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Article

The impact of enterprise digital transformation on employee health management: A study of physiological responses from biomechanics perspective

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Abstract: This paper discusses the impact of enterprise digital transformation on employee health management from the perspective of biomechanics, especially the change law of employee physiological response and the underlying mechanism under the new work mode and technology application. By introducing a theoretical framework of biomechanics, this study evaluates the specific impact of changes such as office automation, remote work and the use of smart devices on the physical load of employees, and uses computer modeling technology to predict the potential health risks under different working conditions. In this study, a hybrid model combining Probabilistic neural Network (PNN) and Gated Recurrent Unit (GRU) was used to deal with complex time-series data analysis tasks to improve the prediction accuracy of employee health status. Experimental results show that the proposed PNN-GRU model performs well in the task of health state recognition, especially in fatigue and pain detection, with the accuracy of 94.7% and 97.1% respectively, which is significantly better than other algorithms.

Keywords: enterprise digital transformation; employee health management; biomechanics; PNN-GRU model

1. Introduction

In the present age of swift technological advancement, corporate digital transformation has emerged as an inevitable trend. As information technology evolves, cutting-edge innovations like artificial intelligence, big data analytics, the Internet of Things (IoT), and cloud computing are increasingly permeating various sectors. These technologies have significantly altered the operational and managerial paradigms of businesses [1]. This transformation not only improves the production efficiency and service quality, but also brings unprecedented opportunities and challenges to the enterprise. At the same time, it also has a profound impact on the most precious internal resources—employees. However, in this process, people often ignore the impact of digital transformation on the health management and physiological response of enterprise employees.

With the implementation of digital transformation in enterprises, the continuous improvement of office automation and the increasing popularity of remote work and virtual team collaboration, the work mode of employees has undergone fundamental changes [2]. The traditional work scene based on face-to-face communication has been replaced by more communication based on network platform. The application of smart devices enables employees to access the work system anytime and anywhere, which increases the flexibility of work, but it may also lead to the blurring of the boundary between work time and personal time, thus affecting the mental state and physical health of employees [3]. From a biomechanical point of view, long-term exposure to unnatural postures or repetitive movements may lead to overuse injuries of the musculoskeletal system, such as neck pain, carpal tunnel syndrome and other problems. Prolonged sitting in front of a computer may also lead to increased risk of cardiovascular disease, metabolic syndrome and other health risks [4]. Therefore, it is particularly important to study how to protect the health of employees while promoting digital transformation.

This study aims to deeply explore the change rules and underlying mechanisms of employee physiological response under the background of enterprise digital transformation by introducing the theoretical framework of biomechanics. Specifically, this study will evaluate the specific impact of new work patterns and technology applications on the physical load of employees, use computer modeling techniques to predict potential health risks under different working conditions, and propose reasonable and effective health management strategies based on the findings. Through these efforts, we hope to help companies better adapt to the changes brought about by digital transformation and ensure that employees can maintain good physical and mental health in the new work environment.

2. Correlational research

The impact of enterprise digital transformation on employee health is a multi-dimensional issue, involving the application of information technology, the transformation of work mode, and the changes of employees ‘physiological and psychological states.

