EfficientNet-Based Prediction Model for Person-Job Matching Values

Hui Zhang[1,2*] Oscar Dousin[2]
[1]Huanghe Jiaotong University Jiaozuo, China
[2]Universiti Malaysia Sabah Kota Kinabalu, Malaysia
E-mail: zhanghui090766@126.com, odousin@ums.edu.my
[*]Corresponding author

Keywords: EfficientNet, person-job matching measure, deep learning, artificial intelligence, convolutional neural network

Received: July 5, 2024

In today's social environment, person-job matching is of significant importance for enhancing employee satisfaction, reducing turnover rate and improving organizational performance. However, traditional job matching methods rely on manual assessment and questionnaire surveys, which not only consume a lot of time and energy, but are also susceptible to the influence of subjective factors, resulting in a significant reduction in the accuracy of the assessment results. To overcome these challenges, this study constructed a job matching prediction model using EfficientNet. Train human resource data in the designed model to obtain feature representations for each individual. Input the obtained features and combine them with personnel job matching to predict each person's performance in a specific position. The results indicate that the proposed model has an accuracy of 86.8% and a loss value of 0.413. By adaptively adjusting the network structure and parameters, the model significantly improves its performance while keeping its size constant. The study shows that the model improves the accuracy and efficiency of person-job matching, which has important research and application value for modern organizational management.

Povzetek: Razvita je bila napovedna metoda, ki temelji na modelu EfficientNet za ujemanje posameznikov z delovnimi mesti. Model omogoča optimizacijo upravljanja človeških virov in organizacijske produktivnosti.

1 Introduction

Human resource management, is one of the key aspects of enterprise operation. However, with the expansion of enterprise scale and the increase of data volume, the traditional method of matching people and jobs can no longer meet the needs of modern enterprises due to its inefficiency and the shortcomings of being highly influenced by subjective factors [1-2]. This motivates the search for a more efficient and accurate job matching method. The development of artificial intelligence (AI) technology brings new possibilities to solve this problem. In the contemporary era of rapid technological advancement, AI and machine learning are possessing an eseential influence on numerous fields. One such area of interest is the prediction of match scores between individuals and jobs in various job roles, a process that is critical for effective human resource management. The ability to accurately predict compatibility between individuals and job roles can greatly improve organizational performance and efficiency [3-5]. For this reason, deep learning models, especially the EfficientNet model, have attracted much attention. Despite its many advantages, the application of EfficientNet in the field of human resources, especially in the prediction of person-job compatibility scores, has not been fully explored. Therefore, the study proposes a deep learning-based HR prediction model and analyzes it in detail on different types of human resources. The study aims to fill this gap and predict individual-job fit scores by utilizing the EfficientNet model and focuses on using the model to analyze the various factors affecting the compatibility of individuals with job roles. The model will be trained and tested using a comprehensive dataset and its performance will be evaluated based on accuracy, precision and recall. The innovation is the first application of the EfficientNet model to predict individual-job compatibility scores, a breakthrough where previous research has relied heavily on traditional machine learning methods and lacked the ability to automatically extract high-level features. In contrast, EfficientNet has the amazing ability to learn complex patterns from data, which is expected for providing more exact and reliable prediction results. The contribution is twofold: first, it lays the foundation for the future application of AI in human resource management; and second, it provides practical tools for those who seek to optimize the staffing strategy within an organization. By accurately predicting individual-job fit scores, organizations can ensure that each employee is placed in the position that best suits his/her skills and potential, thus further enhancing overall productivity and operational efficiency.

Therefore, this study is of great significance to both the academic and business communities. The research question addressed in the study involves determining how to enhance the performance of the EfficientNet architecture for the purpose of improving the accuracy of predictions in person-job fit within the context of human resource management. This includes exploring ways to fine-tune the network's parameters, utilizing higher quality datasets, and employing advanced training methods. The study seeks to validate whether EfficientNet's superior computational efficiency, scalability, and image recognition accuracy can be effectively translated to the domain of human resource management for complex person-job matching tasks, leveraging datasets that encompass in-depth personal career histories, skill evaluations, and job performance records. The aim is to align the features identified by the EfficientNet model with established human resource management theories to ensure practical relevance and applicability.

The study will be conducted in four parts: the first part is an overview of the EfficientNet-based matching methodology, the second part is the EfficientNet-based model for predicting and empirically investigating the matching value of the job measure, the third part is the experimental validation of the second part, and the fourth part is the summary of the study and points out the shortcomings. Comparison of research novelty, as shown in Table 1.

In Table 1, the first uses traditional machine learning with standard datasets, achieving medium accuracy. The second improves on this with early deep learning models applied to custom company data. The current study innovates by employing the EfficientNet model on a comprehensive dataset, anticipating higher accuracy and reliability, marking the first use of EfficientNet in HR for predicting individual-job compatibility.

2 Related works

In modern industrial production, human-job matching is a key factor in improving productivity and employee satisfaction. EfficientNet achieves the goal of improving model accuracy while maintaining parameter size by flexibly adjusting the depth, width, and resolution of the network. Xu D et al. proposed a highly efficient neural network structure for image quality assessment, called FQA-Net [6]. The network effectively prevents network overfitting by reducing the number of parameters and output dimensions, effectively preventing network overfitting. Results on seven image databases show that FQA-Net outperforms other methods in terms of computational complexity, computational speed, and accuracy Krishnan G's team investigated the effect of the Perceived Person-Environment Matching Scale (PEMS) on employees' intention to leave their jobs. By analyzing the data of 332 employees, the results showed that Person-Supervisor, Person-Group, Person-Organization, and Person-Job Matching Scales were significant predictors of Personal Consumption Expenditures (PCE) and PPEFS had an effect on employees' intention to leave [7]. Chang H W et al. proposed an efficient neural network structure, Fast Quality Assessment Network, for image quality prediction. Experiments proved that FQA-Net outperforms other image quality prediction methods in terms of computational complexity, speed and accuracy [8].

