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Diagnostic Analysis of the Graiman Field Base Bearing in the Splasma Rain Uniion Model

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ABSTRACT

Employee selection is the process of searching and attracting workers who have the potential to fill job vacancies. Quality workers have a big influence on the company's progress. The decision-making process for accepting new employees is still influenced by subjective factors and companies often experience difficulties in selecting employees, because there are many prospective employees who apply while those who will be accepted as employees are very limited. The aim of this research is to design a decision-making application that can help recruit prospective new employees. One of the methods used for decision-making is the WP method because the WP method is a multi-criteria completion method where in recruiting or selecting prospective employees many criteria must be considered. The development method for this system uses the waterfall method. The programming language used is PHP and MySQL as the database server. From the results of this research, it makes it easier to make decisions to determine employees who suit the company's needs and criteria.

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Selection
Employees
Quality
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1. Introduction

The recruitment process is a process of accepting prospective workers to fulfill the need for workers (job vacancies) in a work unit in an organization or company, while the selection process is the process of selecting the most qualified workforce candidates to fill job vacancies [1]. Employees are human resources owned by an organization that are used to mobilize or manage other resources so they must really be used effectively and efficiently according to the real needs of the organization, a quality workforce will make it easier for the company to manage its activities so that the goals set can be achieved . The demand or need for an organization's human resources in the future is the center of personnel planning activities [2]. Almost all companies must make predictions of employee needs (at least informally) in the future, although they may not need to estimate resources. the supply.

It is not easy to get quality Human Resources (HR) workers. One of the ways used to get quality workers is to select prospective new employees. The selection of prospective new employees is a stage in deciding whether an applicant is accepted or not. It is hoped that the decisions that will be taken will be in accordance with expectations so that no party will be harmed, because from this process prospective employees will be obtained who meet the criteria desired by the company. However, in this case the process of accepting new prospective employees is still carried out conventionally, namely through administrative tests, psychological tests, and interviews or still manually so that all data on prospective new employees does not yet have fixed criteria and weights, the process of accepting new employees takes quite a long time, and the calculation process is still not accurate. So we need a system that can help the employee selection process more effectively, namely a decision support system.

A Decision Support System is a computer-based information system that takes an approach to generating various alternative decisions to help certain parties in dealing with problems using data and models[3]. Decision making is the result of a selection process from various alternative actions that may be chosen using a certain mechanism, with the aim of producing the best decision [4]. The model that describes decision making consists of four phases [5], including intelligence, design, selection, and implementation. The decision support system used for employee selection problems is one that uses the Weighted Product (WP) method [6]. Weighted Product (WP) is a method of using multiplication to connect attribute ratings, where the rating of each attribute must first be raised to the power of the corresponding weight. This process is the same as the normalization process [7]. Just like all FMADM methods, WP is a finite set of decision alternatives described in terms of several decision criteria. The advantage of the WP method is that companies can determine the importance weight of each criterion themselves [8]. By applying the WP (Weighted Product) method to the process of accepting prospective new employees, the system for accepting prospective new employees has fixed criteria and weights and the calculation process is faster. Apart from that, the accuracy of prospective new employee data is also maximized.

Meanwhile, in research conducted [9], regarding a decision support system for purchasing motorbikes using the WP method, results were obtained by implementing the Weighted Product (WP) method. The system was able to sort motorbike products as a result of recommended product recommendations based on the selection of alternative brands and types of motorbikes, as well as determining the level of importance of each criterion. And the system can help potential consumers in the decision-making process to choose a motorbike that suits the needs, desires and abilities of potential consumers.

The Weighted Product (WP) method is a method using multiplication as a link for attribute ratings, where the rating of each attribute must first be raised to the power of the corresponding weight [8]. Preferences for alternative Si include determining the weight value W, determining the Vector S value and determining the Vector V value. The steps in calculating the Weighted Product (WP) method begin by transferring all attributes for all alternatives with the weight as a positive rank for the cost attribute, Next, the results of the multiplication are added up to produce a value for each alternative. After that, divide the V value for each alternative by the value for each alternative. And finally, find the best alternative sequence that will be the decision.

2. Method

The most commonly used method for traditional CNN models to achieve stronger feature extraction capabilities was to increase the depth of the model. However, when the model's depth reaches a certain level, further increasing the number of layers can lead to a decrease in accuracy, resulting in a phenomenon known as model degradation. The introduction of residual networks has largely addressed this problem (He et al., 2016). By using residual blocks, the depth of the model can reach over 1,000 layers without experiencing model degradation.

