Construction of mental health monitoring system based on model transfer learning algorithm

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Abstract: In order to monitor people's mental health in real-time and effectively, this study has conducted in-depth research on the model transfer learning algorithm, including its learning process, classification criteria, network structure optimisation, etc. The research takes model transfer learning algorithm as the main research method, and innovatively adopts residual learning and gradient descent algorithm to optimise the performance of model transfer learning algorithm, and then compares and analyses the application effects of model transfer learning algorithm and traditional machine learning algorithm in various data sets of mental health monitoring, so as to ensure the accuracy of monitoring results. The results show that the model transfer learning algorithm is significantly better than the traditional machine learning algorithm in accuracy, recall and F1 score, and it requires less network training time. This shows that the mental health monitoring system based on model transfer learning algorithm has good performance and can monitor mental health accurately and efficiently.

Keywords: model; transfer learning; mental health; monitoring system.

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1 Introduction

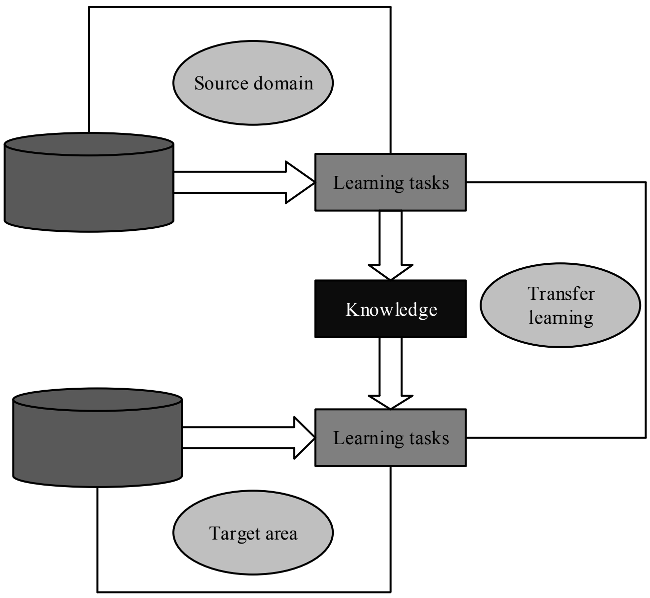
With the sustainable development of society, the pressure people face in their daily production and life has increased significantly, resulting in a large number of people in a state of mental sub-health. Mental health problems have been paid more and more attention. Serious mental health problems will not only have a great negative impact on individuals, hinder the development of their normal life activities, but also pose a certain threat to the society. Generally, researchers collect information about people's social perception and behaviour to accurately analyse their mental health status (Lasheng et al., 2019). Social perception signals have certain diversity, including audio signals, behavioural signals, psychological perception signals and other types. Audio signals cover a large amount of emotional and social information, so they are usually used as the main evaluation feature for analysing mental health status (Xu et al., 2019; Li et al., 2019). Under this condition, more and more wearable devices are put into use to extract and collect people's audio signals in daily situations. Transfer learning is a widely used machine learning algorithm, which can effectively solve the problem of lack of training data in machine learning. Relevant research shows that transfer learning algorithm can improve the stability and recognition accuracy of network training in the process of wireless signal modulation and classification (Gu and Dai, 2021). In view of this, this research focuses on the model transfer learning algorithm, applies the algorithm to wearable devices and constructs the corresponding mental health monitoring system, aiming to improve the accuracy of mental health prediction, mine and predict people's mental health status and provide reliable data support for physical and mental health assessment.

2 Model-based transfer learning algorithm and its system construction

2.1 *Definition and classification of transfer learning algorithm*

Transfer learning algorithm is a machine learning algorithm based on model level. It usually adopts the way of relaxing training data and test data to realise the effective transfer of knowledge from source domain to target domain, so as to solve the problem of lack of training data in machine learning. In the process of transfer learning, it mainly includes two basic concepts: domain and task. Domain mainly refers to data and its generated probability distribution, which is divided into source domain and target domain. The former refers to the region covering a large amount of knowledge or data annotation, that is, the object of transfer learning algorithm. The latter represents the objects that need to be labelled. The task represents the goal of transfer learning, which includes the label and the function corresponding to the label (Kang et al., 2019; Li et al., 2020). Transfer learning helps to improve the lack of data in network model training, and can have a significant positive impact on many research fields. Its learning process is shown in Figure 1.

