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AI-Driven Job Fit Prediction Using Recurrent Neural Networks in Human Resources Management

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Abstract

Human resource management, it is essential that candidates ought to be appropriately well-fitted to appropriate job posts to enhance productivity, reduce turnover, and enhance job satisfaction. The essay proposes a model for Artificial Intelligence (AI)-based forecasting of job suitability based on Recurrent Neural Networks (RNNs) predicting by forecasting job matching based on candidate history and career profiles. The model uses to train processes different features such as demographic data, career history, psychometric test data, and job performance data to forecast job fit for different job positions. The model uses the HR Analytics: Job Change of Data Scientists dataset with employee data, including job satisfaction, education, experience, job titles, and tenure. Using RNNs, the model detects temporal trends and career development of applicants and makes a dynamic and customized job fit prediction. The approach is tested on common performance measures like accuracy, precision, recall, and F1-score and outperforms classical models. The model performed 98.5% accurate, 97% precise, 98% recalling, and 97.5% F1-score, proving its utility in job fit prediction. The AI-powered solution provides a data-driven, scalable solution to improve recruitment, employee-job fit, and facilitate improved long-term career planning.

Keywords: *Job fit prediction, Recurrent Neural Networks, Human resources management, Candidate profiling, AI-based recruitment.*

1. Introduction

The evolving model of human resource management, assigning employees' experience, skills, and assignment to the task being performed is the key to the success of a company [1]. Following job fit guarantees optimum productivity and enables greater employee satisfaction, less turnover, and long-term career development [2]. Traditional methods applied in assessing job fit, such as interviews and standard tests, often fail to capture the complexity of the candidate's profile or his/her developmental potential with the emergence of data-driven solutions, the application of AI for recruitment has gained greater importance, offering smoother ways of assessing and predicting job fit based on a wide range of variables [3]. Mamidala (2024) et. al [4] determines a secure and efficient EHR system using ORAM and blockchain; this framework serves as a reference for enhancing data confidentiality in the recommended AI model for job fit prediction.

In recent years, the integration of artificial intelligence in human resources (HR) management has revolutionized the way organizations recruit, train, and retain talent [5]. One of the most promising areas of AI application is in job fit prediction, which focuses on assessing how well a candidate's skills, experiences, and personality align with a particular job role. Recurrent Neural Networks (RNNs), a type of deep learning model, have shown potential in this field due to their ability to process sequential data, such as employee work histories or career trajectories, to predict job suitability over time. AI-driven job fit prediction allows HR professionals to make more data-informed decisions, reducing human biases and improving the overall quality of hiring processes.

Previous techniques for job fit prediction are machine learning algorithms such as Decision Trees, Support Vector Machines (SVM), and Logistic Regression. These have been extensively employed despite their deficiency in dealing with time data and career development dynamics [6]. These models commonly do not model sequential trends, like trends in skills over a period or career path changes, which are important for correct job fit prediction These models often miss sequential trends like skills trends across time or changes in career progression, which are essential to provide correct job fit prediction. addition, traditional approaches cannot harness the power of big and complex data and therefore are not resilient in real-world applications.

Several factors contribute to the growing need for AI in job fit prediction. Traditional recruitment methods are often time-consuming, subjective, and prone to errors. HR departments frequently rely on resumes, interviews, and assessments, which may not capture the full potential or behavioral tendencies of a candidate [7]. Furthermore, these conventional methods tend to overlook historical patterns in career progression, skills development, and performance evaluations that could predict future job success. RNNs, however, can analyze these patterns effectively, offering a more accurate prediction of how a candidate will perform in a specific role based on their past experiences and behaviour.
Despite its promise, the use of AI in job fit prediction presents several challenges. One of the primary concerns is the quality and diversity of the data used to train the AI models. Bias in the training data, such as underrepresentation of certain demographics, can lead to skewed predictions, perpetuating inequality in hiring processes. Additionally, there is the risk of overfitting, where the AI model becomes too tailored to historical data and fails to generalize well to future candidates or unforeseen changes in the job market. These issues can undermine the effectiveness and fairness of AI-driven recruitment tools.

