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Research on Enterprise Human Resource Management Process Optimization Supported by Artificial Intelligence Technology

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Using artificial intelligence (AI) in management and other organizational functions may prove revolutionary. AI is revolutionizing business structures and decision-making processes. When it comes to vital capabilities and business operations like information management, as well as consumer outcomes like perceptions of and satisfaction with service quality, artificial intelligence (AI) has an immediate and substantial influence. Human resource management (HRM) process optimization, reduced HRM manager effort, and higher productivity are the key objectives of this study. Using BPNN and AI digitizing techniques, we create a salary prediction model (SPM) and then optimize it using a hybrid of Nadam algorithms. Nadam is the Nesterov and Adaptive Moment Estimation. The next step is to verify the model by estimating the candidates' starting wages from their resumes. Human resource management (HRM) process optimization, reduced HRM manager effort, and higher productivity are the key objectives of this study. Using BPNN and AI digitizing techniques, we create a salary prediction model (SPM) and then optimize it using a hybrid of the Nadam algorithms. The next step is to verify the model by estimating the candidates' starting wages from their resumes. The study achieved notable results, with the optimized BPNN-based salary prediction model scoring 0.7732 on the training set and 0.7730 on the test set. These results indicate superior learning and prediction efficiency compared to other methods. This advancement in AI technology has significant implications for HRM by enabling more accurate salary predictions, reducing managerial effort, and increasing overall enterprise productivity.

Keywords: human resources management (HRM), enterprise, optimization, artificial intelligence (AI), digital technology

1. INTRODUCTION

Along with the growing digital economy, the increasing adoption of AI technologies is transforming how organizations run [1-3]. Performance management is another area where AI might significantly impact [4]. AI algorithms analyze data from sensors and devices to identify potential safety hazards and provide preventative measures [5, 6]. AI can enhance productivity, accuracy, and decision-making across various HR functions, including talent management, recruitment, performance management, learning and development,

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and workplace safety [7]. However, addressing worries about discrimination and job loss is necessary to ensure that AI's benefits are realized without compromising ethical and social difficulties [8]. The success of AI in HR will depend on how successfully firms balance the benefits of automation and the need for human empathy and judgment in HR practices [9, 10]. As businesses rapidly digitize HR processes, the impact of AI on metrics, including real-time feedback, staff productivity [11]. This research examines the connections between HR digitization and other aspects of organizational network analysis and design [12, 13]. The use of AI in human resource management and examines its effects on enhancing its implementation and providing better technical support [14, 15]. AI research aims to create machines with intelligence and human-like capabilities [16]. Businesses and HR managers must now face the challenge of figuring out the digital technology implementation of human resource management in large organizations [17]. This review thoroughly explores the most successful strategies and recent research results in AI for wind, solar, geothermal, bioenergy, ocean, hybrid, hydro, and hydrogen energy [18].

2. LITERATURE REVIEW

Big data and AI technologies have revolutionized talent acquisition in the digital age through continuous updates, improved organizational structures, and rationalized competency distribution [19, 20]. In that case, the organization will need to reap the product's benefits and the ease of modern technology [21]. Traditional recruitment focuses on issues such as inefficient screening, ineffective job matching, and the loss of technological advantage [22, 23]. Zhang [24] introduced a decision tree ensemble classifier method for analyzing HRM data based on a unified decision tree algorithm. Wei and Jin [25] used machine-learning techniques to improve the HRM system. Zhu [26] implemented machine learning strategies for HR administration and analysis. Human resource management efficiency and effectiveness were greatly enhanced by implementing machine learning technologies into the HR system [27]. Tambe et al. [28] reported that the time and money spent on human resource management tasks like staffing and selection are being cut significantly increasing prevalence of AI deployments in these areas. Examples of major HRM areas that AI has already altered are provided by Ryken [29], and these include things like considering a Large Number of Resumes. Jarrahi [30], AI dramatically alters management styles and how businesses make decisions. The Licensed Medical Practitioner-Centric Heterogeneous Network Powered Efficient e-Healthcare Risk Prediction for Health Big Data achieves a comprehensive prediction analysis and accuracy [31]. The utilization of solar and wind energy to generate electricity is covered in this study, along with topics including variability, cost considerations, and non-concentrated and diluted energy [32].

3. METHODOLOGY

3.1 Human Resource Management Model

Human resource management (HRM) models are typically developed and maintained by a single company or management group. These models offer a comprehensive view of HRM objectives, procedures, content, methods, and other related aspects [33].