The basic principle of residual networks is to use a shortcut connection channel between convolutional layers, which allows the effective features extracted from the previous layer to be directly transmitted to the subsequent layers through this channel. This approach prevents the convolutional layers from redundantly extracting the features already captured by the previous layers. After passing through the shortcut channel x

The channel attention model enhances the accuracy of classification tasks by adaptively focusing on useful channel information. The introduction of this model enables neural networks to better comprehend and leverage crucial features within the input data, so as to improve performance across various application domains. Qin, Zhang & Wu (2021) utilized the DCT from the signal processing field and proposed a multi-spectral attention module. This method allows for better aggregation of frequency energy. And the principle of this method aligns with the fundamental concept of the channel attention model. Therefore, incorporating it into the channel attention model is a highly effective attempt. This article uses 2D DCT, and the working principle is briefly explained as below. The base model used in this article is a 34-layer ResNet. Frequency channel attention modules are embedded in the convolutional blocks of the intermediate layers, forming the Fca-ResNet model. The input images are processed into 224×224 images in the preprocessing stage. Therefore, in order to obtain a larger receptive field, the first convolutional layer uses a convolutional kernel with the size of 7×7. The convolutional kernels in the intermediate layers are set to the size of 3×3 . After average pooling, the input is passed to fully connected layers for classification, and the results of classification diagnosis are obtained through the Softmax layer.

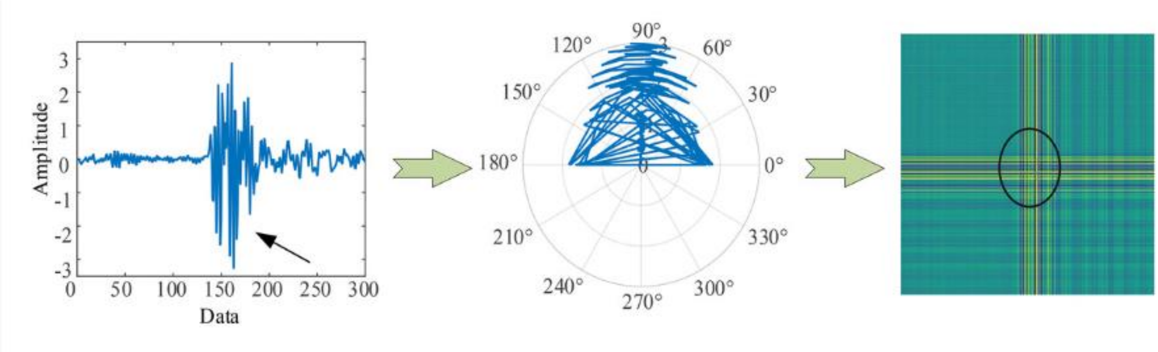

Fig. 1. System Accuracy Testing

3. Results and Discussion

The channel attention model enhances the accuracy of classification tasks by adaptively focusing on useful channel information. The introduction of this model enables neural networks to better comprehend and leverage crucial features within the input data, so as to improve performance across various application domains. Qin, Zhang & Wu (2021) utilized the DCT from the signal processing field and proposed a multi-spectral attention module. This method allows for better aggregation of frequency energy. And the principle of this method aligns with the fundamental concept of the channel attention model. Therefore, incorporating it into the channel attention model is a highly effective attempt. This article uses 2D DCT, and the working principle is briefly explained as below.

To validate the superiority of the Fca-ResNet model, the experiment divided the load of the motor into four categories (0, 1, 2, 3 hp), while this article selected the condition of 1 hp (approximately 0.735 kw) and a speed of 1,772 r/min; And selected three different fault diameters of three types, namely outer ring (@6, where @6 indicates the fault location at 6 o'clock), inner ring, and rolling element as data samples, as well as one sample of normal state data, 10 categories in total. The number of sampling points of a cycle of the bearing is 400, and 300 data points were selected each time (the points collected within 3/4 cycles) (Tong, Pang & Wei, 2021). The original vibration signals were processed using a sliding window approach with a step size of 150. Using the overlapping sampling method, 400 samples were constructed for each category. These samples were then divided into training and validation sets in accordance with a specific ratio, as shown in

To validate the reliability of our model, we conducted experiments using a partitioned dataset. The comparative experimental models selected were ResNet, ResNet with SE attention modules, group-processed ResNeXt, and traditional CNN models such as GoogleNet and AlexNet. Figure 6 clearly demonstrates the validation accuracy and training loss variations of different models during the training process. As shown in the graph, ResNet, SE-ResNet, and ResNeXt achieved the highest validation accuracies of 98.5%, 98.8%, 98.5%, 98%, and 96.5% respectively. The fluctuation stability was average and the accuracy was not high. While, after 50 rounds of training, Fca-ResNet model tended to stabilize, reaching a peak validation accuracy of 99.3%, and exhibited the lowest training loss compared to other models in the first 100 rounds. This indicates that our model possesses strong robustness and feature extraction capabilities, far superior to the other models considered.