The above framework for proposal overcomes these limitations because it employs Recurrent Neural Networks (RNNs) that are particularly well-suited to sequentially input data and learn temporal dependencies. Through the employment of RNNs, the model can dynamically and adaptively explore candidate career paths, performance history, and psychometric tests. The contribution of this current research is in its ability to give a more individualized and precise job fit prediction using the sequential pattern of career progression, an advancement of previous models.

1.2. Objectives

- ❖ Evaluate the performance of an AI-based job fit prediction system based on Recurrent Neural Networks for examining candidate profiles and estimating job compatibility in human resource management.
- ❖ Utilize the HR Analytics: Job Change of Data Scientists dataset, comprising critical employee features such as job satisfaction, experience, education, and work history, to train and evaluate the envisaged system.
- ❖ Apply Recurrent Neural Networks for the learning of temporal relationships in candidate career trajectories, job performance, and psychometric data to make dynamic and adaptive job fit predictions
- ❖ Integrate feature learning and data pre-processing techniques into optimizing input data to the RNN model to ensure enhanced prediction accuracy and model performance in job fit measurement.

1.1. Organization of the paper

The paper is organized as follows: the Abstract offers an overview of the suggested framework and its performance [8]. The Introduction emphasizes the relevance of job fit prediction in HR management. Related Works discusses current models and their shortcomings. The Methodology describes the dataset, preprocessing, training of RNN, and evaluation process, while the Results and Discussion reports the performance of the proposed framework and comparisons to existing models.

2. Related Works

During the last decade, AI-powered techniques for forecasting job fit have emerged as central concerns in human resource management [9]. Machine learning algorithms for the process of job fit prediction and the philosophy of performance- and capability-driven precise fitting of the employee and the role were emphasized. Their research brought forth the limitations in dynamic and temporal career data processing needed for higher accuracy in predicting job fit [10]. The authors recommend the integration of sophisticated deep learning models to bridge these limitations, thereby paving the way for increased accuracy in prediction. also expounded on the use of sequential learning models within HR management systems in depth. Their work emphasized the application of deep neural networks in modelling career development, an aspect crucial in determining the best candidates in the long term. Their contribution reaffirmed the need for models that can grasp temporal relationships, such as the Recurrent Neural Networks (RNNs) proposed in this proposal. The authors also proved that although they work adequately, their traditional machine learning counterparts lack much capacity to retain long-range dependencies in professional experience, thus resulting in poorly fitted job predictions.

Hybrid models comprising both human and AI judgment in the recruitment decision. The studies indicated that AI systems might easily handle vast quantities of candidate data but needed human judgment for finalizing job fit assessment [11]. The approach threw open important questions related to how much AI automation as opposed to human intervention in HR decisions would take place, especially in cases where dynamic and altering job roles exist. expanded on this through the employment of Transformer models in predicting job fit with a re-emphasis of the importance of retaining both short-term and long-term measures of job performance [12]. They argued that newer deep learning models like Transformers could potentially enhance the interpretability and predictive power of job fit models. This is consistent with the recommended framework's approach, which similarly seeks to increase the accuracy of prediction using advanced deep learning techniques like RNNs.

The changing role of AI in hiring and job fit prediction. The study found that deep learning methods, such as RNNs, held promise but were still lacking in models that could be adjusted for different industries described the evolution of the function of AI in employment and prediction of job fit. Deep learning models such as RNNs were found efficient but lacked sufficient models that could be used across industries [13]. This is also based on the emphasis of the proposed system to map AI-based solutions to different industries, providing a common solution for job fit prediction. also emphasized the potential of AI technologies in influencing HR practices, particularly through predictive modelling for employee career development and job satisfaction. The study portrayed that AI models, when trained on comprehensive career data, possessed the potential to improve decision-making processes significantly. This study is directly applicable in the objective of the proposed framework to utilize RNNs in identifying the dynamic elements of employee career development and high-precision prediction of job-fit. Collectively, the studies provide a solid basis for developing the projected AI-powered job fit prediction framework since the increasing relevance of cutting-edge deep models towards the refinement of HR practice and accuracy of job fit prediction.