Figure 1 Schematic diagram of learning process of transfer learning



According to Figure 1, the learning process of transfer learning is usually divided into three parts: transfer learning process, source domain and target domain. The source domain target task in transfer learning has a large data set, which can help the smooth development of model training; Migration learning also includes target tasks composed of a given finite data set. The transfer learning model will screen the target tasks in the source domain, eliminate the useless knowledge, mine the useful knowledge and then transfer it to the target task (Cai et al., 2020). The marked source domain and the unmarked target domain are set as D_s and D_t, respectively, and $D_s = \{x_i, y_i\}_{i=1}^{n}$ and $D_t = \{y_i\}_{i=n+1}^{n+m}$. Let the data distribution of the data set located in the source domain and the target domain be $P(X_s)$ and $P(x_t)$ respectively, and $P(X_s) \neq P(x_t)$. The purpose of transfer learning is to learn the knowledge from D_s to D_t. The research focus of this topic is to segment the mental health data information in the target task in the source domain, so as to make it smoothly migrate to the specific scene covering limited information, that is, the target domain. Its core idea is shown in Figure 2.

Figure 2 Schematic diagram of the core idea of the transfer learning algorithm

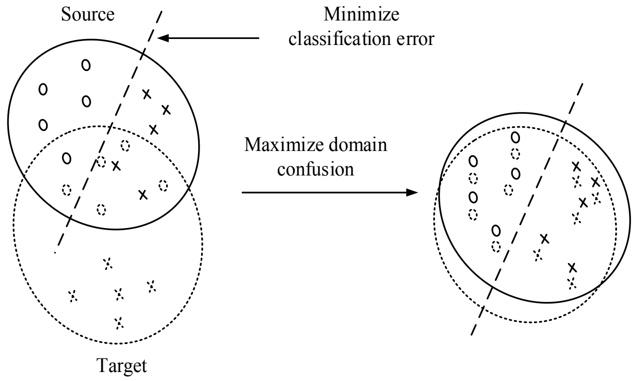


Figure 2 shows that the transfer learning algorithm needs to minimise the differences between different domains and the category loss in the source domain by matching the feature distribution of different domains, so as to obtain the invariant features in the domain, and finally realise the adaptive processing of the domain (Lin et al., 2021). Transfer learning can be classified according to different standards. If the target domain data set has labels or not as the classification standard, it can be divided into three types: supervised learning, semi supervised learning and unsupervised learning. If features are used as classification criteria, they can be divided into two types: one is isomorphic transfer learning, which is a transfer learning algorithm with the same feature semantics and dimension; The second is heterogeneous transfer learning, which means that its characteristic semantics and dimensions are not completely consistent. If the learning method is used as the classification standard, it can be divided into four learning types for transfer learning based on samples, features, models and relationships (Starly et al., 2020). Among them, model-based migration learning is a model level, and the remaining three are data-level migration learning algorithms. The former can make full use of the similarity between the source domain data set and the target domain data set model in practical application, so as to learn the common knowledge between the two domain data sets in the migration process (Liu et al., 2019). The comparison between traditional machine learning algorithm and transfer learning algorithm in the learning process is shown in Figure 3.