Zhang X and other scholars have proposed a systematic approach that combines life cycle cost analysis, benefit-cost analysis and dynamic building performance simulation for evaluating the economic performance of NZEB technologies and technical strategies. A case study demonstrated the effective application of this methodology in office buildings in the Yangtze River Delta region of China. Evaluating Zero Energy Buildings Using a Systematic Approach to Achieve Energy Savings and Emission Reduction [9]. Liu J et al. proposed a lightweight approach on the ground of an attention mechanism for the semantic segmentation problem.

Table 1: Comparison of research novelty

Study	Methodology	Dataset Used	Performance Metrics	Main Findings	Novelty
Previous Study 1	Traditional Machine Learning Algorithms	Standard Human Resources Dataset	Accuracy, F1 Score	Medium-level job match prediction	Lack of advanced feature extraction capabilities
Previous Study 2	Early Deep Learning Models	Custom Company Data	Precision, Recall	Improved accuracy over machine learning algorithms	Limited by shallow architecture
Current Study	EfficientNet Model	Comprehensive Human Resources Dataset	Accuracy, Precision, Recall	Expected higher accuracy and reliability	First application of EfficientNet in predicting compatibility scores for individuals and jobs in the HR field

Table 2: Summary of related work

Author	Methodologies	Performance metrics	Main findings
Xu D et al. [6]	FQA-Net (highly efficient neural network structure for image quality assessment)	Computational complexity, speed, accuracy	FQA-Net outperforms other methods on seven image databases, effectively preventing overfitting.
Krishnan G et al. [7]	Perceived Person-Environment Matching Scale (PEMS)	Intention to leave jobs, PCE	PEMS is a significant predictor of PCE, affecting employees' intention to leave.
Chang H W et al. [8]	Fast Quality Assessment Network (neural network structure for image quality prediction)	Computational complexity, speed, accuracy	FQA-Net outperforms other image quality prediction methods.
Zhang X et al. [9]	Systematic approach combining life cycle cost analysis, benefit-cost analysis, dynamic building performance simulation	Economic performance of NZEB technologies	Effective application in evaluating Zero Energy Buildings in the Yangtze River Delta region.
Liu J et al. [10]	Lightweight approach with attention mechanism for semantic segmentation	Segmentation accuracy, runtime speed	Improved segmentation accuracy and runtime speed in experiments on Cityscapes and Camvid datasets.
Jia W et al. [11]	Lightweight neural network (EEPNet) for palmprint recognition	Recognition accuracy, efficiency	EEPNet outperforms other methods in recognition performance on seven palmprint databases.
Li H et al. [12]	Data-driven hybrid petri net for energy behavior meta-modeling	Prediction accuracy in energy management	High accuracy in predicting energy behavior in extrusion and die casting processes.

An efficient bottleneck residual module and an efficient asymmetric bottleneck residual module were designed, and the attention mechanism was introduced in the jump connection between encoder and decoder. Experiments on Cityscapes and Camvid datasets showcase that the model does well in segmentation accuracy and runtime speed, which improves the runtime speed and segmentation accuracy [10]. Jia W et al. focused on palmprint recognition technology and proposed a lightweight neural network. They designed two new loss functions and added five strategies for enhancing the recognition. Tests on seven palmprint databases showed that the recognition of EEPNet is better and more efficient than other methods. The recognition performance of palmprint recognition technique is improved by designing a lightweight neural network EEPNet [11]. Li H et al. developed a data-driven hybrid petri net for energy behavior meta-modeling, which is used to generate a virtual data space for energy management. The model demonstrated high accuracy in predicting energy behavior in applications of extrusion process and die casting process [12].

In modern industrial production, human-job matching is critical, and deep learning methods, especially EfficientNet, have demonstrated strong performance in areas such as human-job measure matching value prediction. Compared with some other prediction models, such as FQA-Net and PPEFS, the EfficientNet-based human-job measure matching value prediction model is superior in terms of model accuracy and computational complexity. Meanwhile, EfficientNet model presents its excellent application value in practice. Its application in human resource allocation and job matching can significantly improve task efficiency, enhance prediction and matching accuracy, and realize environmental protection goals. Therefore, the EfficientNet-based human-job measurement matching value prediction model will provide an important reference for realizing more efficient, precise and environmentally friendly human-job matching prediction.

The summary of related work is shown in Table 2.

3 EfficientNet-based matching value method for person-position measurements

An EfficientNet-based person-job matching prediction method is used. The method includes two main steps: first, the human resource data are trained using EfficientNet model to get the feature representations of each person; then, these feature representations are used as inputs to predict the performance of each person in a specific position by calculating the person-job matching degree.

3.1 Modeling of EfficientNet in manpower measurement

EfficientNet is a neural network-based model that is unique in that it automatically adjusts the size and complexity of the model according to the complexity of the task. In the study, the task of EfficientNet is to extract useful features from a large amount of human resource data, which are used to calculate the person-job match. EfficientNet can predict the performance of different people in different jobs by comparing their feature representations, thus achieving accurate person-job matching. In order to improve prediction accuracy, a Convolutional Neural Network (CNN) optimizer is introduced into the EfficientNet network. The loss function of the CNN Optimizer is a computational method used for measuring the gap between the predicted and actual values of a neural network. The process of neural network training or optimization is minimizing the loss function, the smaller the calculated value of the loss function, the closer the predicted value of the model is to the real value, and the more excellent the accuracy, as shown in Eq. (1).

$$MSE = \frac{1}{2n}\sum_{i=1}^{n}\left(y_i - f\left(x_i\right)\right)^2 \tag{1}$$

In Eq. (1), y_i serves as the actual value, $f\left(x_i\right)$ serves as the predicted value, and n serves as the quantity of samples. The backpropagation of gradient information is the key to self-learning and updating of the neural network algorithm. The optimized EfficientNet algorithm, as shown in Eq. (2).

$$\theta_k = \theta_{k-1} - \alpha \cdot g \tag{2}$$

In Eq. (2), θ_k is the parameter value at the current moment, α is the learning rate, and g is the gradient. Growing the width of the network, i.e. growing the quantity of channels in the network, gets more features by increasing the number of feature layers. Increase the depth of the network, i.e., increase the quantity of layers in the network, use more layer structure for enhancing the performance, and utilize deeper neural network to enhance the feature extraction (FE) capability. Increase the resolution of the input network, i.e., increase the resolution of the input image to improve the accuracy, so that the features input to the network are richer and minimize the loss of image information. As a result, the tensor of the network output, as shown in Eq. (3).