3.1.1 The 3P model of HRM

The 3P Model of Human Resource Management consists of the following fundamental links in a chain: The job analysis is used to delegate tasks to workers; (ii) Indicators and plans for evaluating workers' performance are tailored to each position; (iii) Salary, perks, and bonus disbursement norms are defined in light of performance review findings [34]. Some room for development in the 3P human resource management model and the 3P model of HRM in action is shown in Fig. 1; (i) Businesses need to consider how HRM influences employee growth, company innovation, and business strategy; (ii) Businesses focus on job requirements and seek suitable employees. Human resource management is crucial for organizations to effectively manage their workforce; (iii) and business expansion tactics should be examined together. Talent acquisition, training, performance management, employee engagement, and pay may all be ensured by integrating HRM and corporate growth initiatives.

3.1.2 Human resource management using a 4P framework

HRM's 4P model expands on the earlier 3P concept. The 4P model, which emphasizes a company's purpose and social influence, builds on the 3P notion of People, Planet, and Profit by adding Purpose. There are two main ideas to keep in mind, and they are "people" and "posts." Perfect compatibility between individuals, individuals and jobs, positions, and individuals and businesses [35] is achieved using a single central factor and two critical difficulties. Fig. 2 depicts the 4P paradigm of HRM philosophy: compensation management, performance management, post-management, and quality management. Among these is "post management," which entails a variety of tasks like "setting" a position, "analyzing" it, "describing" it, and "evaluating" it [36]. It is a cyclical process that begins with defining expectations and moves through coaching, monitoring, assessment, acknowledgement, and modification.

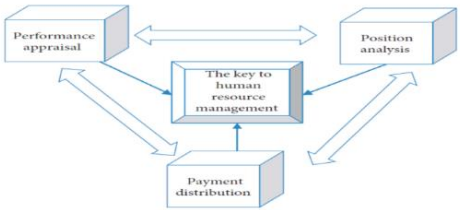

Fig. 1. Human resource management's 3P approach.

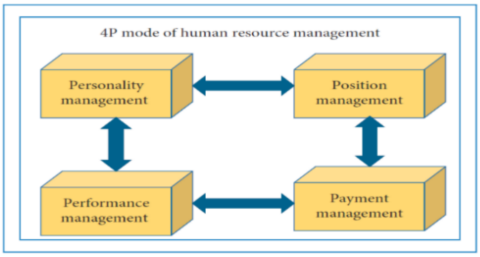

Fig. 2. Human resource management's "4P" framework.

3.1.3 5P model of human resource management

As indicated in Fig. 3, the 5P human resource management model entails the following five core functions: perception, selection, placement, professional development, and preservation. Perception is that the organization breaks into sections based on business needs and procedures and that each team then creates a job description and hires people who best fit the requirements of that job description. Businesses must "pick," or actively seek, select the best personnel available and evaluate that talent using objective criteria [37]. There are five facets to the 5P model of HRM: job analysis and quality assessment; selection and recruitment; usage and configuration; development and training; performance evaluation and compensation; and performance evaluation and balance [38]. HRM's 5P model offers a thorough method for assessing performance and paying employees, considering potential, pay, promotion, and performance. While it addresses complexity and biases, it fosters progress, openness, and alignment with organizational goals.

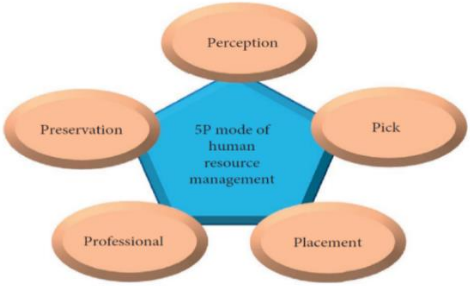

Fig. 3. HRM's 5P framework.

3.2 Demand Analysis for Future Salaries

Conventional hiring practices involve a manual review of resumes to see if candidates match minimum standards (such as age, education, work experience, *etc.*). This strategy calls for qualified individuals with good judgment, and human error is always possible [39]. Each job has a predetermined salary range, but the contract management team usually decides based on several arbitrary and subjective factors [40]. Due to a lack of data supporting the significance of subjective elements and a need for more objective evaluation standards, HRM can only rely on qualitative analysis [41]. HRM may use qualitative analysis to comprehend perceptions of organizational culture and employee engagement and satisfaction. The predicted wage can be a starting point for salary negotiations and adjusted for market conditions. As a result, the model relies heavily on the accuracy of the collected characteristics. Fig. 4 depicts the data features used for pay forecasting.