In recent years, the rapid advancement of intelligent algorithms and big data technology [5] has made these tools pivotal in personal health monitoring and management. To enhance the precision and reliability of health assessments, researchers worldwide have developed a range of sophisticated algorithms, such as genetic algorithms, neural networks, ensemble methods, and fuzzy logic. However, Jones et al. [6] showed that the introduction of automation systems may lead to the disappearance of some jobs or the transformation of skill requirements, thus bringing uncertainty and anxiety to employees. In addition, Li and Wang [7] believed that long-term use of electronic equipment may also increase the incidence of visual fatigue, cervical spondylosis and other occupational diseases. As for the impact of new work patterns on employees, Brown [8] suggested that telecommuting and flexible work hours grant employees increased autonomy and flexibility. but they may also lead to blurring of the boundary between work and life and increase of psychological pressure. From a biomechanical point of view, Chen et al. [9] showed that maintaining poor posture or performing repetitive movements for a long time can easily cause problems in the musculoskeletal system. Research has shown that sedentary working in front of a computer can lead to chronic pain in the lower back, neck, and shoulders, and this condition is becoming more common as digital transformation accelerates. In addition, Kim et al. [10] proposed that frequent use of keyboard and mouse may also cause upper limb diseases such as carpal tunnel syndrome. And some deep learning methods applied to human behavior recognition have better predictions for the prediction of employee health. Matsui et al. [11] found that the hierarchical structure of CNN adopts a pyramid design, which can effectively aggregate the basic local features layer by layer into complex semantic patterns, and this process promotes the learning of higher quality features. In addition, the network architecture has excellent transfer learning ability, that is, the knowledge acquired in a specific domain can be easily applied to different domains. For example, by introducing new hidden layers and customizing the weights, the recognition accuracy and generalization ability of the model are significantly improved.

Hariharan et al. [12], a Malaysian scholar, emphasized that the human voice can be used as an effective indicator of health status. Based on this idea, they proposed a technique combining wavelet transform and PNN, which aims to assist medical staff in assessing the pathological state of infants by analyzing their cries. In order to reduce the number of variables in RNN and the parameter scale of hidden units, N Jaouedi, et al. [13] integrated a GRU in each node of the standard RNN. This improvement not only helps to construct long-term dependencies, but also effectively solves the problem of vanishing gradients. In their study, Imran et al. [14] applied GRU in both forward propagation and back propagation to process human bone joint data, and the results showed that the bidirectional GRU method performed better than the traditional unidirectional LSTM model. Lin et al. [15] devised a fall detection framework utilizing Open Pose for extracting human skeletal information from video frames, which is then processed through a GRU to perform fall detection. Experimental results indicate that the proposed model achieves a fall detection accuracy of up to 98.2%. For the detection task of sedentary and other behaviors, Okai et al. [16] proposed a data augmentation technique to ensure that the model can perform well even when the sensor data is incomplete.

Despite the significant technological advances and economic benefits of enterprise digital transformation, existing research often ignores its impact on employee health [17]. The introduction of automation systems may bring uncertainty and anxiety, long-term use of electronic devices may lead to visual fatigue and cervical spondylosis, telecommoing and flexible working hours may increase flexibility, but they also blur the boundary between work and life and increase psychological stress. In addition, new work patterns and technology applications may also lead to musculoskeletal problems, such as chronic pain caused by sedentary work patterns and carpal tunnel syndrome caused by frequent use of the keyboard and mouse [18].

Therefore, it is particularly important to explore the change law of employee physiological response from the perspective of biomechanics. This study not only fills a gap in this field, but also provides a new perspective for understanding and addressing the health challenges brought about by digital transformation. By introducing a biomechanical theoretical framework, we are able to more deeply analyze the health challenges faced by employees in novel work environments and develop effective interventions. This not only helps to improve the quality of life and work efficiency of employees, but also lays a solid foundation for the sustainable development of enterprises.

3. Method

In this paper, from the perspective of biomechanics, a powerful hybrid model is constructed, which can not only deal with complex time-series data analysis tasks, but also perform well in different application scenarios to improve the effectiveness of employee health management after enterprise digital transformation.

3.1. Principle of biomechanics

In the context of enterprise digital transformation, the biomechanical perspective provides an important theoretical framework for understanding the physiological response of employees. Biomechanics studies the structure and movement of the human body, and explores the reaction of muscles, bones and joints under different working conditions [19]. By introducing biomechanical principles, we can more deeply analyze the health challenges faced by employees in novel work environments and develop effective interventions.

