EMPIRICAL ANALYSIS ON THE REDUCTION OF SPORTS INJURY BY FUNCTIONAL MOVEMENT SCREENING METHOD UNDER BIOLOGICAL IMAGE DATA

ORIGINAL ARTICLE
ARTIGO ORIGINAL
ARTÍCULO ORIGINAL

ANÁLISE EMPÍRICA SOBRE A REDUÇÃO DE LESÕES ESPORTIVAS PELO MÉTODO DE TRIAGEM DE MOVIMENTO FUNCIONAL SOB DADOS DE IMAGENS BIOLÓGICAS

ANÁLISIS EMPÍRICO SOBRE LA REDUCCIÓN DE LAS LESIONES DEPORTIVAS MEDIANTE EL MÉTODO DE DETECCIÓN DEL MOVIMIENTO FUNCIONAL CON DATOS DE IMÁGENES BIOLÓGICAS

Lian Duan[1]
(Physical Education Professional)

1. Yanshan University, Hebei, China.

Correspondence:
Lian Duan
Yanshan University, Hebei, China.
duanlianysu@yeah.net

ABSTRACT

Introduction: Sports recognition technology gradually mature. Among them, wearable sensors have attracted wide attention because of their accurate recognition. Objective: The following squats are used as an example to determine whether CNN and EMG signals determine whether functional motion is standard. Methods: Based on the FMS of EMG, 80 students of the same grade are randomly selected from the Physical Education School of XX University for the experiment and the results are verified. Results: The results show that the GBC can classify the EMG signal of the three functional movements more accurately, and the classification accuracy rate of squat, stride, and straight lunge squat is 91%, 89%, and 90%, respectively. The decision tree has a good ability to judge whether the functional movement is standard or not, and the accuracy of judgment can reach more than 98%. In conclusion, EMG-based FMS can effectively detect early sports injuries and plays a good role in reducing sports injuries. Conclusions: The classification effect of the squat is the most obvious, reaching 91%, and its recognition ability is the strongest. ***Level of evidence II; Therapeutic studies - investigation of treatment results.***

Keywords: Functional movement; Biological image; Exercise; Wounds and injuries.

RESUMO

Introdução: A tecnologia de reconhecimento esportivo amadurece gradualmente, entre as quais, os sensores atraíram grande atenção devido ao seu reconhecimento preciso. Objetivo: Os seguintes agachamentos são usados como exemplo para ver se os sinais CNN e EMG determinam se o movimento funcional é padrão. Métodos: Com base no EMG FMS, 80 alunos da mesma série da XX Escola Universitária de Educação Física são selecionados aleatoriamente para o experimento e os resultados são verificados. Resultados: Os resultados mostram que o GBC pode classificar o sinal EMG dos três movimentos funcionais com maior precisão, e a taxa de precisão da classificação do agachamento, estocada e agachamento estocada reta é de 91%, 89% e 90%, respectivamente. A árvore de decisão tem uma boa capacidade de julgar se o movimento funcional é padrão ou não, e a precisão de julgamento pode chegar a mais de 98%. Em conclusão, a EMG baseada em EMG pode detectar efetivamente lesões esportivas precoces e desempenha um bom papel na redução de lesões esportivas. Conclusões: O efeito de classificação do agachamento é o mais evidente, chega a 91%, e sua capacidade de reconhecimento é a mais forte. ***Nível de evidência II; Estudos terapêuticos- investigação dos resultados do tratamento.***

Descritores: *Movimento funcional; Imagens biológicas; Exercício físico; Ferimentos e lesões.*