Figure 3 Comparison of learning processes of different learning algorithms

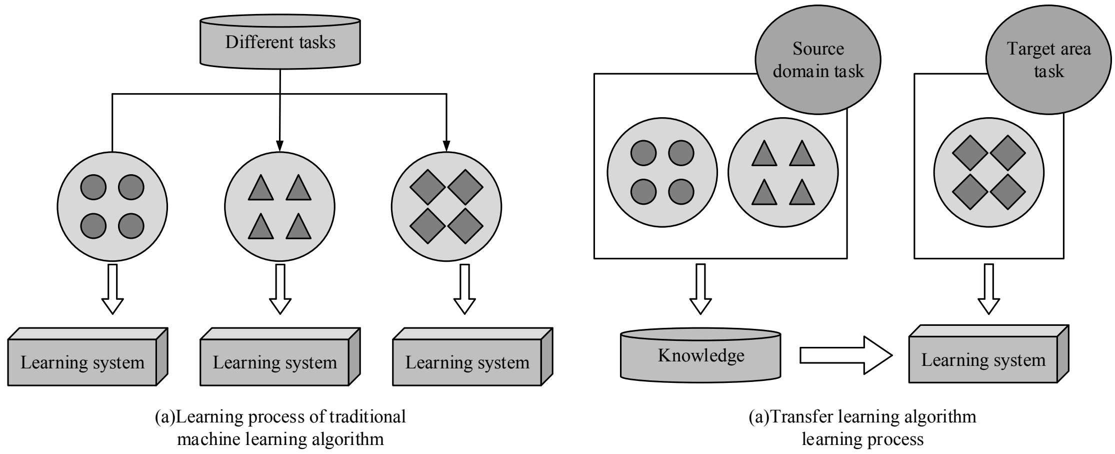


Figure 3(a) shows the learning process of the traditional machine learning algorithm, from which it can be seen that the algorithm needs to effectively obtain independent information from each sub-task and match each sub-task to a separate learning system. According to Figure 3(b), the transfer learning algorithm can transfer the source domain task to the target domain task according to the high-quality training data contained in the target task, and obtain the corresponding knowledge. This method requires less learning systems, has higher training and learning efficiency and can achieve better transfer learning effect.

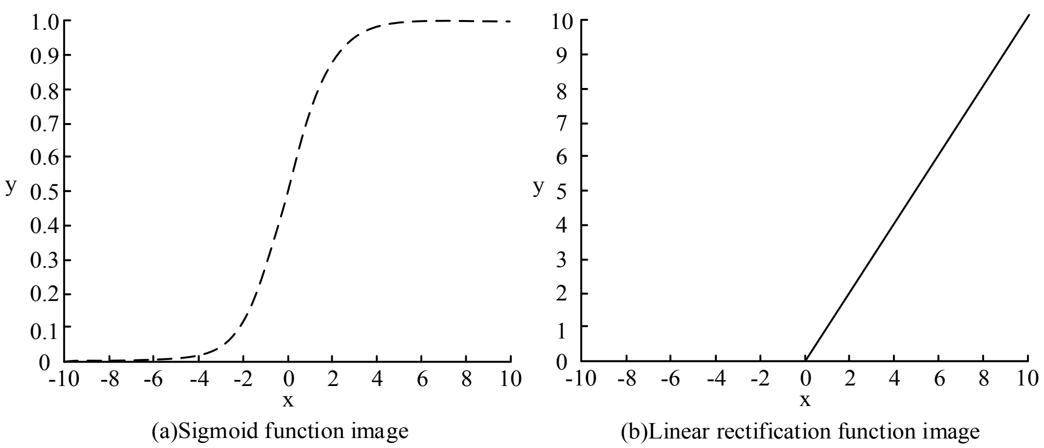
2.2 *Improved VGG network structure based on residual learning*

In the model-based transfer learning algorithm, there are two different types of basic networks, and their original structure is Visual Geometry Group (VGG) network. The difference between the two basic networks lies in the size of their convolution kernel, one of which is 5 × The convolution kernel of 5 is 3 × Convolution kernel of 3. In different stages of migration learning, there are certain differences in the similarity between data sets and the degree of similarity determines the number of useful knowledge and migration network layers in the process of migration learning. Therefore, it is necessary to improve and optimise the VGG network structure (Daniel and Kumar, 2020). There are different network layers in convolutional neural network. The input layer is used to pre-process the image, including whitening, de averaging and normalisation; The convolution layer uses discrete convolution to obtain the local information of the target image; The function of activation function layer is to realise nonlinear mapping and increase the network expression ability. Common activation functions include Sigmoid function and linear rectification function, and the function image is shown in Figure 4.

Figure 4(a) is a Sigmoid function image with a mapping range of [0, 1], which is usually regarded as the threshold function of neural network. Figure 4(b) is an image diagram of a linear rectification function. It is a modified linear unit, which is usually regarded as a slope function under the mathematical definition. The definition of Sigmoid function is shown in equation (1).