3.1.1. Fundamentals of biomechanics

Biomechanics uses the laws of physics to describe human motion and the mechanism of action of forces. Newton's second law is one of the basic formulas that explains the effects of external forces on the body:

$$F = ma \tag{1}$$

where F represents the net force acting on the object (in Newtons, N), m denotes the mass of the object (in kilograms, kg), and a signifies the acceleration (in meters per second squared, m/s^2). In the case of the human body, this can be used to calculate the impact of external loads or postural changes on the human body. Another key concept is the lever principle, which describes the relationship of moments M as follows.

$$M = rF\sin(\theta) \tag{2}$$

Here r is the moment arm length, F is the applied force, and θ is the Angle between the direction of the force and the moment arm. This principle is particularly useful for analyzing spinal load, especially when poor posture is maintained for long periods of time.

3.1.2. Influence of digital transformation on biomechanical parameters

With the implementation of digital transformation in enterprises, the work patterns of employees have changed significantly, including more sedentary time and frequent use of keyboards and mice. These new work habits can lead to problems such as muscle fatigue, postural stress, and repetitive motion injuries. For example, staying in the same position for a long period of time causes the muscles to contract continuously, which causes fatigue. According to the Hill muscle model, the tension T of the muscle can be expressed by the following equation:

$$T = a + be^{-cL} \tag{3}$$

When the muscle is in a shortened state, energy expenditure increases, leading to faster fatigue accumulation. Poor working posture will increase the stress on the spine and joints, especially in the case of hunched back, the pressure on the lumbar spine is increased. The cumulative damage theory suggests that small but frequent stress accumulation may eventually lead to tissue damage, which is mathematically expressed as follows.

$$D = \sum_{i=1}^{n} f_i \cdot d_i \tag{4}$$

In order to accurately assess the physiological response of employees in the digital work environment, we need to establish a comprehensive evaluation system that includes multiple biomechanical parameters. This system can be implemented by computer modeling and machine learning algorithms. The specific steps include: first, real-time data such as muscle activity and posture changes in daily work are obtained through sensor devices (such as electromyography and pressure pads). Secondly, signal processing techniques were applied to extract key features, such as maximum muscle activation level and average posture Angle. Then, a predictive model was used, which was able to predict potential health risks based on the input biomechanical parameters. Finally, the accuracy and reliability of the model were ensured by cross-validation of the experimental data.

3.2. Probabilistic neural network, PNN

3.2.1. Basic theory of PNN

PNN is a probabilistic classifier based on Bayes theorem, which is especially suitable for pattern recognition and classification tasks. It estimates the posterior probability by calculating the distance between the input sample and the center of each class in the training set. The advantage of PNN lies in its faster learning ability and its ability to handle nonlinear data [20].

The PNN consists of four main layers: The input layer receives the data points to be classified $x = (x1, x2, ..., xd)$, where d is the feature dimension; The pattern layer (also called kernel layer) treats each training sample x_i as the center of a Gaussian kernel function, and for a given test sample x, the pattern layer computes the similarity between that sample and all training samples. A common kernel is the Gaussian kernel:

$$K(x, x_i) = \exp\left(-\frac{\parallel x - x_i \parallel^2}{2\sigma^2}\right) \tag{5}$$

The summation layer performs a weighted sum of all pattern layer outputs belonging to the same category to obtain the likelihood value for each category. Let the total number of categories be C, then the likelihood value S_j of class j can be expressed as follows.

$$S_j(\mathrm{x}) = \sum_{i \in \mathrm{Class}\, j} K(\mathrm{x}, \mathrm{x}_i) \tag{6}$$

The output tier computes the posterior probability of each category in accordance with Bayes' theorem and designates the class possessing the highest posterior probability as the ultimate classification outcome. Precisely, for a particular test sample x, the posterior probability $P(C_j|x)$ can be formulated as follows.

$$P(C_j|x) = \frac{S_j(x) \cdot P(C_j)}{\sum_{k=1}^{C} S_k(x) \cdot P(C_k)} \tag{7}$$

3.2.2. Optimize the smoothing factor

In this paper, the Artificial Fish Swarm Algorithm (AFSA) is employed to optimize the smoothing factor of the Probabilistic Neural Network (PNN). AFSA is a swarm intelligence-based optimization algorithm inspired by the behavioral patterns of fish in nature. The algorithm simulates the behaviors of fish foraging, flocking and obstacle avoidance, and searches for the global optimal solution through the cooperation and competition among individuals. AFSA performs well in dealing with complex optimization problems, especially in multi-modal, nonlinear and high-dimensional space optimization tasks [21].