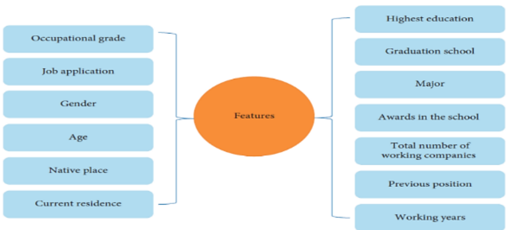

Fig. 4. Typical SPM data properties.

3.3 BP Neural Network (BPNN)

The BPNN relies heavily on error backpropagation learning, with the backpropagation process constantly adjusting and correcting the network's weights and thresholds [42]. Realizing the input-to-output mapping function is a prerequisite for BPNN to solve complex internal issues and discover nonlinear mappings. With repeated adjustments to weights and biases based on error estimations, BPNN acquire sophisticated mappings. This work includes the computation, backpropagation of errors, forward propagation of input data, and refinement across several epochs. Fig. 5 depicts the overall layout of the BPNN. The network has three layers: the input, the hidden, and the output. The buried layer is intense and complex. Each layer's neurons are autonomous within BPNN. Adjacent neurons only communicate with one another across two layers. Data from the input layer is sent to the hidden layer and then to the output layer after being processed by the function of the hidden layer.

3.4 BP Neural Network-Based SPM

3.4.1 The network's topological structure

The salary estimate is a univariate mapping with multiple inputs. The demand analysis data format specifies that the network has one neuron in the output layer and 14 neurons in the input layer. As shown below, there is no surefire way to determine the number of neurons in the buried layer.

$$n_h = \sqrt{n_i + n_o} + k \tag{1}$$

In Eq. (1), k is a constant between 1 and 10, the number of neurons in the hidden layer is n_h, the number of nodes in the input layer is n_i, the number of nodes in the output layer is n_o, and n_h is the neuron numbers in the layer of the hidden layer. For repeated training, BPNN is employed. Last but not least, there are 15 neurons in the hidden layer.

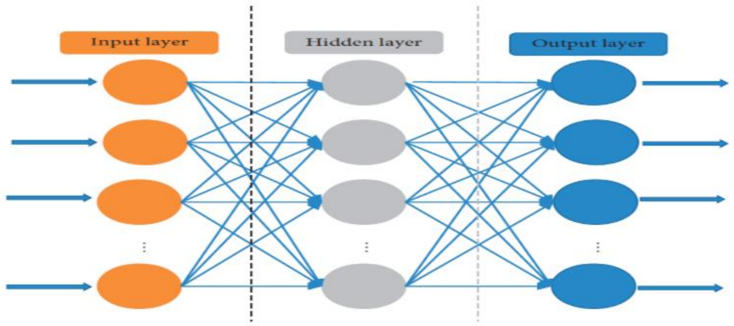

Fig. 5. BPNN architecture.

3.4.2 Activation function

Both nonlinear and linear activation functions exist in theory. However, in practice, the latter is preferred when the linearity of the problem is unclear. One of the most used activation functions today is the sigmoid function, which can be found by solving:

$$f(x) = \frac{1}{1+e^{-x^3}}. \tag{2}$$

The sigmoid function is often used to improve BPNN's nonlinear mapping capability. It is differentiable and possesses saturated nonlinearity, and its output is constrained to be in the interval [0, 1], where e is a natural constant.

3.4.3 Value at initiation of parameter

The parameters' initial value significantly impacts whether or not the model training outcome can maximize and converge. Each neuron's state value is close to 0 after the initial connection weights are accumulated, making it difficult to enter the Eat region accidentally. The initial state is preferable at this time. As a result, the algorithm yields the same results every time, and the gradients and updates applied to them never change [43] when the weight of the link is a small random number.

3.4.4 Loss function

The loss function is typically employed to quantify the deviation from the network's expected value. It's how we evaluate whether the training learning model has converged. The function of the mean square error that is quadratic in regression prediction, E, is the most used loss function, and its definition is

$$E = \tfrac{1}{2}(y-z)^2. \tag{3}$$

Where y is the goal vector (y_0, y_1, …, y_k) and z is the resultant vector (z_0, z_1, …, z_k). An SPM is created using BPNN. Model training is depicted in Fig. 6.