RESUMEN

Introducción: La tecnología de reconocimiento deportivo va madurando gradualmente, entre los cuales, los sensores han atraído gran atención por su preciso reconocimiento. Objetivo: Las siguientes sentadillas se utilizan como ejemplo para saber si las señales CNN y EMG determinan si el movimiento funcional es estándar. Métodos: Con base en el FMS de EMG, se seleccionan al azar 80 estudiantes del mismo grado de la Escuela de Educación Física de la Universidad XX para el experimento y se verifican los resultados. Resultados: Los resultados muestran que el GBC puede clasificar la señal EMG de los tres movimientos funcionales con mayor precisión, y la tasa de precisión de clasificación de sentadilla, zancada y sentadilla con estocada recta es 91%, 89% y 90%, respectivamente. El árbol de decisiones tiene una buena capacidad para juzgar si el movimiento funcional es estándar o no, y la precisión del juicio puede alcanzar más del 98%. En conclusión, la EMG basada en EMG puede detectar de forma eficaz las lesiones deportivas tempranas y desempeña un buen papel en la reducción de las lesiones deportivas. Conclusiones: El efecto de clasificación de la sentadilla es el más evidente, alcanza el 91%, y su capacidad de reconocimiento es la más fuerte. ***Nivel de evidencia II; Estudios terapéuticos- investigación de los resultados del tratamiento.***

Descriptores: *Movimiento funcional; Imagen biológica; Ejercicio físico; Heridas y lesiones.*

DOI: http://dx.doi.org/10.1590/1517-8692202127042021_0110

Article received on 04/27/2021 accepted on 05/10/2021

INTRODUCTION

In sports, due to incorrect posture or excessive exercise, it is often easy to cause movement damage, which may greatly affect our lives.[1,2] When motion damage is not completely treated and recovered, long--term chronic diseases, such as habitual sprays and strains.[3] In order to reduce the occurrence of this situation, the prevention and prediction of the motor injury should be strengthened. FMS can detect and identify the characteristics of human groups in early stages of motion barriers, but the body has not been damaged.[4,5] With the development of the computer, motion recognition is gradually possible.6 Therefore, EMG is combined with motion identification to provide a reliable standard for functional motion screening.[7,8]

FMS can be moved through a video image, which is not limited to the injury screening of athletes. However, these actions still have problems such as unreasonable quantization. If you want to further develop FMS, you need to explore and study in the theoretical field. At present, most of the research on FMS research focuses on athletes' exercise damage, and a few studies on the early stage of sports injury.[9-11]

Along with the development of computer technology, sports recognition technology gradually mature.[12,13] Among them, wearable sensors have attracted wide attention because of their accurate recognition.14,5 Wearable sensors include those based on accelerometer signals, based on EMG signal.[16,17] Therefore, the FMS is combined with the EMG sensor in the study to provide some ideas for the standardization of FMS and to make it possible to reduce motion damage earlier.

METHODS

Feature extraction

I. Integral EMG (IEMG) value, which represents the area under the curve of EMG, which reflects the discharge of exercise muscle unit over a period of time.

$$IMEG = \int_{n2}^{n2} X(t)\,dt \tag{1}$$

II. Absolute value integration Iva is the average value of the absolute value of the signal samples in the discrete signal.

$$Iva = \frac{1}{n-1}\sum_{i=1}^{n} |x_i| \tag{2}$$

III. Maximum value, the maximum value of the discrete signal in a period of time.

$$Max = \max(x(t)) \tag{3}$$

IV. Mean Ave, the average value of discrete signals over a period of time.

$$Ave = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

V. The minimum value Min, the smallest value of the discrete signal in a period of time.

$$Min = \min(x(t)) \tag{5}$$

VI. RMS, the average level of muscle discharge over time.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i)^2} \tag{6}$$

VII. Variance Var, average power of random signal.

$$Var = \frac{1}{n}\sum_{i=1}^{n} (x_i)^2 \tag{7}$$

Feature classification

$$Y(x) = \sum_{m}^{M} \alpha_m H_m(x) \tag{8}$$

In which, Hm(x) is called "weak learner" in Boosting. In Gradient Boosting, a fixed-size decision tree is used as a weak learner. The decision tree plays an important role in Boosting, including the processing power of mixed data and the ability to model complex functions.[18,19]

Gradient Boosting builds the model through greedy methods.

$$Y_m(x) = Y_{m-1}(x) + \alpha_m H_m(x) \tag{9}$$

Adding the tree Hm will feed back the minimum loss S to the previous tree Ym-1.