In AFSA, each "artificial fish" represents a candidate solution and its position corresponds to a point in the problem space. Schools of fish guide their behavior through a series of rules, including foraging behavior, flocking behavior, and obstacle avoidance behavior. These behaviors help the fish swarm to explore the problem space and gradually converge to the optimal solution or near the optimal solution.

1) Foraging behavior

Foraging behavior is the process of artificial fish searching for a better solution. For each artificial fish x_i, it tries to move towards other fish in its neighborhood to find a better food source (i.e., a better solution). If there is a better solution x_j in the neighborhood than the current one, the fish will move one step toward x_j:

$$x_i = x_i + \text{step} \cdot \frac{x_j - x_i}{\| x_j - x_i \|} \tag{8}$$

Here, step is the step size parameter that controls the distance moved each time. If there is no better solution in the neighborhood, the fish will randomly choose a direction to move tentatively.

2) Group behavior

The swarming behavior allows the fish to maintain a certain degree of aggregation, thus increasing the chance of finding the global optimal solution. When a particular fish finds itself surrounded by more of its own kind and has a higher average fitness, it tends to move closer to these fish. Specifically, if the number of fish in the neighborhood Nneighbor reaches a certain threshold and the average fitness Favg is higher than the set threshold, the fish will move toward the center of the neighborhood *x* center [22]:

$$x_i = x_i + \text{step} \cdot \frac{x_{\text{center}} - x_i}{\| x_{\text{center}} - x_i \|} \tag{9}$$

3) Obstacle avoidance behavior

The obstacle avoidance behavior ensures that the fish does not get stuck in local optimal solutions or invalid regions. When a certain fish finds that its surroundings are not suitable to continue (for example, the fitness is too low or there are obstacles), it will randomly choose a new direction and try to move. This behavior helps the fish to escape from the local extreme points and continue to explore the broader solution space.

3.3. Gated recurrent unit, GRU

GRU is a variant of Recurrent Neural Network (RNN), which aims to solve the problem that long-term dependencies are difficult to capture in traditional RNNS. GRU effectively alleviates the vanishing gradient problem by introducing the update gate and reset gate mechanism, and can better deal with the time dependence in sequence data. The core concept of the GRU involves controlling information flow via two gating mechanisms—the update gate z_t and the reset gate r_t, to determine which information should be retained or discarded. Specifically, at each time step t, the GRU receives the current input x_t and the previous hidden state h_{t-1}, and updates the current hidden state h_t based on this information [23].

3.3.1. Update gate

The update gate z_t determines the extent to which old information should be retained and new information should be added to the current hidden state. It is calculated using a sigmoid activation function:

$$z_t = \sigma(W_z[x_t; h_{t-1}] + b_z) \tag{10}$$

where W_z represents the weight matrix, b_z stands for the bias term, $[x_t; h_{t-1}]$ implies combining the input x_t and the previous hidden state h_{t-1} to create a vector, and σ is the sigmoid activation function with its output falling within the range (0, 1).

3.3.2. Reset gate

The reset gate r_t controls which parts of the hidden state h_{t-1} at the previous time instant should be ignored. Again, it is calculated using a sigmoid activation function:

$$r_t = \sigma(W_r[x_t; h_{t-1}] + b_r) \tag{11}$$

3.3.3. Candidate hidden state

Next, the candidate hidden state $\tilde{h}_t$ is calculated based on the current input x_t and the hidden state $r_t \cdot h_{t-1}$ at the previous moment after adjustment by the reset gate. A tanh activation function is used to make sure the output is within reasonable bounds:

$$\tilde{h}_t = \tanh(W_h[x_t; r_t \cdot h_{t-1}] + b_h) \tag{12}$$

where enotes element-wise multiplication, the Hadamard product.