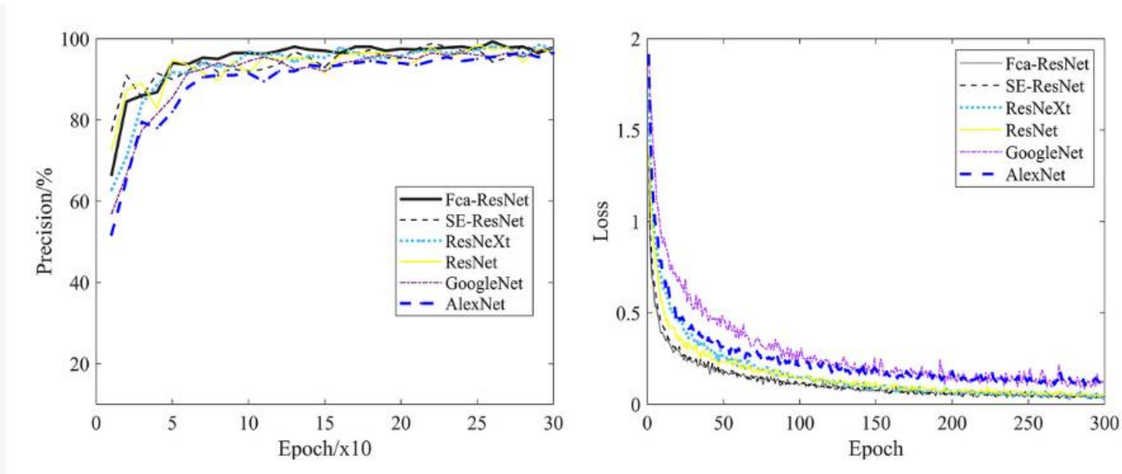

Fig. 2. Validation accuracy and training loss of different models

Fig. 2, we compared the classification results of multiple models on the validation set. By observing the confusion matrix, we can gain a visual understanding of how the models perform in different categories. Each node on the horizontal and vertical axes of the confusion matrix represents a different fault type, and the values on the diagonal indicate the degree of correspondence between the correct labels and predicted labels. From Fig. 7A, it can be observed that Fca-ResNet only misclassified three images, that is, two labels of the 4th class (0.014 in inner ring failure) were misclassified as the 5th class (0.014 in rolling element failure) and the 6th class (0.014 in outer ring failure (@6)) labels; and one label of the 9th class (0.014 in outer ring failure (@6)) was misclassified as the 7th class (0.021 in inner ring failure) label. However, all other data achieved a perfect classification result. Although several other models achieved full classification for multiple fault types, their individual performance for certain faults was inferior to that of this model.

4. Conclusion

This section will validate the effectiveness of various model architectures for different features' extraction, using the t-distributed stochastic neighbor embedding (t-SNE) method to visualize the training set in the dataset. The main purpose of t-SNE is to reduce the feature space. Similar categories are modeled by nearby points, dissimilar categories are modeled by high-probability distant points, to simplify a high-dimensional dataset into a low-dimensional feature map that retains a large amount of original information, and clustering to visualize the distribution of different features.

Figure 2 illustrates the distribution of high-dimensional feature information in the original dataset, while Fig. 9 presents the visual clustering effects of the fully connected layers in different models. From Fig. 8, it can be observed that the high-dimensional feature information of the original dataset is scattered throughout the sample space, and each type of feature information is randomly mixed together. Figure 9A shows that the clustering effect of the last fully connected layer in Fca-ResNet almost completely separates the data samples of different fault types, and directly clustered samples of the same type. Only a few categories are incorrectly clustered into other categories. The visualization of features aligns perfectly with the confusion matrix. From Figs. 9B–9F, it can be observed that SE-ResNet and ResNeXt exhibit significant overlap between two fault classes, while ResNet, GoogleNet, and AlexNet demonstrate substantial overlap among several fault classes. Though all these models achieve the accuracy of over 96.5%, their dimensionality reduction effect is notably inferior to that of Fca-ResNet. This suggests that Fca-ResNet possesses very powerful feature extraction and classification capabilities.

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