3.5 Process of SPM Optimization

Despite its ease of use and outstanding learning capabilities, the conventional BPNN has considerable limitations, such as a slow convergence speed. Gradient-based searches become stuck in the parameter space's local minimum. Therefore, BPNN requires optimization [44] for application in practice. You may find the updated cost here:

$$\Delta\theta_t = \frac{n}{\sqrt{vt+\varepsilon}} m_t. \tag{4}$$

In this expression, 7 represents the learning rate; for a non-zero denominator, the smoothing factor is 8, ???? which is the added momentum component. The additional momentum term m_t and the adaptive learning rate term v_t have their following equations.

$$m_t = \beta_1 m_{t-1} + 1 - \beta_1 g_t \tag{5}$$

$$v_t(i, i) = \beta_2 v_{t-1}(i, i) + (1 - \beta_2) g_2(i) \tag{6}$$

In this expression, attenuation factors β_1 and β_2 are squared gradients of parameters, $g_t^2(i)$ is the squared gradient of the ith parameter in the tth iteration, g_t is the gradient of the parameter, and $vt(i, i)$ is the expected value of the squared gradient of the tth iteration.

Therefore, the coefficients are adjusted using the deviation formula. Eqs. (7) and (8) illustrate the discrepancy:

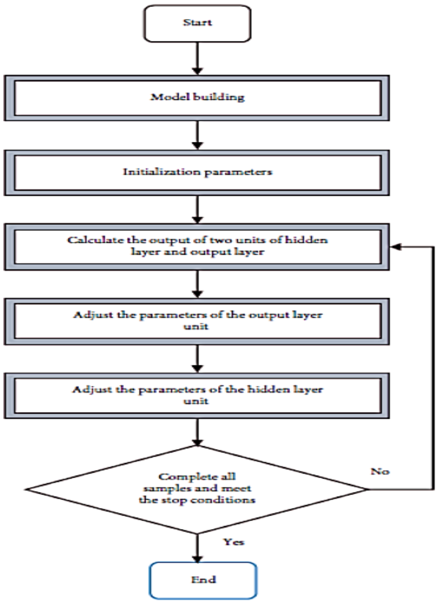

Fig. 6. BPNN-supported SPM.

$$\hat{m}_t = \frac{m_t}{1-\beta^{t_2}}, \tag{7}$$

$$\hat{v}_t = \frac{v_t}{1-\beta^{t_2}}. \tag{8}$$

Where $\hat{m}_t$ is used to replace mt in Eq. (4), and $\hat{v}_t$ is used to replace v_t in Eq. (4), which can avoid the problem of tending to 0. Commonly used coefficients in Adam are $\eta = 0.002$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\varepsilon = 1e - 8$. By fusing NAG with Adam, we can increase the convergence rate from fast-starting points [45]. Nadam's parameter refresh rate is denoted as

$$\Delta\theta_t = \frac{n}{\sqrt{v_t - \varepsilon}}\left(B_1, m_t + \frac{(1-B_1)g_t}{1-B_1^t}\right). \tag{9}$$

The parameters for Adam's Eq. (9) are described. As a result, their convergence rates are higher, and they experience fewer oscillations [46-49].

3.6 Preliminary Data Processing and Experimental Parameters

A three-layer BPNN with 14 input neurons, 15 hidden neurons, and 1 output neuron was used for wage forecasting. The model was trained on 1000 samples and tested on 100 samples from a dataset of 1100. As a result, the information is standardized as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \tag{10}$$

In the given dataset, x_{max} is the highest value, and x_{min} is the lowest. The SPM's ultimate prediction result is also beyond the normalized numerical range.

4. RESULTS AND DISCUSSION

4.1 Preliminaries

The study compares various optimization methods, including Nesterov Accelerated Gradient (NAG), Stochastic Gradient Descent (SGD), Adaptive Gradient (Adagrad), and Root-Mean-Square Propagation (RMSProp), against Adam and Nadam. The analysis, as depicted in Figs. 7 and 8, shows that hybrid methods like Adam and Nadam are more stable during updates and outperform other techniques in terms of convergence rate and prediction scores. The Adam optimization method has a final prediction score of 0.7502 and a training time of 192 seconds. The Nadam optimization algorithm predicts an outcome score of 0.7504 after 186 seconds of training.