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

Figure 4 Function image diagram of common activation functions



By deriving equation (1), equation (2) can be obtained.

$$f'(x) = f(x)(1 - f(x)) \tag{2}$$

The linear rectification function is usually expressed as equation (3).

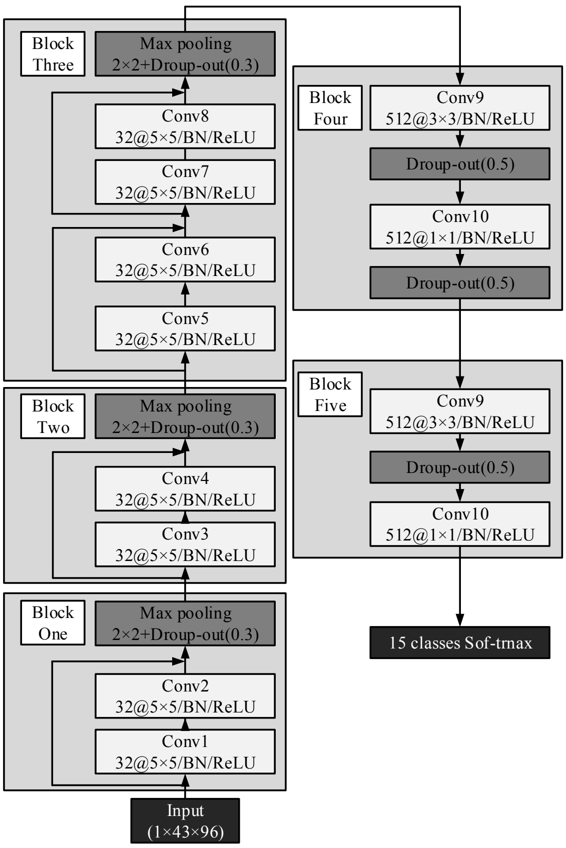
$$\phi(x) = \max(0, x) \tag{3}$$

If the derivative of equation (3) is obtained, there is equation (4).

$$\phi'(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{4}$$

In convolutional neural network, the activation function of neuron is usually acted as by linear rectification function, so the output result of the neuron after linear transformation will be defined as the output result of the whole neural network. Therefore, compared with Sigmoid function, linear rectifier function has stronger generalisation ability and can effectively avoid the phenomenon of gradient dispersion or gradient disappearance. Therefore, linear rectifier function is selected as the activation function in VGG neural network. In order to completely avoid the network training risk caused by the disappearance of gradient, a shallow network structure is usually used as the framework of network training. At the same time, in order to ensure the generalisation ability of network model, it is necessary to add residual learning unit (Meng, 2020). The residual learning unit is mainly used to change the size of the convolution kernel according to the implementation of the data set, and finally obtain comprehensive receptive field information. Figure 5 shows the improved VGG network structure.

Figure 5 VGG network structure based on residual learning unit



According to Figure 5, based on 5 × 5, adding residual learning unit to VGG network with convolution kernel can make it not only show strong generalisation ability as a shallow network structure, but also show its superior performance in transfer learning. Size 3×3, the convolution kernel of 3 can be improved in the same way as the former by adding residual learning units to enhance its generalisation ability and learning performance, and the time it takes is far less than that of 5 × 5.

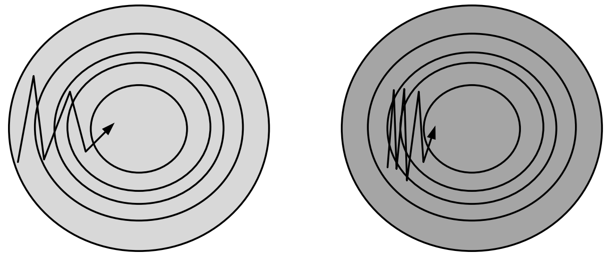
2.3 Model migration learning algorithm based on wearable data set