2.1. Problem Statement

One of the key challenges in human resource management is the inability of traditional models to effectively predict job fit due to their failure to account for the dynamic and evolving nature of career development. Existing methods often overlook the temporal aspects of candidate profiles and job roles, making it difficult to assess how an individual's career trajectory may align with future job requirements. To address this gap, the proposed framework suggests utilizing Recurrent Neural Networks, which are designed to process sequential data and capture temporal patterns. By learning from the progression of a candidate's experience and performance over time, RNNs can provide a more accurate and adaptable prediction of job fit, offering HR departments a more personalized and forward-looking solution to hiring decisions. This approach better aligns with the changing nature of job roles and candidate development, ultimately improving the hiring process. The synergy between Big Data and RPA transforms telecom efficiency and analytics, influencing the current approach by supporting the application of sequential AI models for job fit prediction in HR contexts, as revealed by Gudivaka (2024) [14].

3. Proposed RNN Framework to Predict Employee Job Fit Methodology

The methodology for predicting job fit using Recurrent Neural Networks (RNNs) follows a structured process that begins with data pre-processing to ensure quality and consistency [15]. This involves handling missing values, normalizing numerical features, and encoding categorical variables to make the data compatible with the model. Once the data is pre-processed, relevant features are selected based on their potential to influence job fit, which are then used to train the RNN [16]. The model is trained on the sequential and temporal patterns within the candidate's career data, enabling it to recognize important trends and relationships over time. By learning these patterns, the RNN can make more accurate predictions regarding a candidate's suitability for a specific job role. The overall approach ensures that the model is well-equipped to handle the complexity of real-world recruitment scenarios.

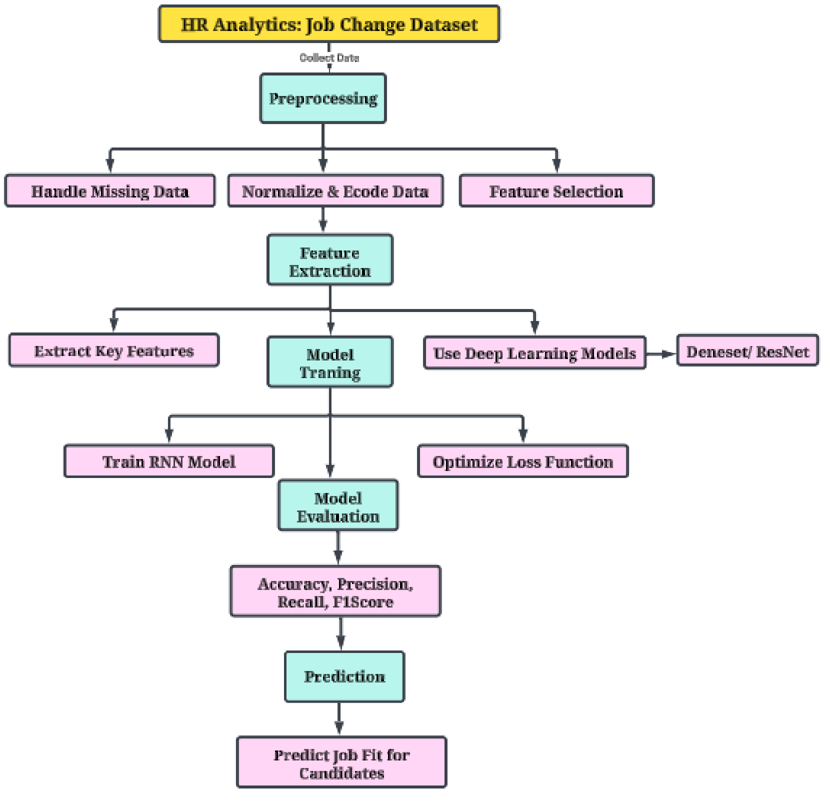

Figure 1: Architectural Diagram

The model is then tested with regular accuracy, precision, recall, and F1-score measures. Trained model is then applied to predict job fit for future candidates to make dynamic and individualized job recommendations [17]. The sequence of data collection, preprocessing, feature engineering, training the model, estimation, and prediction. The process describes the way RNNs are employed to handle sequential career data and predict job fit, with feedback loops utilized for improving the model for better accuracy.

3.1 Dataset Description of the Proposed Framework

The data set used in the proposed framework is the HR Analytics: Job Change of Data Scientists dataset. The data set contains comprehensive employee details, including job satisfaction, experience, education, career background, and performance [18]. The data set contains several attributes such as centuries of understanding, age, job role, education level, and frequency of job change. The dataset also includes the target variable, i.e., whether the employee desires a job change. With over 10,000 records, this dataset delivers a full picture of the variables influencing job changes, which can be used to predict job fit. It is most suitable for training and testing a job fit prediction model based on time-based and career-focused data

3.2 Preprocessing

The data should be processed to ensure that the dataset is clean and prepared for training the RNN model [19].