$$Y_i = F_i\left(X_i\right) \tag{3}$$

In Eq. (3), X_i is the tensor of a particular convolutional layer, for a deep neural network consisting of k convolutional layers as shown in Eq. (4).

$$N = F_k \text{ e K e } F_2 \text{ e } F_1\left(X_1\right) = \underset{j=1\text{K}\,k}{\text{e}} F_j\left(X_1\right) \tag{4}$$

In Eq. (4), e is the concatenated multiplication operation, i is the stage number, and F_i is one operation operation. Scaling the model improves the accuracy of the network under the limits of memory and computation as shown in Eq. (5).

$$\begin{cases} \max\limits_{d,w,r} Accuracy\left(N\left(d,w,r\right)\right) \\ s,t,N\left(d,w,r\right) = \underset{i=1\text{K}\,S}{\text{e}} F_i^{d,\hat{L}}\left(X_{r\cdot\hat{H}_i^r \hat{W}_i^R \hat{C}_i}\right) \end{cases} \tag{5}$$

In Eq. (5), d, w, and r denote the depth, width, and resolution after scaling, respectively. In EfficientNet, scaling the three dimensions at the same time with appropriate proportions to achieve composite optimization can improve the performance and classification accuracy of the network, reduce the computation of the model, and enhance the performance of the network [13-14]. Among them, the internal MBConv module is adopted as the core structure, which is the unique FE structure of EfficientNet, and the two-dimensional view completes the efficient FE in the continuous stacking of Block layers. The MBConv module is shown in Figure 1.

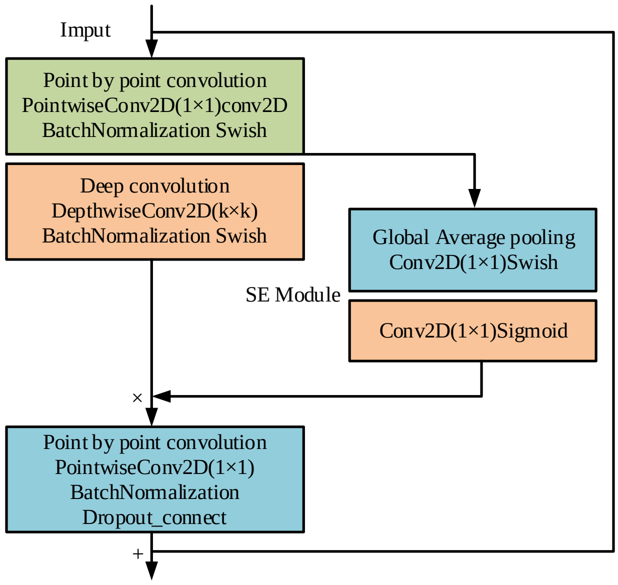

Figure 1: MBConv module.

In Figure 1, a 1X1 point-by-point convolution of the input feature map is first performed, and the output channel dimension is varied in view of the expansion ratio of the

A further k Xk deep convolution is performed to reduce the dimension to the original number of channels and again using point-by-point convolution, this module introduces the Compressing and Energizing Network Attention (SENet) focus on the channel features. The view features are processed by 16 Mbconvs in a stacked fashion, sequentially using Convl X 1, GlobalAveragePooling2D and FC layers to obtain feature vectors of dimension 1280. By using deep convolution and point-by-point convolution, the EfficientNet network reduces the computational complexity of the network compared to conventional convolution operations [15-16]. The EfficientNet network structure is schematically shown in Figure 2.

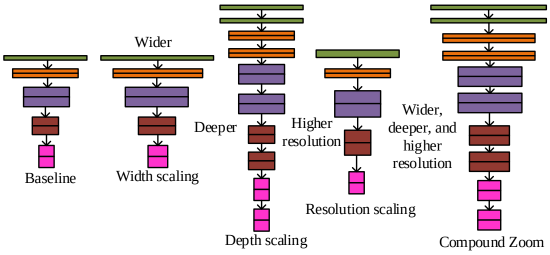

Figure 2: EfficientNet network structure diagram.

In Figure 2, EfficientNet utilizes the MBConv from MobileNet V2 as the backbone network. The MBConv mainly consists of a 1x1 ordinary convolution, a k×k Depthwise Convolution (containing BN and Swish), an SE module, a 1x1 ordinary convolution (with downscaling effect, containing BN), a A Droupout layer is composed. The SE module includes a global average pooling two fully connected layers (CL). The quantity of nodes in the first fully CL is the number of channels in the input MBConv feature matrix (FM), using Swish as the activation function (AF). The quantity of nodes in the second fully CL is equal to the quantity of FM channels output from the Depthwise Conv layer, using Sigmoid as the AF.

3.2 Calculation of the degree of match between man and job

In the calculation of person-job matching degree, it is mainly carried out by comparing personnel feature representations and job requirements. Firstly, through the EfficientNet model, each information of personnel is transformed into characteristic characterization. Then, a set of job demand parameters are formulated, which can quantitatively describe the demand characteristics of a job. Finally, the personnel's characteristic characterization is compared with the job demand parameters, and the similarity between the two is calculated to derive the value of the degree of matching between the person and the job [17-18]. According to the human resource management theory, the KSAO theoretical model is shown in Figure 3.

Figure 3: KSAO theoretical model.