In neural network, the input object is usually image information. However, this subject needs real-time monitoring for mental health, so audio information should also be used as the input of neural network. This topic will build a model migration learning algorithm based on wearable data sets, that is, with the help of wearable data sets, the model migration learning algorithm will be used to input speech features (Subramaniyam et al., 2019). In the actual network training process, it is necessary to re train the network in the task data set of the target domain to make it learn the characteristics of the data set of the source domain and the target domain. Because there are some differences in the tensor dimensions of input features in different network training stages, in the process of migration learning, the layers of different baseline networks migrating to the target domain data set are also different, so the gradient descent algorithm is often used to minimise the objective function. Let the learning rate be ε_k, where ε_k represents the number of iterative training; If the initial parameter is expressed as θ, the calculation formula for calculating the gradient estimation is shown in equation (5).

$$\hat{g} \leftarrow +\frac{1}{m}\nabla_\theta \sum L\left(f\left(x^i, \theta\right), y^i\right) \tag{5}$$

In formula (5), $\hat{g}$ represents gradient; m represents the number of samples selected in the training set; x^i represents the training object and y^i represents its corresponding target (Zhang et al., 2021). In order to improve the operation efficiency of the gradient descent algorithm and shorten the time of model training, the random gradient descent algorithm with momentum can be used to optimise it, so as to improve the convergence speed of the model. The renderings of the two gradient descent algorithms are shown in Figure 6.

Figure 6 Effect diagram of gradient descent algorithm before and after optimisation



(a)Traditional gradient descent algorithm

(b)Gradient descent algorithm with momentum

Figure 6(a) shows the traditional gradient descent algorithm, which has the main disadvantage of low efficiency in the learning process; Figure 6(b) shows a gradient descent algorithm with momentum, which can improve the efficiency of processing gradients with noise and accelerate the convergence speed of network training. Its update rules are shown in equation (6).

$$v \leftarrow \alpha v - \varepsilon \nabla_\theta \left(\frac{1}{m} \sum L\left(f\left(x^i, \theta\right), y^i \right) \right) \tag{6}$$

In equation (6), v represents the velocity at which gradient elements are accumulated; α represents the super parameter, whose value range is [0, 1], which can play a decisive role in the rate of attenuation of gradient contribution. The greater the value of α, the greater the influence of gradient on direction. The gradient descent algorithm with momentum can effectively adjust the gradient descent rate, make the gradient descent process more controllable and finally optimise the network learning process (Ytabc et al., 2021). When monitoring mental health status, measurement parameters need to be used to accurately evaluate the detection performance (Guo et al., 2022). IoU is a parameter that can give the proximity of the prediction object between the prediction area and the real area. First, four values need to be defined, as shown in Table 1.

Table 1 Confusion matrix of classification results

Real situation		*Positive example*	*Counterexample*
Prediction results	Positive example	*TP* (Real example)	*FP* (False positive cases)
	Counter example	*FN* (False counterexample)	*TN* (True counterexample)

According to Table 1, IoU can be defined, and its calculation formula is shown in equation (7).

$$IoU = \frac{TP}{FP + TP + FN} \tag{7}$$

It can be seen from equation (7) that score IoU is a count-based measure, and the probability value is usually used to approximate the score of IoU, so the accuracy rate P and recall rate R are defined and the former is shown in equation (8).

$$\mathrm{P} = \frac{TP}{TP + FP} \tag{8}$$

The accuracy rate P represents the ratio of TP to all targets determined as positive samples, and the calculation formula of recall rate R is shown in equation (9).

$$\mathrm{R} = \frac{TP}{TP + FN} \tag{9}$$

The recall rate R in equation (9) represents the ratio of TP to all true positive samples. In general, the higher the *p*-value, the lower the *R*-value and there is a negative correlation between them. Based on this, the average F1-score of P and R is usually used to verify the accuracy of the prediction results of the network model, and the calculation formula is shown in equation (10).

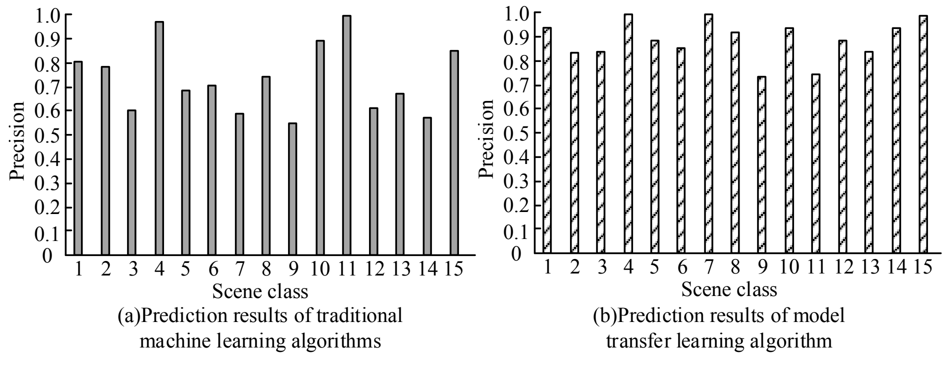
$$F1\text{-}score = \frac{2 \times P \times R}{P + R} \tag{10}$$