3.3.4. Final hidden state

The final hidden state h_t is determined in combination by the update gate z_t and the candidate-hidden state $\tilde{h}_t$. The equation is presented as follows:

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ \tilde{h}_t \tag{13}$$

This formula states that if the update gate z_t is close to 1, more new information will be added; If it is close to 0, more old information is retained.

3.4. Innovative optimization algorithm PNN-GRU

Firstly, the input time series data is preprocessed, including normalization, segmentation of training and test sets, and construction of time Windows. Normalization ensures that all feature values are scaled to reasonable intervals. The training set and test set were divided to ensure the accuracy of model evaluation. A fixed-length time window T is constructed so that the GRU captures the timing features. The preprocessed data format is suitable for subsequent GRU and PNN processing [24]. Next, the GRU layer is used to process the time series data and extract the feature representation with time dependence. At each time step t, by computing the update gate, reset gate, candidate hidden state and final hidden state, the GRU takes in the current input x_t and the hidden state h_{t-1} from the previous time step and modifies the current hidden state h_t. Following T time steps, the GRU produces the final hidden state h_t, which serves as the temporal characteristic representation for this sample.

To more effectively align the features extracted by GRU with the input prerequisites of PNN, these features need to be appropriately transformed and standardized. Dimensionality reduction methodologies like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) are employed to diminish the feature dimensions while preserving the essential information. Moreover, the feature values are modified to possess zero mean and unit variance via the Z-score normalization technique to enhance the classification efficacy of PNN. Subsequently, the features that have been extracted and transformed by GRU are fed into PNN for classification determination. A PNN is composed of an input layer, a pattern layer, a summation layer, and an output layer [25]. The pattern layer regards each training sample as the epicenter of the Gaussian kernel function and computes the resemblance between the test sample and all the training samples. The summation layer conducts a weighted summation of all the outputs from the pattern layer that pertain to the same category to procure the likelihood value for each category. The output layer computes the posterior probability of each class in accordance with Bayes’ theorem and designates the class with the highest posterior probability as the ultimate classification outcome.

To ensure the effectiveness and generalization ability of the model, it needs to be fully trained and optimized. After randomly initializing the weight matrix and bias term of GRU and PNN, the forward propagation operation of GRU layer and PNN layer is performed in turn to calculate the prediction results. The model parameters are updated by backpropagation and iteratively updated using optimization algorithms such as Adam or SGD. Hyperparameters (like learning rate, batch size, regularization coefficient, etc.) are tuned by methods like grid search or random search to get the best performance.

In summary, through the above steps, we can successfully fuse GRU and PNN to form a new algorithm model PNN-GRU. This hybrid model not only inherits the advantages of GRU in processing time series data, but also makes full use of the efficiency and robustness of PNN in classification tasks. Through reasonable design and optimization, the model can show excellent performance in a variety of application scenarios. This study aimed to assess the specific impact of new work patterns and technology applications on the physical load of employees. To achieve this goal, we chose the PNN-GRU model due to its ability to handle complex time series data and its excellent performance in capturing long-term dependencies. From a biomechanical point of view, the model can accurately predict potential health risks under different working conditions. For example, the GRU component captures temporal patterns of employee activity, while the PNN part classifies these patterns into health states based on biomechanical parameters. Specifically, GRU effectively alleviates the gradient disappearance problem through the update gate and reset gate mechanism, which can better deal with the time dependence in sequence data. As a probabilistic classifier based on Bayes theorem, PNN is especially suitable for pattern recognition and classification tasks. It estimates the posterior probability by calculating the distance between the input sample and the center of each class in the training set, so as to achieve efficient classification.