In Figure 3, in human resource management theory, the KASO model proposed by Harvey (1991) is usually used to evaluate corporate talent in a multidimensional way. The KSAO theoretical model is a framework for analyzing the qualifications of personnel, which is widely used in the recruitment work of many American companies. Among them, K stands for Knowledge, which refers to the specific information, professional knowledge or common sense of the position required to accomplish a certain task; S stands for Skill, which refers to the proficiency in using a certain tool or operating a certain piece of equipment required to accomplish a specific task in the job, involving practical work skills and experience; A stands for Ability, which refers to the capability and quality of human beings, including human beings' basic expressive ability, Problem solving ability, logical thinking ability, observation ability, self-management ability, and learning ability, etc.; O stands for Others, which refers to other traits necessary to be able to effectively complete a job, including the employee's personal experience, personality attitude, and other special requirements. After building the fully-connected feature form converter and setting the hyperparameters of the fully-connected neural network, the output value of the fully-connected neural network is calculated, as shown in Eq. (6).

$$a=\sigma\left(\sum w\cdot C+b\right)=\frac{1}{1+e^{-\left(\sum w\cdot C+b\right)}} \tag{6}$$

In Eq. (6), C is the dimension vector, b is the neuron bias, and w is the weight of the number of talent evaluation features accepted by each neuron in the fully connected feature transformation layer. The talent evaluation feature data equation formed by folding the output values of the fully connected neural network is showcased in Eq. (7).

$$\begin{pmatrix} a_1 & \cdots & a_{16} \\ \vdots & \ddots & \vdots \\ a_{241} & \cdots & a_{256} \end{pmatrix} \tag{7}$$

In Eq. (7), a is the output value. At this point, the construction of the fully connected neural network feature converter of the person-gang matching measurement model is completed, and the talent feature data formed by the Internet technician person-gang matching measurement evaluation system is converted from a vector to a 16 x 16 square matrix. The fully connected neural network feature converter is showcased in Figure 4.

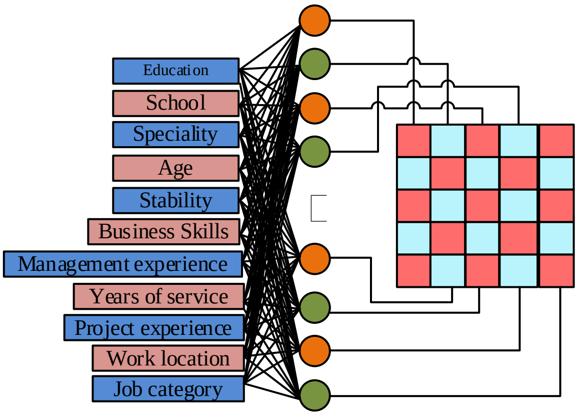

Figure 4: Structure of fully connected neural network feature converter.

In Figure 4, the fully connected neural network feature converter plays a crucial role in this process. It is a network structure consisting of multiple layers, each of which is connected to the next through a series of weights, and in this way it transforms the input raw data into a new set of feature representations.

3.3 EfficientNet algorithm for human post measurement recognition system design

Some optimizations are performed on the original EfficientNet model to improve its performance on the task of human-job matching prediction. These optimizations mainly include adjusting the network structure, modifying the AF, and adopting new optimization algorithms [19-20]. In terms of data preprocessing, the original data was first cleaned to remove missing and outlier values, ensuring data consistency and integrity. Next, the cleaned data was normalized to eliminate the impact of dimensional differences on model training. Considering the complexity and diversity of the dataset, a data enhancement strategy was adopted to increase the diversity of the samples by means of means such as random rotation, scaling, etc., for enhancing the generalization capability. In the label matching problem, a label smoothing strategy is used to enhance the robustness of the model. The label smoothing method is to change the one-hot label, which is shown in Eq. (8).

$$Q_i \begin{cases} 1-\lozenge & if i = true \\ \dfrac{\lozenge}{K-1} & else \end{cases} \tag{8}$$

In Eq. (8), $\lozenge$ is a predefined hyperparameter much less than 1, i is the sample prediction label, and K is the number of categories under the classification. It changes the format of one-hot coding so that the optimization objective in softmax loss is not just 0 and 1. Label smoothing makes the model output no longer as high as possible, thus enhancing the robustness of the model. The parameters of the model are updated as shown in Eq. (9).

$$\omega_t = \omega_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \lozenge}} \tag{9}$$

In Eq. (9), ω_t and ω_{t-1} are the updated parameter values, α is the updated learning rate, $\hat{m}_t$ serves as the exponentially weighted moving average of the gradient, and $\hat{v}_t$ is the exponentially weighted average of the squared gradient. The relationship between the update formula and the learning rate and hyperparameters is shown in Eq. (10).

$$\omega_t = \omega_{t-1} - \alpha \frac{\beta_I m_{t-1} + (1-\beta_I) g_t}{\sqrt{\beta_2 v_{t-1} + (1-\beta_2) g_t^2}} \tag{10}$$

In Eq. (10), β_I and β_2 are hyperparameters. For enhancing the network model's recognition accuracy and generalization ability for images with matching values of the human post measure and reduce the training time for later modeling, a migration learning method is used to pre-train the network by first using the image dataset of the Canadian Institute for Advanced Research-10 categories (Canadian Institute for Advanced Research-10 (CIFAR-10)) The trained network parameters are used as the initial parameters of the to-be-built model to complete the initialization of weights. Then, the CNN model was improved by changing the last fully CL to 5 outputs for making the model applicable to the five classification problem. Addtionally, Softmaxt is chosen as the AF of the last layer, and the loss function is selected as the classification cross entropy. The functions of the recognition system include three major functional modules: person and post information, measure recognition, and personal center. The architecture of the overall system function is shown in Figure 5.

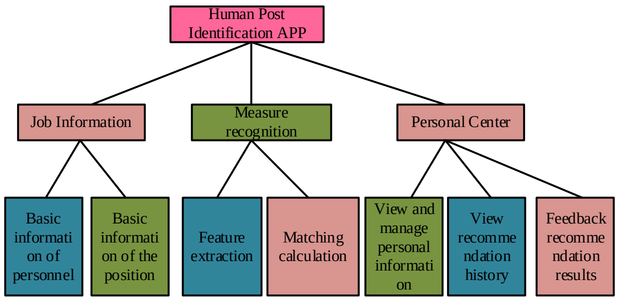

Figure 5: System functional architecture diagram.

