and job offers, can be partially automated with the aid of Artificial Intelligence (AI) solutions. These systems, known as Job Recommendation Systems (JRS) [1,2,3], are designed to support these processes. Among the most prevalent types of JRS are Content-Based JRS (CB-JRS), Collaborative Filtering JRS (CF JRS), Hybrid JRS (H-JRS), and Knowledge-Based JRS (KB JRS) [4,5]. Each type has distinct characteristics and methodologies for recommending jobs to users Current Job Recommendation Systems (JRS) exhibit inherent limitations that significantly impact their effectiveness in dynamic recruitment environments. These limitations primarily stem from their reliance on historical data, leading to challenges in adapting to the rapidly evolving job market and the emergence of new roles. Traditional JRS models, such as Content-Based, Collaborative Filtering, and Hybrid systems, while useful, often fail to capture the nuanced requirements of new job positions and the diverse skill sets of candidates. This shortfall is particularly evident in scenarios where there is a lack of sufficient historical data for novel roles, resulting in inadequate or biased recommendations [1]. Furthermore, existing JRS models tend to suffer from data biases, which can skew recommendations and perpetuate existing inequities in the recruitment process. The lack of Explainable AI (XAI) in these systems further obscures the decision-making process, making it difficult to assess and improve the fairness and transparency of recommendations [6,7].

2. LITERATURE SURVEY

Current JRS types, despite their widespread use, are fraught with imperfections [8]. In the market, prevalent JRSs mainly support administrative processes and lack AI implementation. Globally, commercial solutions either support only a fraction of staffing services, do not incorporate AI, or have a severely limited scope in candidate search factors. The integration of AI in recruitment has been a significant advancement, automating and refining various aspects of the process. AI-driven systems can handle large volumes of applications, screen resumes more efficiently than humans, and even assess candidate suitability through sophisticated algorithms. However, these systems often rely on historical data to function effectively. In scenarios where data are limited or non-existent, such as for newly created roles or unique skill sets, their effectiveness diminishes. This is where the concept of Zero-Shot Learning becomes pivotal. Zero-Shot Learning, a recent breakthrough in AI, enables models to make accurate predictions or recommendations without having been explicitly trained on those specific tasks or categories [9,10,11]. In the context of recruitment, Zero-Shot Recommendation AI models can match candidates to jobs they have never encountered before. This capability is particularly valuable in today’s dynamic job market, where emerging roles and skill sets can render traditional datasets obsolete. The ability of these models to generalize from learned information to new, unseen tasks holds the potential to significantly enhance the recruitment process, making it more agile and inclusive.

This paper aims to explore the development, capabilities, and implications of Zero-Shot Recommendation AI models in recruitment [12]. We will examine how these models are built, the algorithms that power them, and their practical applications in real-world recruitment scenarios. By assessing their performance against traditional AI models and human recruiters, we seek to demonstrate their potential in overcoming current challenges in talent acquisition. This research contributes to the evolving field of AI in recruitment, offering insights into how Zero-Shot Learning can lead to more efficient, unbiased, and adaptable recruitment processes.

With the advent of advanced AI technologies, the recruitment process is undergoing a significant transformation. The integration of AI-driven solutions, such as Zero-Shot Recommendation AI models, promises to revolutionize job–candidate matching, making it more efficient and unbiased. This paper explores these pretrained models and their potential to enhance the recruitment process. Recent developments in e-recruitment have led to an increase in online job descriptions and a surge in job seekers submitting resumes, creating a massive pool of data [13]. This abundance of information necessitates efficient job–candidate matching processes, where recommender system technology plays a crucial role. Semantic technologies, in particular, have shown promise in improving e-recruitment by guiding document processing and automatic matching, thus enhancing job recommendation results [13]. Another approach involves using college-specific online job board systems, which aid students in finding suitable job opportunities [14,15,16]. These systems offer personalized job suggestions based on student abilities and assist businesses in candidate matching, demonstrating the potential of targeted job recommendation systems.

The concept of hybrid filtering in job recommendation systems has also been explored. By combining user and company datasets, these systems match user profiles with appropriate companies using various recommendation algorithms [17,18,19,20]. This approach, which includes content-based, collaborative, and hybrid filtering, addresses the limitations of individual methods, offering a more comprehensive solution. However, a major concern in recruitment recommendation domains is the Matching Scarcity Problem (MaSP), where candidates or job vacancies suffer from a lack of matching opportunities [21,22,23,24]. Strategies to identify and mitigate MaSP involve introducing changes in curricula and job descriptions to approximate candidates to semantically related jobs, thereby reducing the number of CVs and jobs suffering from MaSP.