4. Application of model

4.1. Dataset

The experimental data in the dataset used in this paper comes from two Samsung smartphones (specific model is Galaxy Nexus I9250, running Android OS 5.1.1) placed in the pants pockets of the subjects. The two phones are equipped with a Bosch BMA220 acceleration sensor and are capable of transmitting data from a three-axis accelerometer, a three-axis gyroscope, and a magnetometer via Bluetooth. The dataset contains 700 samples from different test subjects, covering the daily activities and physiological behaviors of enterprise employees, and the age range of subjects is 18 to 60 years old, including men and women.

4.2. Experimental environment

The deep learning models within this study were realized by means of the PyTorch library. The computing platform is furnished with an AMD Ryzen 7 6800H processor that operates at a clock speed of 3.59 GHz, featuring 8 cores, along with 16 GB of RAM and a 6 GB NVIDIA GeForce GTX 1660 SUPER GPU. All parameters of the model were initialized through a random orthogonal initialization approach. During training, SGD (Stochastic gradient Descent) optimizer is used for backpropagation learning. The training Settings included a batch size of 32, a training period (epochs) of 2000, and a learning rate of 1×10^{-3}.

4.3. Comparison model

In order to show that the PNN-GRU proposed in this paper is very suitable for the application of enterprise employee health assessment, the experiment evaluates PNN with Generalized Regression Neural Network (GRNN), Convolutional Neural Network (CNN) and Backpropagation (BP) Neural Network respectively.

GRNN is a non-parametric neural network model specifically designed for regression tasks, which is able to provide accurate predictions quickly without the need for extensive training. GRNN fits the input data by smoothing spline interpolation method, which is suitable for continuous numerical prediction problems. Its structure is simple and mainly includes four layers: The input layer receives the original data features, the pattern layer calculates the similarity between each training sample and the input, the sum layer summarizes the target variable value weighted by similarity, and the output layer generates the final prediction results. The advantages of GRNNS are their faster learning ability, no iterative training, and robustness to noisy data, making them particularly suitable for dealing with small sample datasets and real-time prediction tasks.

CNN is a deep learning model specially designed for processing grid-structured data (such as images and videos), which performs well in computer vision tasks. CNN applies multiple filters to extract local features through convolutional layers, introduces nonlinearity by combining activation functions (such as ReLU), and uses a pooling layer to reduce the spatial dimension of the feature map and provide translation invariance. Subsequently, the fully connected layer maps the extracted features to the output categories, and finally the output layer generates the prediction results. The advantage of CNNS lies in their local perception, parameter sharing mechanism, and hierarchical feature extraction, which enables them to efficiently capture features from low-level (such as edges) to high-level (such as object shapes).

BP Neural Network is a commonly utilized feedforward artificial neural network. It conducts supervised learning via the back propagation algorithm and is applicable to classification and regression tasks. Generally, a BP network comprises an input layer, one or more hidden layers, and an output layer. The input layer takes in the original data features, the hidden layer non-linearly transforms the data by employing an activation function (such as Sigmoid, ReLU, or Tanh), and the output layer produces the final prediction. During the training phase, the BP network utilizes the back propagation algorithm to adjust the weights so as to minimize the error between the predicted value and the true label. Its advantage is that it can automatically learn complex nonlinear mapping relationships, and its structure is flexible, and more hidden layers or neurons can be added according to the task requirements.

4.4. Experimental results and analysis

In each overall health assessment model, 300 separate neural networks were originally used. In order to improve the operation efficiency, this paper proposes to integrate these 300 neural networks into a single neural network, that is, 300 sets of sample data are merged into a set of comprehensive data. The steps are as follows:

Principal Component Analysis and Dimension Unification: First, Principal Component Analysis (PCA) was performed on 300 groups of sample data. After processing, 242 sets of data have 4-dimensional variables, while 58 sets of data have 3-dimensional variables. To unify the dimensions, 58 sets of 3-dimensional variables were extended to 4 dimensions, ensuring that all data had consistent feature dimensions.

Standardization: Next, 300 groups of 4-dimensional variable data are standardized to make the eigenvalues of each group of data fall within the preset normal parameter range (xmin, xmax). Standardization helps to eliminate the dimensional differences between different features and improves the stability and efficiency of model training.