In Figure 5, the Person and Position Information module, this module is mainly responsible for collecting and managing all personnel and position information. This information includes the basic information of the personnel (such as age, gender, educational background, work experience, etc.) and the detailed description of the position (such as job responsibilities, required skills, work location, etc.). The job information module summarizes and organizes this information to form a detailed and rich job information database, which provides the basis for subsequent matching and recommendation. Measurement Recognition Module, this module mainly carries out FE and matching degree calculation for personnel and job information through EfficientNet model. Specifically, it first takes the information of the personnel as input and extracts the characteristics of the personnel through the EfficientNet model; then, it compares these characteristics with the parameters of the job requirements and calculates the similarity between the two to arrive at the value of the matching degree between the personnel and the job. Personal center module, this module mainly provides personalized services for each user. It recommends the most suitable jobs for users based on their historical behavior and the results of the measurement recognition module.

4 Prediction and empirical analysis of matching values of person-gang measurement based on EfficientNet

This section introduces and evaluates the EfficientNet-based model for predicting the matching values of person-post measures. First, the training process and parameter selection of the EfficientNet model are described. Then, the model parameters are further optimized by comparing the model performance under different learning rates. Finally, the prediction accuracy and efficiency of the EfficientNet model are empirically analyzed using the example measure results and training validation data to verify its application effect in the actual person-post matching problem.

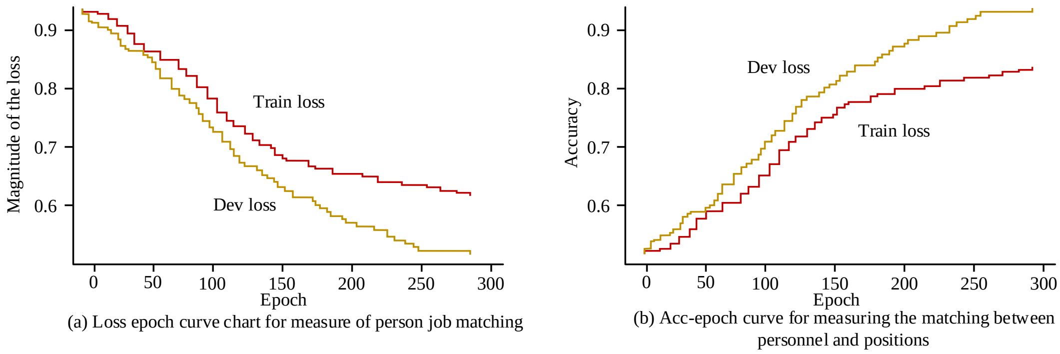

Figure 6: Structure of fully connected neural network feature converter.

4.1 Prediction of matching value of EfficientNet manpower and job measures

The model was compiled in a Windows environment with an I7-8700 CPU, 8C RAM, and an NVIDIA CTX1060 6C graphics card. All code was on the ground of TensorFlow version 2.0, implemented with the Keras framework. Data processing was done using Exce12019 version. The Loss-epoch plot and Acc-epoch plot of the human-post matching measure are shown in Figure 6.

In Figure 6, after 300 iterations, the loss values of both the training set and the test set reduced to below 0.5, and the training set and the test set reduced synchronously without overfitting. In addition, as can be seen from the graph of the change in the accuracy of the person-gang matching measurement, at the end of 300 Epoch iterations, the highest classification accuracy on the ground of the CNN method is able to reach 0.844, indicating that the model is able to classify the data effectively. Using the method of dividing samples, under the premise of ensuring enough training samples, randomly disrupt 19,832 talent evaluation data, first extract 3,500 as the test data set, and then extract 8,000, 10,000, 12,000, 14,000, and 16,000 data as the training data, respectively, and train the CNN classifiers with different amounts of training data, and use the test data set to were tested separately. The performance of the model under different training set data is shown in Figure 7.

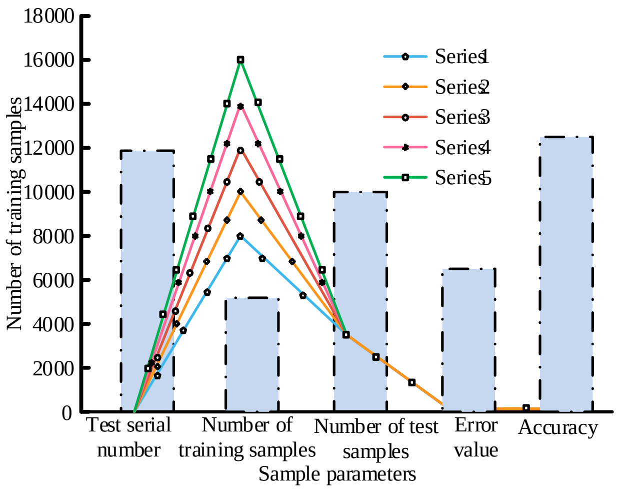

Figure 7 Model performance under different training set data.

In Figure 7, when the quantity of training samples is 14000, the error value has reached below 0.5, and the prediction accuracy of the model has reached 0.827, which makes the model's classification effect more ideal. When the quantity of training samples reaches 16000, the prediction accuracy is 0.844, which is slightly improved, and the fitting error decreases to 0.413. In order to see whether the generalization ability of the optimize

EfficientNet model is optimal or not, we adopt the same 19,832 empirical datasets with the CNN human-height matching measurement model, and use the decision tree and the plain Bayesian two traditional multi-classification methods to make classification predictions, and compute the classification error for each of the traditional multi-classification methods. Classification prediction, and calculate the prediction accuracy under each classification algorithm, as well as the duration of different models, as shown in Table 3.

Table 3: Accuracy, duration, and significance test results of different models

Serial Number	**Model algorithm**	**Accuracy**	**Duration (min)**	***P***
1	Decision tree	0.742	4.8	>0.05
2	EfficientNet	0.635	4.8	>0.05
3	Optimize EfficientNet	0.868	3.7	<0.0
4	Random Forest	0.759	5.2	>0.05
5	Support Vector Machine	0.704	6.2	>0.05
6	Gradient Boosting	0.782	5.1	>0.05
7	Neural Network	0.721	6.5	>0.05
8	CNN	0.823	4.6	>0.05

In Table 3, optimize EfficientNet model has the highest accuracy, is 86.8%, while the decision tree algorithm is again superior to the plain Bayesian algorithm. Next in terms of model efficiency, the decision tree algorithm took the longest time and the optimize EfficientNet algorithm took the shortest time. The P<0.01 of the optimize EfficientNet model indicates that its performance is statistically significantly better than other baseline models, while P>0.05 indicates no significant difference. The performance at different learning rates is shown in Table 4.