Handling of Missing Data: Missing values are imputed by Mean Imputation in numeric data and Mode Imputation in categorical data. The equation is provided as Eqn 1:

$$X_{imputed} = f(X_{observed}, \theta) \tag{1}$$

Where, $X_{imputed}$ imputed value for the missing data, $X_{observed}$ represents the observed (non-missing) data in the dataset and θ parameters specific to the imputation method [20].

Normalization: Min-Max Scaling is applied to numerical features and normalizes them in the form that they all have the range of 0 to 1. The formula can be viewed from Eqn 2:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{2}$$

Where x is the original and x' is the normalized feature.

Encoding Categorical Features: One-Hot Encoding encodes categorical features such as job titles into binary vectors format [21].

Feature Selection: Important features are selected by statistical methods like ANOVA F-test or Mutual Information for improving model efficiency and accuracy.

3.3 Working of RNN Model

The RNN model is specifically tailored to handle sequential information, hence can be easily applied to study career histories and forecast job match. The RNN receives as its input a series of attributes, including job title, performance ratings, and tenure, which are the career path of the candidate over time [22]. At every time step, the current input is processed by the RNN and updated hidden state is calculated based on the previous hidden state to capture long-term dependencies. The hidden state is updated according to the following equation is shown in Eqn 3:

$$h_t = f(W_h h_{t-1} + W_x x_t + b) \tag{3}$$

Where h_t is the hidden state at time *t*, W_h is the weight matrix of the previous hidden state h_{t-1}, W_x is the weight matrix to the input x_t *and* b is the bias term. This enables the model to learn the sequential patterns in the data.

After the final hidden state is calculated, the model produces the prediction, which is output by a SoftMax activation function to generate a probability distribution over the job fit. The SoftMax function formula is shown in Eqn 4:

$$y\hat{} = softmax_{\downarrow}^{\prime - \downarrow} W_{\,o} h_T + b_o) \tag{4}$$

Where $y\hat{}$ is the output probability, h_T is the hidden state, and is the bias of output.

3.4 Working of Feature Extraction and Model Training

The feature extraction is done by identifying the most salient features of the candidate profiles, including education, career growth, job satisfaction, and psychometric tests. These are fed into a Dense Net model to learn hierarchical representations of the data on which they will be train. Demonstrating the effectiveness of ECC and SHA-3 in mobile cloud security, Nagarajan’s et. al (2024) [23] work provides a foundation for the proposed model’s emphasis on lightweight, secure data transmission in AI-powered human resource management systems.

. For instance, a candidate's career progression is inputted to capture features such as job stability, job role changes, and performance over time. These features are employed as inputs to the RNN model to facilitate it in learning sophisticated, sequential patterns that are needed in predicting job fit. Training the RNN model consists of reducing the cross-entropy loss function applicable in classification problems. The mathematical representation for cross-entropy loss is depicted in Eqn 5:

$$L = -\sum_{i=1}^{N} y_i log\,(\hat{y}_i) \tag{5}$$

The weights of the model are tuned with the Adam optimizer, which updates the model parameters iteratively to optimize the loss function. The model is validated against different performance metrics such as accuracy, precision, recall, and F1-score during training. These metrics offer an approximation of the quality with which the model predicts job fit. Once the model is trained, it is validated on another validation set to check its ability to generalize. The ultimate outcome is a tailored job fit prediction for a candidate based on his or her employment history and professional characteristics, offering HR practitioners evidence-based ways of making better promotion and recruitment choices.