Data integration: Finally, 300 groups of 100 × 4 matrix data are integrated into a set of 30,000 × 4 matrix data. In this way, all sample data are merged into one large dataset, which is convenient for subsequent neural network processing and training.

In this experiment, Precision, Recall and $F1$-score are chosen as the model evaluation metrics, and the specific calculation formulas are presented in Equations (14)–(16). In this context, TP stands for the quantity of positive examples that are correctly recognized as the positive class, FP denotes the number of negative examples that are wrongly identified as the positive class, and FN represents the number of positive examples that are incorrectly classified as the negative class.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{14}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{15}$$

$$F1 = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{16}$$

4.4.1. Classification results and analysis

Table 1 presents the classification results of the model on the test set, showing high recognition accuracy in healthy states such as walking, sitting, falling, fatigue and pain. This proves the effectiveness of the image feature extraction and classification method based on PNN-GRU in the health monitoring of enterprise employees. The system can identify the health status of employees in real time and accurately, and provide strong support for health management and intervention.

Table 1. Classification result statistics.

Categories	Number of samples	Identifying the exact quantity	Accuracy (%)
Walking	450	424	94.2
Sit down	500	465	93.0
Fall down	120	111	92.5
Fatigue	340	322	94.7
Pain	420	408	97.1

As can be seen from the data in **Table 1**, the PNN-GRU model performs well in the recognition of all kinds of health states, especially in the detection of fatigue and pain. Specifically, the model achieves 94.7% accuracy in recognizing the fatigue state and 97.1% accuracy in recognizing the pain state. These results show that the PNN-GRU model not only has strong classification ability, but also can provide highly reliable predictions in complex health assessment tasks.

4.4.2. Comparative experiments

Experiments were carried out for the four comparison models, and each group was repeated for 10 times to form 10 times of models, and the accuracy and running time of each model were recorded. As shown in **Figures 1** and **2**, and **Table 2**.

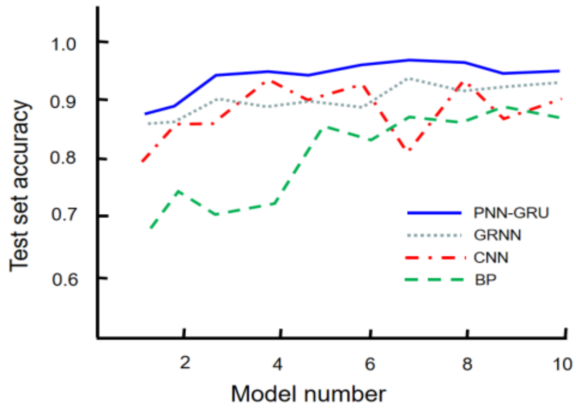

Figure 1. Accuracy of four algorithms.

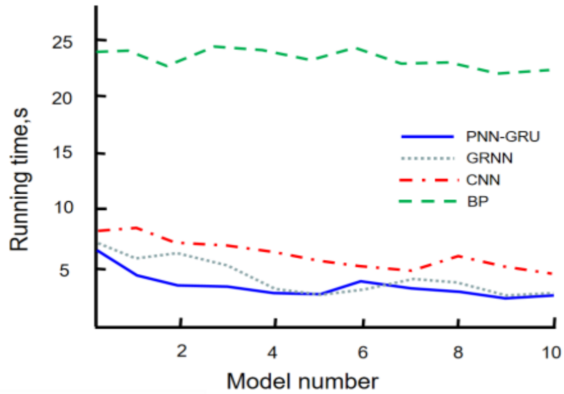

Figure 2. The running time of the four algorithms.

Table 2. Comparison of four algorithms for health assessment.