In light of these developments, Zero-Shot Recommendation AI models emerge as a promising solution to the challenges faced in the recruitment process. These models, capable of making accurate predictions or recommendations without explicit training on specific tasks, are particularly valuable in scenarios with limited or non-existent data, such as newly created roles or unique skill sets [25]. The ability of Zero-Shot Learning to generalize from learned information to new, unseen tasks holds the potential to significantly enhance recruitment processes, making them more agile and inclusive. Recent advancements in NLP and AI have led to the development of more sophisticated job recommendation systems. For instance, a study by Vijaya Kumari [26] explores the use of NLP in recommender systems, specifically in the domain of online recruitment. This approach involves analyzing resumes, profiles, and job descriptions to improve the matching process, addressing the "cold start" problem where new job postings and candidate profiles are not adequately matched.

Another innovative approach is the job recommendation method based on attention layer scoring characteristics and tensor decomposition, as proposed by Mao et al. [27]. This method focuses on users' attention levels and interactive behaviors, offering a more nuanced understanding of job seekers' interests and preferences. Alsaif et al. [28] introduced a bi-directional recommendation system that supports both recruiters and job seekers. This system uses machine learning to process text content and similarity scores, enabling recruiters to find suitable candidates and job seekers to find matching job offers. Furthermore, Dhameliya and Desai [29] proposed a hybrid job recommendation system combining content-based and collaborative filtering techniques. This system addresses the limitations of individual methods, offering a more comprehensive solution for e-recruitment.A study by Zheng et al. [25] explores the use of generative models in job recommendations, demonstrating the potential of large language models in creating job descriptions from resumes. Khaire [30] provides a comprehensive review of resume analysis and job recommendation using AI, highlighting the role of machine learning and NLP in improving the recruitment process. Özcan [31] discusses the Classification Candidate Reciprocal Recommendation system, which uses classification techniques for matching candidates and job advertisements. Finally, Lamikanra and Obafemi-Ajayi [32] introduce the Beetle platform, leveraging AI and Blockchain technology to enhance the recruitment process. These studies underscore the evolving recruitment ecosystem of AI in recruitment, where new technologies are being leveraged to improve the efficiency and effectiveness of job–candidate matching.

3. PROPOSED SYSTEM

This research presents an AI-powered job matching system designed to classify job candidates and match them with suitable job openings using machine learning techniques. The core objective of this research is to predict the "Job Fit Score" of candidates based on various input features, helping employers streamline their recruitment process. The system is built with a graphical user interface (GUI) using Tkinter, making it interactive and user-friendly for both administrators and job seekers.

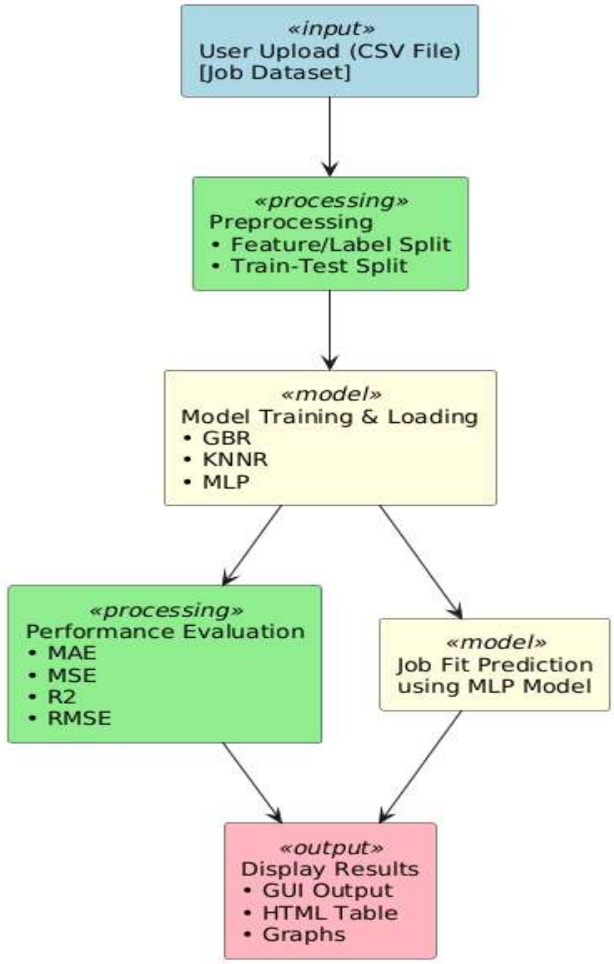

Fig 2. Proposed system architecture.