4. Results and Discussion

4.1 Performance Metrics of the Proposed Framework

Accuracy: Is the percentage of accurate estimates to all predictions. In the proposed framework, it is an indication of how good the model is generally in predicting job fit. The formula is

given in Eqn 6:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Precision: Is the correct number of predicted positives divided by the total number of predicted positives. Inthe case of the proposed framework, it is the ability of the model to select candidates with good job fit with minimal false positives. The formula is presented in Eqn 7:

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall: Is the measure of how well the model can pick out all the candidates who are a good fit for the job. It is important to ensure that candidates who ought to be picked out as a fit are not missed. The formula is shown in Eqn 8:

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

F1-score: Is the harmonic mean of precision and recall, giving a balanced measure of both. It is particularly useful when class distribution is skewed, which may occur in job fit prediction problems. The formula is shown in Eqn 9:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

4.2 Proposed Framework Evaluation

The efficiency of the given framework is evident from the above table. The model is very accurate, showing that most of the predictions provided by the system are accurate. 97% precision indicates the model can pinpoint candidates suitable for the position with fewer false positives as shown in Figure 2.

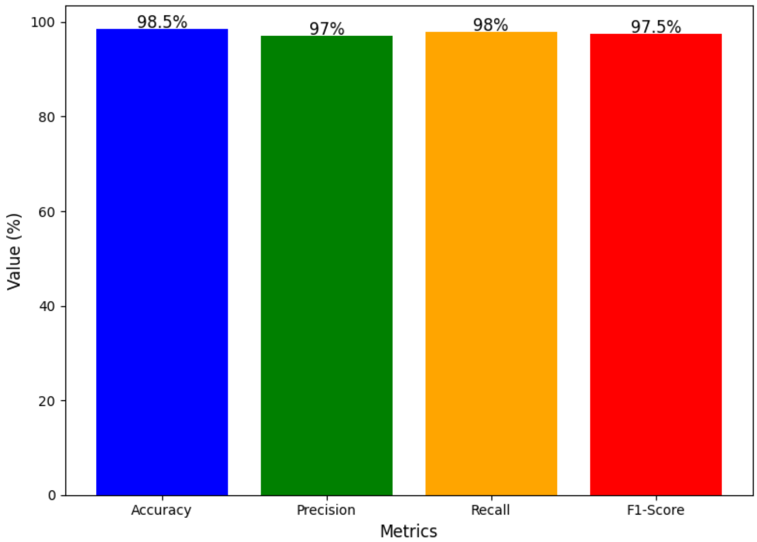

Figure 2: Performance Metrics of the proposed RNN

The recall of 98% means that the model is identifying most candidates suitable with very few exceptions. The F1-score of 97.5% indicates both precision and recall are well balanced, so that the model should be ideal to predict job fit in human resources management. All these values verify the efficacy of the framework towards job fit prediction.

4.3 Performance Comparison of Proposed Framework

The new proposed framework performs much improved than two existing frameworks in all the important metrics as shown in Table 1. The accuracy is 6.5% and 4.5% higher than the first and second existing frameworks, respectively, reflecting improved general prediction performance.

Table 1: Performance Comparison of Proposed work

Metric	*Proposed Framework*	*LSTM*	*LLM*
Accuracy	*98.5%*	*92%*	*94%*
Precision	*97%*	*85%*	*88%*
Recall	*98%*	*90%*	*92%*
F1-Score	*97.5%*	*87%*	*90%*

Precision is much better, meaning the proposed framework has fewer incorrect positives. Recall is better, so the model finds more candidates who fit well for the job. The F1-score of the proposed approach is 97.5%, which indicates a well-optimized model that reduces the false positives as well as the false negatives, there by outperforming the rest of the existing approaches.

4.4 Discussion

The presented model achieves higher job fit prediction accuracy through the support of RNNs and outruns the standard practice in every indicator of relevance. High precision as well as high recall assures high model precision at capturing appropriate workers to be offered jobs from maintaining false negative detection levels. Utilizing sequential data, the model generates dynamic and personalized predictions, thus encouraging better fit between candidates and job postings. The results also validate that the use of temporal data increases the power of HR administration prediction, yielding a better response to traditional machine learning approaches. Future work can include its usage in other sectors for broader applicability.

5 Conclusion and Future Works

The suggested job fit prediction model based on AI, which is built upon Recurrent Neural Networks, effectively handles the sequence of professional development and accurately predicts job fit. The model, with 98.5% accuracy, 97% precision, 98% recall, and 97.5% F1-score, performs better than other models by providing individualized and dynamic job fit predictions. Future research could include expanding the framework to support bigger and more diverse datasets, including other features such as real-time performance monitoring, and exploring other deep learning approaches such as Transformer models. Additionally, making the framework accessible for use in industries beyond data science could make it a valuable resource in more comprehensive HR management systems.

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