Table 4: Model performance under different learning rates

Serial Number	**Learning rate**	**Accuracy**	**Duration (min)**
1	0.1	0.668	1.2
2	0.01	0.765	2.5
3	0.001	0.895	2.8
4	0.0001	0.838	4.9
5	0.00001	0.835	5.2
6	0.000001	0.834	5.4
7	0.0000001	0.865	6.1
8	0.00000001	0.824	6.5
9	0.000000001	0.924	6.9

In Table 4, the learning rate decreases from 0.1 to 0.001, the prediction accuracy of the model is gradually increasing, but when the learning rate is adjusted to 0.0001, the accuracy falls back, and at this time the model is likely to fall into the local optimum, which indicates that the learning rate of 0.001 is the most suitable for the training of this model. A series of actual personnel and job information was collected, and the trained EfficientNet model was applied to make predictions and compared with the actual results. To carry out the person-job matching measurement model, talent evaluation data need to be collected first. Therefore, combined with the actual recruitment work of the enterprise, the study collected a total of 8273 resumes of all resumes received by the technical department of enterprise A from January 1, 2019 to November 4, 2019 as training data. And additionally, all the resumes received by the technology department of enterprise A on November 5, 2019 totaling 43 resumes were collected as test data and numbered.

4.2 Empirical measurement of the matching values of EfficientNet's person-to-position measures

The performance of the EfficientNet model was evaluated by the example measurement results and the change in accuracy of the training validation data. The results of the example measurements for the application of the person-post matching model are showcased in Table 5.

In Table 5, for the same number of resumes with categorization requirements, the manual method of matching and scoring was used for 23 minutes, and the person-job matching model measure was used for 2 minutes. For studying the convergence of the proposed network, the following experiments were conducted. Effective features are extracted from the training data, the initial learning rate is set to 1 E-4, the batch size (Batchsize) is set to 16, and the quantity of iterations (Epoch) is set to 200.Finally, the changes in the accuracy of the training set view data and the accuracy of the validation set view data are obtained for different quantity of iterations as showcased in Figure 8.

Table 5: Measurement results of application examples of the human job matching model

Method	Number of Samples	Screening Rate	Time Taken	Filter Results	Inconsistent Results
Manual	43	25%	23min	3,7,14,19,22,23,25,30,37,39,42	1 Different Result (30⇔32), 1 Different Order (14,19⇔19,14)
Automated (Decision Tree)	50	28%	3.5min	2,5,10,15,20,24,28,30,35,40,43,45,47,50	1 Different Result (24⇔28), 1 Different Order (10,15⇔15,10)
Automated (Random Forest)	50	30%	3.2min	2,6,10,15,20,25,30,33,38,43,46,49	1 Different Result (33⇔38), 1 Different Order (15,20⇔20,15)
Automated (Gradient Boosting)	50	27%	2.8min	1,6,11,17,22,27,31,35,40,45,48	1 Different Result (31⇔35), 1 Different Order (11,17⇔ 17,11)
Automated (Neural Network)	50	25%	3.6min	3,8,13,18,23,28,32,37,41,46,50	1 Different Result (32⇔37), 1 Different Order (13,18⇔18,13)

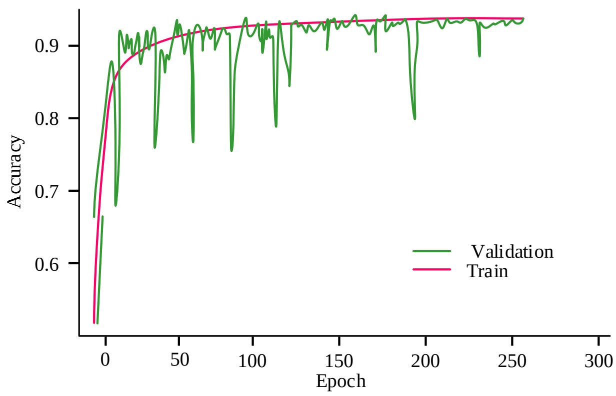

Figure 8: Accuracy of training and validation sets.

In Figure 8, it depicts a clear initial upgrade in training accuracy, indicating that it can be quickly learned from the provided data. After the initial fluctuation, the verification accuracy showed relative stability. after 50 iterations of training, the classification accuracy of both training data and validation is more than 90%, which is more obvious. The training curve stabilizes at 100 times, while the validation curve reaches stability at 175 times. These two curves indicate that the proposed network is well trained at 175 times, while it reaches the best results at 200 iterations. Comparing the recall of different models on different datasets is shown in Figure 9.

In Figure 9, for the dataset under consideration, EfficientNet outperforms traditional algorithms, achieving a significant recall rate of 98.27%. This number exceeds the recall rates of decision tree and random forest models by 2.47% and 3.25%, respectively. In addition, when evaluated on different datasets including professional archives, EfficientNet maintained a good recall rate, with a registration rate of 93.27%. Compared with the performance of support vector machines and gradient boosting models, this proportion was significantly higher, at 1.94% and 2.87%, respectively. These results emphasize the robustness of EfficientNet in retrieving relevant instances across different datasets in the field of predictive analysis.

Obtain real recruitment data from the recruitment database of actual online recruitment platforms, covering data samples from different positions, industries, and regions. These data not only include the basic information of candidates, but also details such as work experience, skill matching, interview feedback, etc. [21]. In order to evaluate the generalization ability of the model, in addition to the conventional dataset, datasets with noise, missing values, and imbalanced labels were also introduced [22]. Three scenarios are set for simulation. Scenario 1 simulates the exact matching requirements for high skilled positions in actual recruitment, and tests the performance of the model in accuracy. Scenario 2 simulates a large number of candidates' application scenarios to test the efficiency and accuracy of the model in processing large-scale data. Scenario 3 introduces a dataset with noise and outliers to evaluate the robustness of the model in cases of poor data quality. The performance of the optimized EfficientNet model in three experimental scenarios is shown in Table 6.

Table 6: Performance of the optimized EfficientNet model in three experimental scenarios.