Gradient Boosting is minimized by gradient descent, and the gradient descent direction is obtained by Ym-1.

$$H_m = \arg\min_H L(y_i, Y_{m-1}(x_i) + H(x_i)) \tag{10}$$

The step size is obtained through α_m linear search.

$$\alpha_m = \arg\min_\alpha \sum_{i=1}^{m} L\left(y_i, H_{m-1}(x_i) - \alpha \frac{\partial L(y_i, H_{m-1}(x_i))}{\partial H_{m-1}(x_i)}\right) \tag{11}$$

EMG-based CNN model

The CNN used in this study is shown in Figure 1.

In this experiment, the RELU function is selected as the activation function instead of the SIGMOID function, because SigmoID has two shortcomings: update slow, not conducive to the calculation of the lower layer. The relu itself has a simple definition of the characteristics of the simple operation, which makes its propagation speed faster.

$$z^s = N^s x^{s-1} + y^s, x^s = \delta(z^s) \tag{12}$$

In which, Ns represents the weight from (s-1) layer neuron to the first layer neuron, xs represents the output of the s layer neuron after ReLU activation function, ys represents the bias of the neuron in layer s, zs represents the input of neuron in layer s, and δ is the ReLU activation function.

The errors generated by the output layer are as follows.

$$\beta^s = \nabla_x D \odot \delta'(z^s) \tag{13}$$

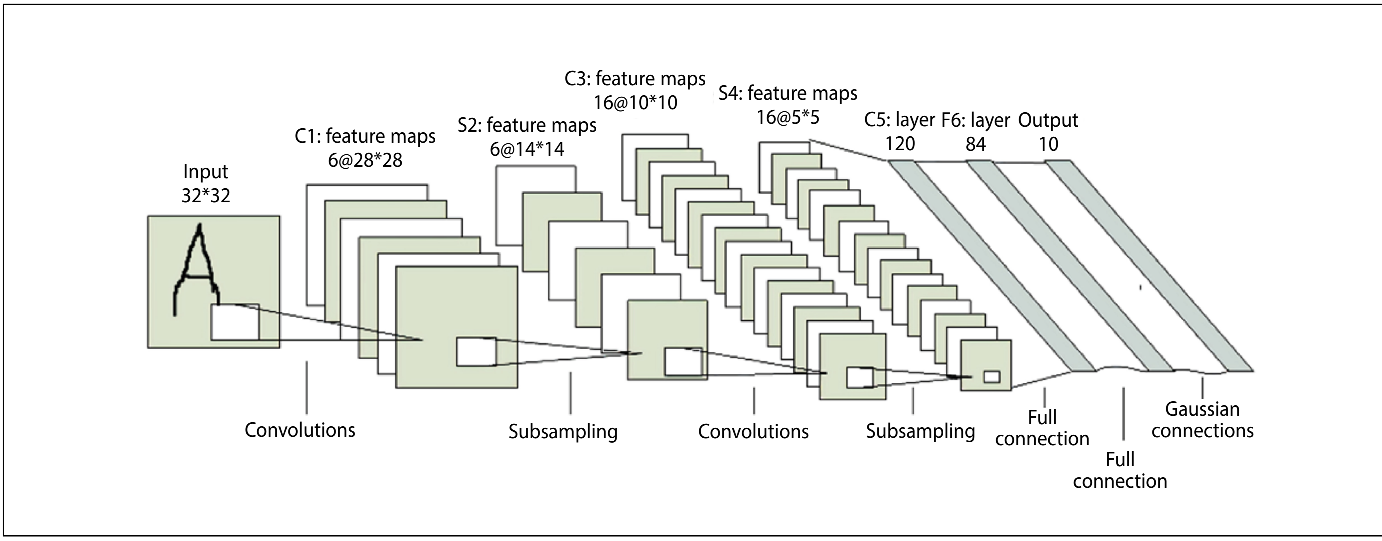

Figure 1. Schematic diagram of CNN.