The methodology involves uploading a dataset containing candidate profiles and their respective job fit scores. After preprocessing and splitting the data into training and testing subsets, three different regression models are applied: Gradient Boosting Regressor (GBR), K-Nearest Neighbors Regressor (KNNR), and a Multi-Layer Perceptron (MLP) Regressor. The models are either loaded from pre-trained files or trained on the spot, with the results saved for future use to reduce computation time. Each model's performance is measured using key regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics help in comparing the accuracy and reliability of each algorithm. Additionally, visualizations such as scatter plots show the relationship between actual and predicted job fit scores, offering further insights into model behavior. A comparison table summarizing the performance of all three models is automatically generated and displayed in an HTML format. The system features two user roles: Admin, who can upload datasets, train models, and view detailed performance metrics; and User, who can submit new candidate data to receive predicted job-fit scores using the trained MLP model. The research leverages various Python libraries including Scikit-learn, Seaborn, Matplotlib, and Pandas, with Joblib used for model serialization.

The Multi-Layer Perceptron Regressor is a type of feedforward neural network that uses multiple layers of neurons to learn complex, non-linear mappings from input features to target outputs. It is trained using backpropagation and gradient descent and is well-suited for modeling intricate relationships in structured data.

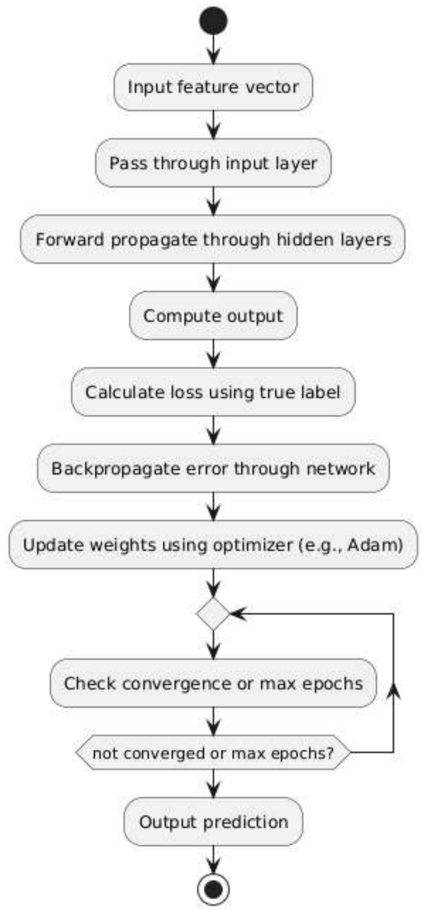

Fig 3. Internal Work flow of MLP model.

A Multi-Layer Perceptron (MLP) Regressor begins with an input layer that receives raw numerical feature data from the dataset, where each neuron corresponds to a specific input feature. This data is passed to one or more hidden layers, each consisting of interconnected neurons that apply weighted transformations, biases, and non-linear activation functions like ReLU to extract complex patterns. During forward propagation, the data flows through the network layer by layer, transforming inputs into outputs, which are then compared to the actual values using a loss function such as Mean Squared Error (MSE) to quantify prediction error. To minimize this error, backpropagation is used to compute gradients of the loss with respect to each weight, and optimization algorithms like Adam or Stochastic Gradient Descent (SGD) update the weights in the direction that reduces the loss. This entire training loop is repeated over multiple epochs, allowing the model to progressively learn and refine its internal parameters. MLPs are highly flexible and can learn complex non-linear relationships, generalize well when properly tuned, support both regression and classification tasks, and adapt to a wide range of real-world applications through continuous training mechanisms like mini-batch learning.