Experimental scenario	Accuracy	Precision	Recall	F1-score	Average processing time (seconds/sample)
1	0.912	0.895	0.918	0.906	0.860
2	0.874	0.861	0.880	0.870	0.720
3	0.835	0.823	0.840	0.831	0.800

In Table 6, the optimized EfficientNet model exhibits high accuracy and robustness in different real-world scenarios, especially in scenarios with high matching requirements. The F1 score of the model reaches 0.906, demonstrating its effectiveness and practicality in practical use. The processing time of the model in large-scale recruitment also shows high efficiency, which can meet the needs of practical applications. HR can quickly screen potential suitable candidates through the model, reducing the initial screening time. At the same time, HR can also conduct secondary screening based on the results recommended by the model, further optimizing the interview list and improving recruitment efficiency.

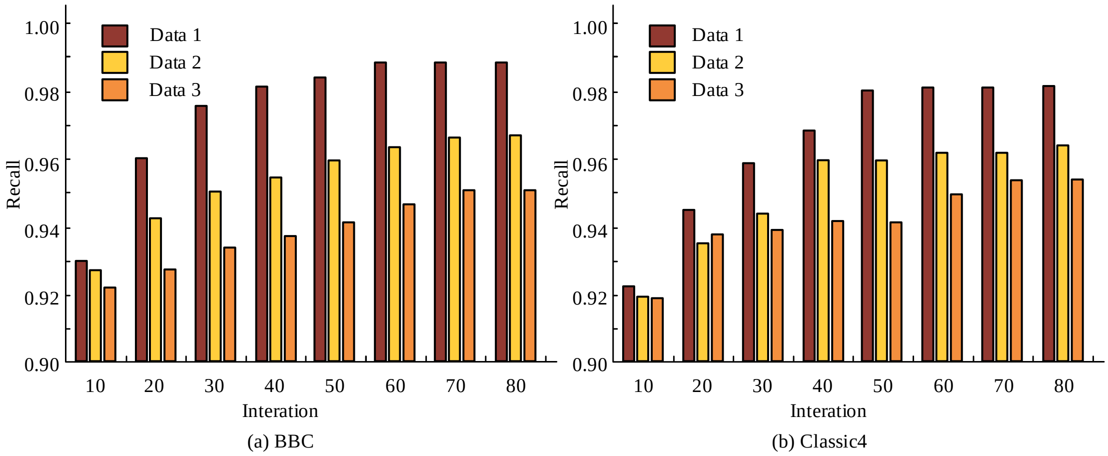

Figure 9: Comparison of recall rates of different models on different datasets.

5 Discussion

Learning rate is an important hyperparameter in the model training process, which can directly affect the step size of model weight updates, thereby affecting the convergence speed, generalization ability, and stability of the model. For the EfficientNet model, choosing the appropriate learning rate is crucial as it can significantly affect the training efficiency and final performance of the model. When the learning rate is 0.001, the prediction accuracy of the model reaches its highest value of 0.895, verifying that this learning rate is the optimal choice for training the proposed model. Compared with different algorithms, the optimized EfficientNet model shows the highest accuracy and the shortest time consumption. Compared with traditional decision trees and naive Bayes models, this significantly improves prediction accuracy and efficiency. Specifically, the EfficientNet model has a high recall rate in regression analysis, especially on different datasets.

The EfficientNet model exhibits fast learning ability in the early stages of training, and after 50 iterations, the classification accuracy of both the training and validation sets exceeds 90%. After 100 iterations, the training curve tended to stabilize, while the validation curve reached stability at 175 iterations, demonstrating good convergence of the model. This indicates that the model achieved optimal performance after 200 iterations. Secondly, by comparing the recall rates with other traditional algorithms, EfficientNet significantly outperforms decision trees and random forest models on the dataset used in this study, with recall rates 2.47% and 3.25% higher, respectively. In addition, on different datasets, EfficientNet still maintains a high recall rate, for example, the recall rate on the professional archive dataset reaches 93.27%, which is 1.94% and 2.87% higher than that of the support vector machine and gradient boosting model, respectively. These results indicate that EfficientNet has good robustness on different datasets and can effectively identify and classify relevant instances.

In summary, this conducted in-depth research on the matching problem between personnel and positions using the EfficientNet model, verifying its advantages in prediction accuracy and efficiency.

6 Conclusion

With AI in modern industrial production, human-job matching is a key factor to improve productivity and employee satisfaction. An EfficientNet-based human-job measure matching value prediction method is proposed, which analyzes and predicts human resource data through deep learning techniques, and the test outcomes showcase that better prediction results can be obtained when the initial learning rate is set to 1E-4, the processing size (Batchsize) is 16, and the number of iterations is 200 during the model training process. This is consistent with previous experiments, which have shown that the model's prediction accuracy continues to improve as the learning rate is decreased from 0.1 to 0.001. However, when the learning rate continues to be lowered to 0.0001, the model accuracy falls back, most likely because the model is stuck in a local optimum. This suggests that a learning rate of 0.001 is the most suitable for training the current model. The study utilized the EfficientNet model, which is an advanced deep learning model that performs well in image recognition and is expected to have efficient predictive capabilities in the field of human resources. Due to EfficientNet being applied for the first time in the field of human resources, there is uncertainty in data adaptability and interpretability. Although a comprehensive dataset was used, its ability to fully represent the target population or cover all relevant variables remains to be verified. The proposed network is well trained at 175 times while reaching the optimum at 200 iterations. A new and accurate means of assessing the match between people and jobs is provided for organizations. The results show that the method exhibits good performance in both accuracy and reliability of the prediction results, and has the potential to change the recruitment process of enterprises to be more scientific and efficient. In the future, EfficientNet needs to be improved and optimized for simulating the person-job matching process more accurately and further improve the accuracy of the person-job measure matching value. However, the study did not consider the application effects in developed and developing regions, as there are differences in labor markets and talent supply and demand relationships between different regions. In the process of developing and applying models in the future, localization adjustments should be made for different economic backgrounds to ensure that the models can adapt to specific needs in different regions.