In which, D is the cost function and βs is the error generated by the neurons in the sth layer.

Backward propagation stage: the difference between the actual output Po and the ideal output Dp is calculated, and the back propagation matrix is adjusted according to the minimization error. The back propagation error is as follows.

$$\beta^{s} = \left(\left(N^{s+1}\right)^{T} \beta^{s+1}\right) \circ \delta'\left(z^{s}\right) \quad (14)$$

SOFTMAX classification algorithm

In this study, SoftMax is the last layer of CNN. The feature extracted by the convolution layer and the pool layer is input to a soft MAX classifier, and the probability is output according to the EGM feature. Assume that the function is as follows.[20]

$$R_{\alpha}\left(x^{(i)}\right) = \begin{bmatrix} g\left(y^{i}=1 \middle| x^{i_n}, \alpha\right) \\ g\left(y^{i}=2 \middle| x^{i_n}, \alpha\right) \\ \dots \\ g\left(y^{i}=k \middle| x^{i_n}, \alpha\right) \end{bmatrix} = \frac{1}{\sum_{n=1}^{k} e^{\alpha_n^T x^{(i)}}} \begin{bmatrix} e^{\alpha_i^T x^{(i)}} \\ e^{\alpha_i^T x^{(i)}} \\ \dots \\ e^{\alpha_i^T x^{(i)}} \end{bmatrix} \quad (15)$$

In which, $\alpha_1, \alpha_2 \dots \alpha_k \in M^{n+1}$ are the parameters of the model, $\frac{1}{\sum_{n=1}^{k} e^{\alpha_n^T x^{(i)}}}$ is to normalize the probabilities so that the sum of all probabilities is 1. In order to make the results simple and easy to use, the same parameter α is used to represent all model parameters. In the implementation of SOFTMAX, α is expressed as kx(n+1), and all the results are listed as follows.

$$\alpha = \begin{bmatrix} \alpha_1^T \\ \alpha_2^T \\ \dots \\ \alpha_k^T \end{bmatrix} \quad (16)$$

The cost function including penalty items in SOFTMAX is as follows.

$$I(\alpha) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k} 1\left\{y^{i}=j\right\} \cdot \log\left(g\left(y^{i}=j \middle| x^{i};\alpha\right)\right)\right] + \frac{\lambda}{2}\sum_{j=1}^{k}\sum_{j=0}^{n}\alpha_{ij}^{2} \quad (17)$$

Partial derivation of α is obtained as follows.

$$\frac{\nabla I(\alpha)}{\nabla \alpha_j} = -\frac{1}{m}\sum_{i=1}^{m} x^{(i)}\left[1\left\{y^{(i)}=j\right\} - g\left(y^{(i)}=j \middle| x^{i};\alpha\right) + \chi\alpha_j\right] \quad (18)$$

Then, the gradient of the cost function of the cost function is obtained. Forma extracts and determines whether the action of the EMG spectrum-based CNN output is after the classification output, whether the operation is determined whether the operation is standard.

The variance is defined as follows.

$$Var = \frac{1}{n} 1 \sum_{i=1}^{n}\left(x_i\right)^2 \quad (19)$$

The average power frequency is defined as follows.

$$APF = \int_0^\infty f \cdot O(f)\,df \,/ \int_0^\infty O(f)\,df \quad (20)$$

Results

This experimental data includes 10 subjects between 20s and 30, 5 male and 5 women. Data is collected in the laboratory. First, the electrode is fixed at the corresponding position on the skin of the subject. Through professional guidance, under the premise of ensuring the operation of the action, the EMG of the squat is shown in Figure 2.