3 Simulation analysis of mental health monitoring system based on transfer learning algorithm

3.1 Analysis of prediction results based on model transfer learning algorithm

In the process of practical application of the traditional model transfer learning algorithm, due to the difference in the number of layers that different baseline networks migrate to the target domain data set, it is necessary to use the gradient descent algorithm to minimise the objective function. The research takes the model transfer learning algorithm after gradient descent algorithm as the main research method, and uses wearable devices to monitor 16 volunteers for a long time to explore their mental health status. All volunteers are recruited for the study, and their age, occupation and life experience cover a wide range, which is universal and representative. During the 30 days experiment, the tester should always wear the wearable device provided by this topic, so that the wearable device can collect its activity information, including image data and audio data, especially the latter. Figure 7 shows the prediction results of different algorithms in data set A.

Figure 7 Comparison of prediction between traditional algorithm and model-based transfer learning algorithm in data set A



(a)Prediction results of traditional machine learning algorithms

(b)Prediction results of model transfer learning algorithm

Figure 7(a) shows the prediction results of the traditional machine learning algorithm in data set a containing 15 different acoustic scenes, decision tree algorithm, and Figure 7(b) shows the prediction results of the model migration learning algorithm. By comparing the two, it can be found that in different types of acoustic scenes, the model transfer learning algorithm has better prediction performance and higher accuracy of prediction results. This shows that for the mental health monitoring system, the model-based transfer learning algorithm can obtain more accurate monitoring results and effectively extract features from rich audio data information. In order to obtain more objective experimental results, a new data set, data set B, is constructed. Compared with data set A containing pure acoustic scenes, data set B also covers a large number of external influencing factors. In addition to the background audio in the scene, it also includes several speakers, which has a great impact on the information extraction of mental health monitoring system based on transfer learning algorithm. The prediction results of the two algorithms in data set B are shown in Table 2.

Table 2 Evaluation results of traditional algorithm and model-based transfer learning algorithm in data set B (%)

Algorithm	*Scene category*	*Model evaluation*		
		Precision	*Recall*	*F1-score*
Traditional machine learning algorithm	Library	59	61	60
	Restaurant	49	64	55
	Road	98	19	32
	English reading	77	98	87
	Chinese reading	73	97	84
	English speech	84	70	76
	Chinese speech	99	70	82
	Average accuracy	78	73	70
Model-based transfer learning algorithm	Library	71	83	77
	Restaurant	70	42	53
	Road	50	25	33
	English reading	55	84	67
	Chinese reading	74	98	84
	English speech	89	74	81
	Chinese speech	94	65	77
	Average accuracy	72	70	69

It can be seen from Table 2, that in the seven different scenes of library, restaurant, road, Chinese (English) reading and Chinese (English) speech, the accuracy of Chinese pronunciation is high, up to 90%; the scenes with high recall rate and F1 score are Chinese reading scenes. In terms of road scenarios, the evaluation results of accuracy, recall and F1-score are poor. In the three scenarios of library, restaurant and road, the evaluation results of the two learning algorithms are not ideal, and the evaluation accuracy is significantly lower than that of Chinese (English) reading and Chinese (English) speech. This shows that in a diversified environment, including a large number of noise factors, it will have a great impact on the prediction and evaluation performance of the mental health monitoring system based on transfer learning algorithm, and negatively affect the accuracy and effectiveness of prediction. This topic uses the autism scale questionnaire to evaluate the testers. The scores of the testers are divided into three types: low-level, medium-level and high-level. Low-level indicates that the score of the tester in the autism scale questionnaire is between 10 points and 20 points, medium-level indicates that the score range is 20 to 30 points, and high-level indicates that the score is 30 to 40 points. Then, take the questionnaire scores of all testers as the label based on the model transfer learning algorithm, and use the tra ditional machine learning algorithm and the model transfer learning algorithm to evaluate the scores of testers, respectively. The results are shown in Table 3.