Acknowledgement

This study is funded by Scheme Design and Application Research of Intelligence Class Collective (Grant NO. ZC2023194).

References

[1] Bin J, Nanxing L, Rui Z, Qinggang W, Huawen C. New research advances in facial expression recognition under partial occlusion. Journal of Computer Engineering & Applications, 2022, 58(12):12-24, https://doi.org/10.3778/j.issn.1002-8331.2112-0268

[2] Poux D, Allaert B, Ihaddadene N, Bilasco I M, Djeraba C, Bennamoun M. Dynamic facial expression recognition under partial occlusion with optical flow reconstruction. IEEE Transactions on Image Processing, 2021, 31(2):446-457. https://doi.org/10.1109/TIP.2021.3129120

[3] Qin C, Zhu H, Xu T, Zhu C, Ma C, Chen E, Xiong H. An enhanced neural network approach to person-job fit in talent recruitment. ACM Transactions on Information Systems (TOIS), 2020, 38(2):1-33. https://doi.org/10.1145/3376927

[4] Yang D, Xu X, Yao Y. Hull deformation measurement with large angles based on inertial sensors. IEEE Access, 2020, 8: 191413-191420. https://doi.org/10.1109/ACCESS.2020.3031955

[5] Yu L, Chen Y, Zhang S, Dai B, Liao S. Excessive use of personal social media at work: antecedents and outcomes from dual-system and person-environment fit perspectives. Internet Research, 2023, 33(3):1202-1227. https://doi.org/10.1108/INTR-05-2021-0287

[6] Xu D, Zhang X, Peng X, Yang G, Chen J. An anti-vibration-shock inertial matching measurement method for hull deformation. IET Signal Processing, 2022, 16(4): 490-500. https://doi.org/10.1049/sil2.12122

[7] Krishnan G, Reeves W J, Bhaskaran R. Perceived person-environment fit and employees' turnover intention. International Journal of Current Advanced Research, 2019, 6(8):5218-5224. http://dx.doi.org/10.24327/ijcar.2017.5224.0675

[8] Chang H W, Wang P, Du C, Bi X, Wang M. FQA-Net: an efficient neural network for blind image quality assessment. Journal of Electronic Imaging, 2022, 31(6):1-17. https://doi.org/10.1117/1.JEI.31.6.063027

[9] Zhang X, Wang A, Tian Z, Li Y, Zhu S, Shi X, Wei, S. Methodology for developing economically efficient strategies for net zero energy buildings: A case study of a prototype building in the Yangtze River Delta, China. Journal of Cleaner Production, 2021, 320(10):1-17. https://doi.org/10.1016/j.jclepro.2021.128849

[10] Liu J, Xu X, Shi Y, Deng C, Shi M. RELAXNet: residual efficient learning and attention expected fusion network for real-time semantic segmentation. Neurocomputing, 2022, 474(2):115-127. https://doi.org/10.1016/j.neucom.2021.12.003

[11] Jia W, Ren Q, Zhao Y, Li S, Min H, Chen Y. EEPNet: an efficient and effective convolutional neural network for palmprint recognition. Pattern Recognition Letters, 2022, 159(7):140-149. https://doi.org/10.1016/j.patrec.2022.05.015

[12] Andela M, van Der Doef M. A comprehensive assessment of the person-environment fit dimensions and their relationships with work-related outcomes. Journal of Career Development, 2019, 46(5): 567-582. http://dx.doi.org/10.1177/0894845318789512

[13] Guan Y, Deng H, Fan L, Zhou X. Theorizing person-environment fit in a changing career world: Interdisciplinary integration and future directions. Journal of Vocational Behavior, 2021, 126(4): 103557-103558. https://doi.org/10.1016/j.jvb.2021.103557

[14] Li H, Yang D, Cao H, Ge W, Chen E, Wen X, Li C. Data-driven hybrid petri-net based energy consumption behavior modelling for digital twin of energy- efficient manufacturing system. Energy, 2022, 239(1):1-17. https://doi.org/10.1016/j.energy.2021.122178

[15] Guo Y, Hou X. The effects of job crafting on tour leaders' work engagement: the mediating role of person-job fit and meaningfulness of work. International Journal of Contemporary Hospitality Management, 2022, 34(5):1649-1667. http://dx.doi.org/10.1108/IJCHM-09-2021-1082

[16] Abualoush S, Obeidat A, Abusweilema M, Khasawneh M. How does entrepreneurial leadership promote innovative work behaviour? Through mediating role of knowledge sharing and moderating role of person-job fit. International Journal of Innovation Management, 2022, 26(1):1-27. https://doi.org/10.1142/S1363919622500116

[17] Heidary-Sharifabad A, Zarchi M S, Emadi S, Zarei G. An efficient deep learning model for cultivar identification of a pistachio tree. British Food Journal, 2021, 123(11):3592-3609. https://doi.org/10.1108/BFJ-12-2020-1100

[18] Cao S, Zhao D, Sun Y, Ruan C. Learning-based low-illumination image enhancer for underwater live crab detection. ICES Journal of Marine Science, 2021, 78(3):979-993. https://doi.org/10.1093/icesjms/fsaa250

[19] Wu B, Zhou J, Yang H, Huang Z, Ji X, Peng D, Shen X. An ameliorated deep dense convolutional neural network for accurate recognition of casting defects in X-ray images. Knowledge-Based Systems, 2021, 226(17):1-18. https://doi.org/10.1016/j.knosys.2021.107096

[20] Chen Z. Research on internet security situation awareness prediction technology based on improved RBF neural network algorithm. Journal of Computational and Cognitive Engineering, 2022, 1(3): 103-108. https://doi.org/10.47852/bonviewJCCE149145205514

[21] Kaur D, Kaur R. Does electronic word-of-mouth influence e-recruitment adoption? A mediation analysis using the PLS-SEM approach. Management Research Review, 2023, 46(2): 223-244. https://doi.org/10.1108/MRR-04-2021-0322

[22] Min H, Yang B, Allen D G, Grandey, A. A., & Liu, M. Wisdom from the crowd: Can recommender systems predict employee turnover and its destinations? Personnel Psychology, 2024, 77(2): 475-496. https://doi.org/10.1111/peps.12551