Algorithm	*P*, %	*R*, %	*F*1, %	Running time, s
GRNN	94.23	92.59	93.40	4.58
CNN	94.45	94.12	94.28	6.27
BP	82.98	81.37	82.17	23.84
PNN-GRU	97.92	96.13	97.02	3.06

According to the experimental data, the proposed PNN-GRU model shows significant advantages in the health state recognition task. Through comparison, it can be seen that the PNN-GRU model not only significantly outperforms other algorithms in terms of classification accuracy, its *F*1 score is 3.62% higher than that of GRNN, 2.74% higher than that of CNN, and 14.85% higher than that of BP algorithm. In addition, the running time of PNN-GRU model is about 1.5 s faster than GRNN, 3.21 s faster than CNN, and nearly 20 s faster than BP algorithm. This high operational efficiency enables the PNN-GRU model to provide fast response in application scenarios such as real-time health monitoring and rapid diagnosis.

The reason why the PNN-GRU model can achieve such excellent performance is mainly due to its combination of the time series feature processing ability of Probabilistic neural Network (PNN) and the effective capture of long-term dependencies by Gated Recurrent Unit (GRU). This combination not only improves the classification accuracy of the model, but also greatly reduces the training and prediction time. Therefore, the PNN-GRU model not only has higher classification accuracy, but also can achieve efficient processing under limited computing resources, which is suitable for a variety of complex health state recognition tasks.

In summary, the proposed PNN-GRU model shows great application potential in the field of health state recognition by virtue of its excellent classification performance and efficient running speed, and provides a solid foundation for related research and practical applications.

To apply these research findings to practical health management, companies should consider implementing ergonomic interventions such as adjustable desks and regular breaks to reduce stress on the musculoskeletal system. In addition, wearable devices can monitor health indicators in real time and help in the early detection of potential health problems. Combining these strategies with the PNN-GRU model can significantly improve employee health and productivity. Specific recommendations include:

Adjust your work environment: Introduce ergonomic office furniture such as height-adjustable desks and curvy chairs to reduce the stress on your spine and joints caused by prolonged sitting.

Promote healthy habits: Encourage employees to perform regular stretching and eye relaxation exercises to reduce visual fatigue and neck pain caused by prolonged use of electronic devices.

Leveraging technology: Deploy wearable devices and iot technologies to monitor employees' health status in real time, provide timely warning of potential health risks, and provide personalized health advice.

5. Conclusions

This study deeply explored the impact of corporate digital transformation on employee health by introducing biomechanical theory and combining with the PNN-GRU model. Experimental results show that the PNN-GRU model performs well in health state recognition, with the precision, recall and $F1$ score of 97.92%, 96.13% and 97.02% respectively, and the running time is only 3.06 s. Especially, the accuracy of fatigue and pain detection reaches 94.7% and 97.1% respectively, which is significantly better than other algorithms. These results show that the PNN-GRU model is not only accurate in classification, but also efficient in dealing with complex health assessment tasks, which is suitable for real-time health monitoring and rapid diagnosis. Future research can focus on optimizing the PNN-GRU model to enhance its generalization ability. The combination of wearable devices and iot technologies can provide continuous health monitoring, enabling real-time adjustment of the work environment. Machine learning techniques can further improve the predictive accuracy of a model, ensuring that it remains effective across different industries and Settings. In addition, integration with other advanced technologies such as big data analytics, cloud computing can be explored to achieve a more comprehensive and intelligent health management solution.

Although this study focused on short-term health effects, future research should explore the health risks associated with long-term exposure to novel work patterns. Longitudinal studies can provide valuable insights about chronic health conditions to help develop sustainable health management strategies. Companies should also consider using predictive analytics to predict long-term health trends and take preventive actions accordingly. Specific recommendations include:

Carry out long-term health monitoring: track the long-term health changes of employees and establish health records through regular physical examinations and health questionnaires.

Create a personalized health plan: Create a personalized health management plan that covers diet, exercise, and mental health based on the individual differences of employees.

Enhance employee training: improve employees' awareness of long-term health risks, provide relevant knowledge training and guidance on preventive measures to help them develop good lifestyle habits.

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