According to Table 3, the traditional machine learning algorithm and the model-based transfer learning algorithm are respectively applied to the evaluation of wearable data sets, and the accuracy, recall and F1-score of the former are lower than those of the latter. The model-based migration learning algorithm uses the acoustic scene data set as the source domain and the data set collected by long-time wearable devices as the target domain. There are significant differences between the evaluation results of the two algorithms, which shows that the model-based transfer learning algorithm can play a superior performance in the construction and evaluation of mental health monitoring system.

3.2 *Training time of mental health monitoring model-based on model transfer learning algorithm*

For data set A and data set B, traditional machine learning algorithm and model transfer learning algorithm are applied to train them respectively. The comparison results of training time are shown in Figure 8.

Figure 8 Comparison of training time between traditional algorithm and model transfer learning algorithm

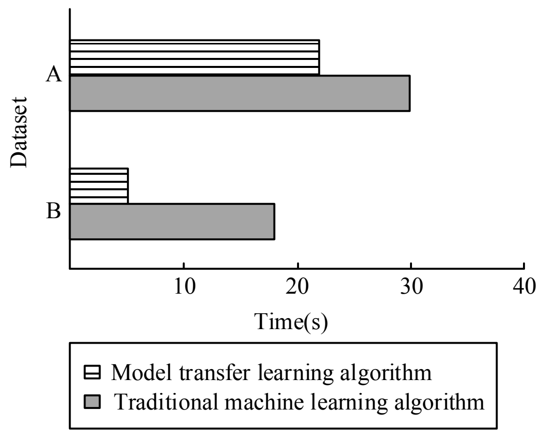


Table 3 Evaluation results based on wearable data set (%)

Algorithm		*Traditional machine learning algorithm*				*Model-based transfer learning algorithm*			
Scene category		*Low-level*	*Medium-level*	*High-level*	*Average index*	*Low-level*	*Medium-level*	*High-level*	*Average index*
Model evaluation	Precision	68	76	69	75	82	82	75	76
	Recall	57	57	69	64	70	65	87	72
	F1-score	62	65	69	69	75	73	81	74

As can be seen from Figure 8, the biggest advantage of the model transfer learning algorithm is that it can significantly shorten the time required for network training. Under the condition of complete training of all training data, the model transfer learning algorithm has less time and higher efficiency. When training data set a, the training time of model transfer learning algorithm is 22 s, and that of traditional machine learning algorithm is 30 s; When training data set B, the training time of model transfer learning algorithm is shorter, which can be completed in only 5 s, while the traditional machine learning algorithm takes 18 s. The main reason for this phenomenon is the difference in the number of transport layers between the two algorithms in the process of network training. For the transfer learning task, the more transfer layers, the less network training time. It can be seen that the model transfer learning algorithm has higher network training efficiency and can achieve good application results in mental health monitoring model. The mental health monitoring model based on model transfer learning algorithm can effectively analyse the tester's mental health status, including the relationship between voice data and social characteristics.

4 Conclusion

In the process of continuous progress and development of modern society, people are facing increasing life pressure and more and more attention has been paid to the monitoring and improvement of their mental health problems. In order to monitor people's mental health in real-time, and then take corresponding measures to improve their mental health, this topic carefully explored the model transfer learning algorithm, optimise its network structure by residual learning and then built a mental health monitoring system based on the model transfer learning algorithm, Finally, wearable devices were used to collect and analyse people's characteristic information. The results show that the accuracy, recall and F1-score of the traditional machine learning algorithm are inferior to the model transfer learning algorithm. Compared with traditional machine learning algorithms, model migration algorithm can complete the training of audio information in data set in less time. This shows that the mental health monitoring system based on model transfer learning algorithm has good application effect and can be widely used. Nevertheless, the number of testers included in this study is small, and the results of the evaluation of their mental health status may lack a certain comprehensiveness, which we hope to improve in the future. When aiming at a large number of test groups, the mental health monitoring system based on model transfer learning algorithm may be difficult to bear too many tasks and obtain the overall comprehensive mental health status evaluation results. If the support vector machine model is added to it, it can be helpful for the classification and batch monitoring of testers.