4.2 Evaluation of the Improved SPM's Efficiency

The evaluation of various machine learning regression algorithms compared to an optimized BPNN-based SPM hybrid approach, particularly focusing on the Nadam hybrid algorithm. Fig. 9 demonstrates that the Nadam-optimized BPNN-based SPM achieves similar training and test set scores, indicating effective optimization. Additionally, Fig. 10 highlights how the optimized BPNN-based SPM's predictions better fit the data, showing the positive impact of the Nadam optimization. Nadam's optimization of a BPNN-based SPM yields respectable performance in prediction and learning phases; the achieved accuracy rate tops at 79.4%.

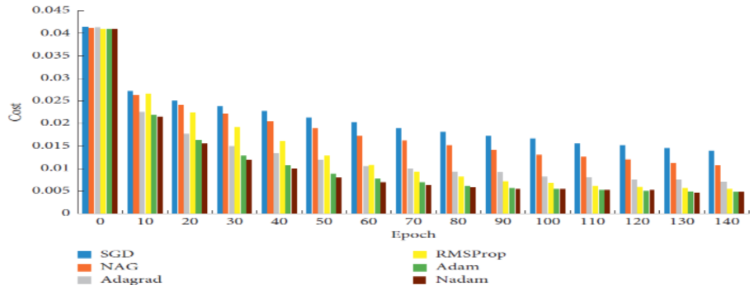

Fig. 7. Rates of convergence of several optimization techniques are compared.

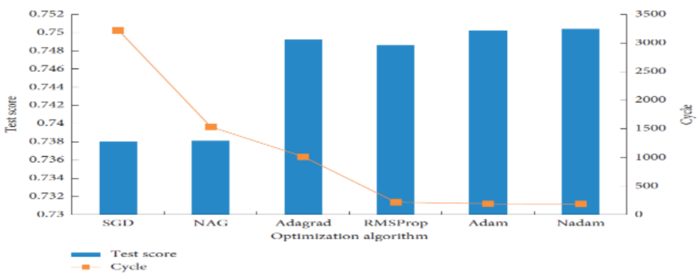

Fig. 8. Different optimization algorithm training results.

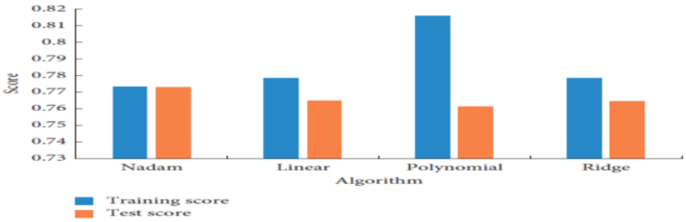

Fig. 9. Algorithms for predicting future salaries using forecasting are compared.

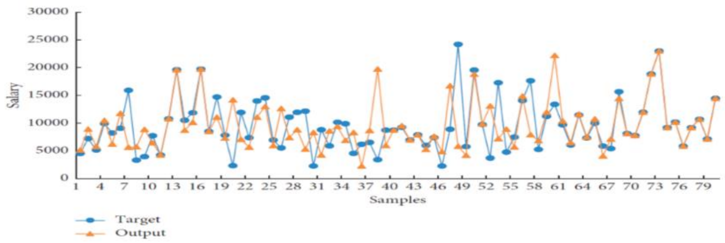

Fig. 10. Nadam's BPNN-optimized SPM's ability to fit data.

A salary prediction model is created using AI digitizing technology and a BPNN. With a 79.4% accuracy rate, the Nadam optimization method offers the fastest convergence speed and the best optimization impact [50].

5. CONCLUSION

Opportunities for hiring have expanded dramatically in the information era because of advancements in big data and artificial intelligence. The problem with conventional HRM systems is that they can't effectively assess data relationships or predict future development from existing information. This research aims to enhance the HRM system's usability by creating an SPM based on BPNN. After the BPNN based on SPM has been optimized using the hybrid optimization approach Nadam, an experimental simulation is used to evaluate the results. Compared to other methods in its class, the Nadam hybrid algorithm's optimization of the BPNN-based SPM achieved superior results, with a score of 0.7732 on the training set and 0.7730 on the test set. The Nadam hybrid algorithm improves the BPNN-based SPM's efficiency in both learning and prediction. The proposed model could be more complex, and there is room for improvement in engineering the data features. Future work will expand the sample data features and add to the model's functionality to further increase the model's accuracy.

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