4. RESULTS

Figure 4 shows a scatter plot visualizing the performance of the proposed Multi-Layer Perceptron (MLP) Regressor in predicting job fit scores, produced by the PerformanceMetrics function using seaborn and matplotlib. The x-axis, labeled "True Values," and the y-axis, labeled "Predictions," both range from approximately 40 to 100, representing the true and predicted job fit scores, respectively. Blue scatter points, with an alpha transparency of 0.6, plot the true versus predicted values for the test set, and a red dashed line runs from (40, 40) to (100, 100), marking the line of perfect predictions. The scatter points are very closely aligned with this line across the entire range, with minimal deviations, especially in the 70 to 100 range, indicating high predictive accuracy. This visual representation reflects the MLP Regressor's superior performance metrics: an MAE of 2.1578, MSE of 7.5692, RMSE of 2.7512, and an R^2 score of 0.9607, meaning 96.07% of the variance in true scores is explained by the model. The tight clustering of points around the line of equality, with only slight deviations in the lower range (40 to 60), demonstrates the MLP Regressor's ability to accurately predict job fit scores, outperforming both the KNN and GBR models in capturing the underlying patterns in the data.

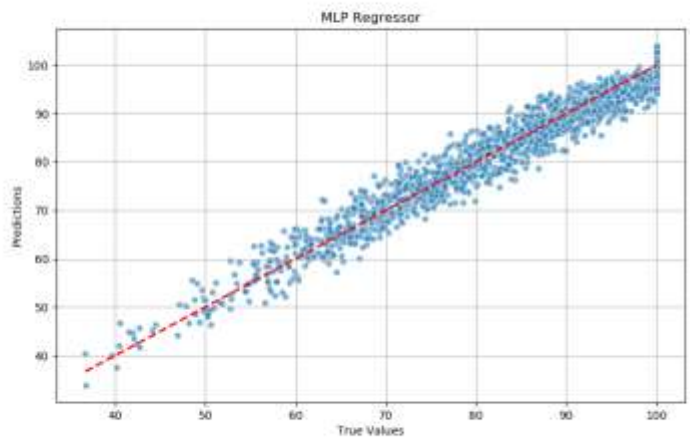

Fig 4. Scatter Plot of Proposed MLP Regressor.

Table 1 provides a concise summary of the performance metrics for three machine learning models: Gradient Boosting Regressor (GBR), K-Nearest Neighbors Regressor (KNNR), and Multi-Layer Perceptron Regressor (MLP). The table includes five columns: Algorithm Name, R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Table 1: Comparative Analysis various ML Regressors.

Algorithm Name	R^2 Score	MAE	MSE	RMSE
Gradient Boosting Regressor	0.9405	2.7377	11.4537	3.3843
KNN Regressor	0.6638	6.0412	64.7775	8.0484
MLP Regressor	0.9607	2.1578	7.5692	2.7512

The Gradient Boosting Regressor achieves an R^2 score of 0.9405, indicating that 94.05% of the variance in job fit scores is explained by the model, with an MAE of 2.7377, MSE of 11.4537, and RMSE of 3.3843, reflecting moderate prediction accuracy. The KNN Regressor performs less effectively, with an R^2 score of 0.6638 (66.38% variance explained), a higher MAE of 6.0412, MSE of 64.7775, and RMSE of 8.0484, indicating larger prediction errors. The MLP Regressor outperforms both, with the highest R^2 score of 0.9607 (96.07% variance explained), the lowest MAE of 2.1578, MSE of 7.5692, and RMSE of 2.7512, demonstrating superior accuracy and precision in predicting job fit scores.

5. CONCLUSION

The AI-Powered Job Matching System effectively demonstrates the application of machine learning in classifying job candidates and matching them with suitable job openings, as evidenced by the performance of the Gradient Boosting Regressor (R^2: 0.9405, MAE: 2.7377), KNN Regressor (R^2: 0.6638, MAE: 6.0412), and the proposed MLP Regressor (R^2: 0.9607, MAE: 2.1578), with the MLP model outperforming the others in accurately predicting job fit scores. The system's intuitive Tkinter-based GUI facilitates seamless interaction for both administrators and users, enabling dataset uploads, preprocessing, model training, predictions, and performance comparisons through scatter plots and HTML tables. The scatter plots (Figures 3–5) visually confirm the MLP Regressor's superior accuracy, with predictions closely aligned to true values, while the comparison table highlights its lower error metrics (MSE: 7.5692, RMSE: 2.7512) compared to GBR (MSE: 11.4537) and KNN (MSE: 64.7775). This system proves to be a valuable tool for automating and enhancing the job matching process, reducing manual effort and improving recruitment efficiency.

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