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References

Cai, H.T., Liu, J. and Chen, J.Y. et al. (2020) 'Soil nutrient information extraction model based on transfer learning and near infrared spectroscopy', *International Journal of AEJ – Alexandria Engineering Journa*, Vol. 60, No. 3, pp.2741–2746.

Daniel, J. and Kumar, S. (2020) 'Tool life prediction of Ti [C, N] mixed alumina ceramic cutting tool using gradient descent algorithm on machining martensitic stainless steel', *International Journal of Mechanical Engineering Science and Technology*, Vol. 4, No. 2, pp.144–152.

Gu, Q. and Dai, Q. (2021) 'A novel active multi-source transfer learning algorithm for time series forecasting', *International Journal of Applied Intelligence*, Vol. 51, No. 2, pp.1–25.

Guo, Y., Mustafaoglu, Z. and Koundal, D. (2022) 'Spam detection using bidirectional transformers and machine learning classifier algorithms', *International Journal of Computational and Cognitive Engineering*. Doi: 10.47852/bonviewJCCE2202192.

Kang, Z., Yang, B., Li, Z. et al. (2019) 'OTLAMC: an online transfer learning algorithm for multi-class classification', *International Journal of Knowledge-Based Systems*, Vol. 176, No. 15, pp.133–146.

Lasheng, Y.U., Xu, W.U. and Yang, Y. (2019) 'An online education data classification model based on Tr_MAdaBoost algorithm', *International Journal of Chinese Journal of Electronics*, Vol. 28, No. 1, pp.21–28.

Li, J., Wu, W. and Xue, D. (2020) 'Research on transfer learning algorithm based on support vector machine', *International Journal of Journal of Intelligent and Fuzzy Systems*, Vol. 38, No. 10, pp.1–16.

Li, P., Chen, Z. and Yang, LT. et al. (2019) 'An incremental deep convolutional computation model for feature learning on industrial big data', *International Journal of IEEE transactions on industrial informatics*, Vol. 15, No. 3, pp.1341–1349.

Lin, J., Liang, L. and Han, X. et al. (2021) 'Cross-target transfer algorithm based on the volterra model of SSVEP-BCI', *International Journal of Tsinghua Science and Technology*, Vol. 26, No. 4, pp.505–522.

Liu, X., Li, Y. and Chen, G. (2019) 'Multimode tool tip dynamics prediction based on transfer learning', *International Journal of Robotics and Computer-Integrated Manufacturing*, Vol. 57, No. 7, pp.146–154.

Meng, H. (2020) 'Solving systems of quadratic equations via exponential-type gradient descent algorithm', *International Journal of Computational Mathematics*, Vol. 38, No. 4, pp.638–660.

Starly, B., Angrish, A. and Bharadwaj, A. (2020) 'MVCNN++: CAD model shape classification and retrieval using multi-view convolutional neural networks', *International Journal of Computing and Information Science in Engineering*, Vol. 21, No. 1, pp.1–27.

Subramaniyam, A., Mahapatra, R.P. and Singh, P. (2019) 'Taylor and gradient descent-based actor critic neural network for the classification of privacy preserved medical data', *International Journal of Big Data*, Vol. 7, No. 3, pp.176–191.

Xu, Y., Li, D. and Wang, Z. et al. (2019) 'A deep learning method based on convolutional neural network for automatic modulation classification of wireless signals', *International Journal of Wireless Networks*, Vol. 25, No. 7, pp.3735–3746.

Ytabc, D., Jxac, D. and Ysabc, D. et al. (2021) 'Improved specular point prediction precision using gradient descent algorithm', *International Journal of Advances in Space Research*, Vol. 65, No. 6, pp.1568–1579.

Zhang, M., Liu, X. and Liu, J. (2021) 'Convergence analysis of a continuous-time distributed gradient descent algorithm', *International Journal of IEEE Control Systems Letters*, Vol. 5, No. 4, pp.1339–1344.