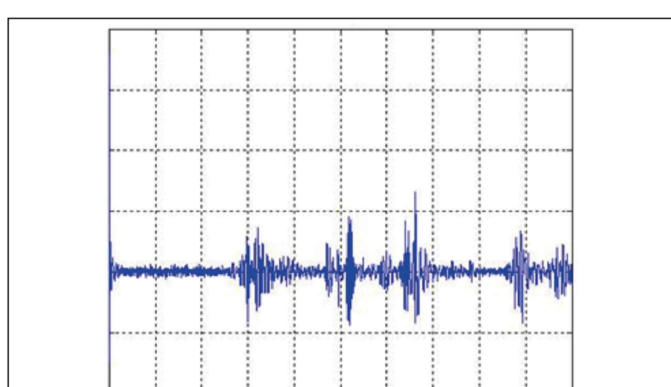

Figure 2. Squat EMG.

RESULTS

Feature classification results

Single feature classification results: it is evident from Figure 3 that the feature IEMG has higher accuracy in the GBC than other features, and the feature Ave performs the worst in the classifier. Overall, the features Iva, Max, Min, RMS, and Var have relatively high accuracy in the classifier. At the same time, it can be found in figure 3 that the separability of features is Min, RMS, IEMG, MAX, Iva, Ave, and Var in order from high to low.

The precision (P), recall (R), and F1-score (F1) are used to further analyze the classification of single feature classification indicators on the classifier. The accuracy rate = true case/(true case+false positive case), which is the proportion of movements that are hardly retrieved to all retrieved sports movements, recall rate=true case/(true case+false counterexample), which is the proportion of movements that should be retrieved to all retrieved sports and health movements, F1 value = 2 (P*R)/(P+R), which is the harmonic mean of precision and recall. In the single-feature classifier, squat, stride, and straight lunge squat are used for 1,2,3 respectively. It is evident from Figure 4 that the overall classification effect of the GBC is better, and the classification effect for squats is the best.

All the single features involved are combined to get the combined features, the combined features are put into the GBC to train the model and get the classification results, and the parameters of the GBC are set as follows: n_estimators=100, learning_rate=1.0, max_depth=13 , Min_samples_split=50, min_samples_leaf=20, max_feature=4. The obtained classification results are shown in Figure 5. The overall classification effect of the GBC is better, and is similar to the single feature classification, and the classification effect of the squat movement is the best.

The average accuracy of the single classification and the combined classification are shown in figure 6. Compared with the single classification, the average accuracy of the combined classification has been significantly improved.

Classification results and analysis of CNNs based on EMG spectrum. (Figure 7)

EMG-based sports injury correction

At the University of XX University, 80 students were randomly selected to participate in the experiment. In order to ensure consistent, students are men, in the same school year. 80 students were randomly divided into two groups, 40 people in each group. The control group was filtered with a general FMS. The experimental group was screened with an EMG biosa image data, as shown in Figure 8. The results showed that the number of sports damage in the control group was lower than the sports injury of the experimental group, but the number of sports injuries in the control group after rehabilitation was not significantly reduced, higher than the experimental group.

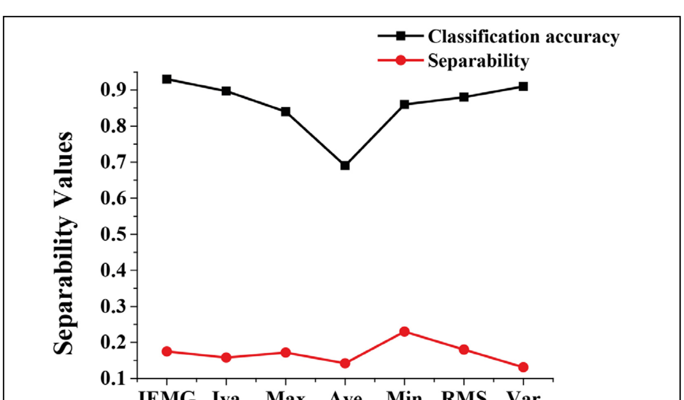

Figure 3. Comparison of the accuracy of various features on the classifier.

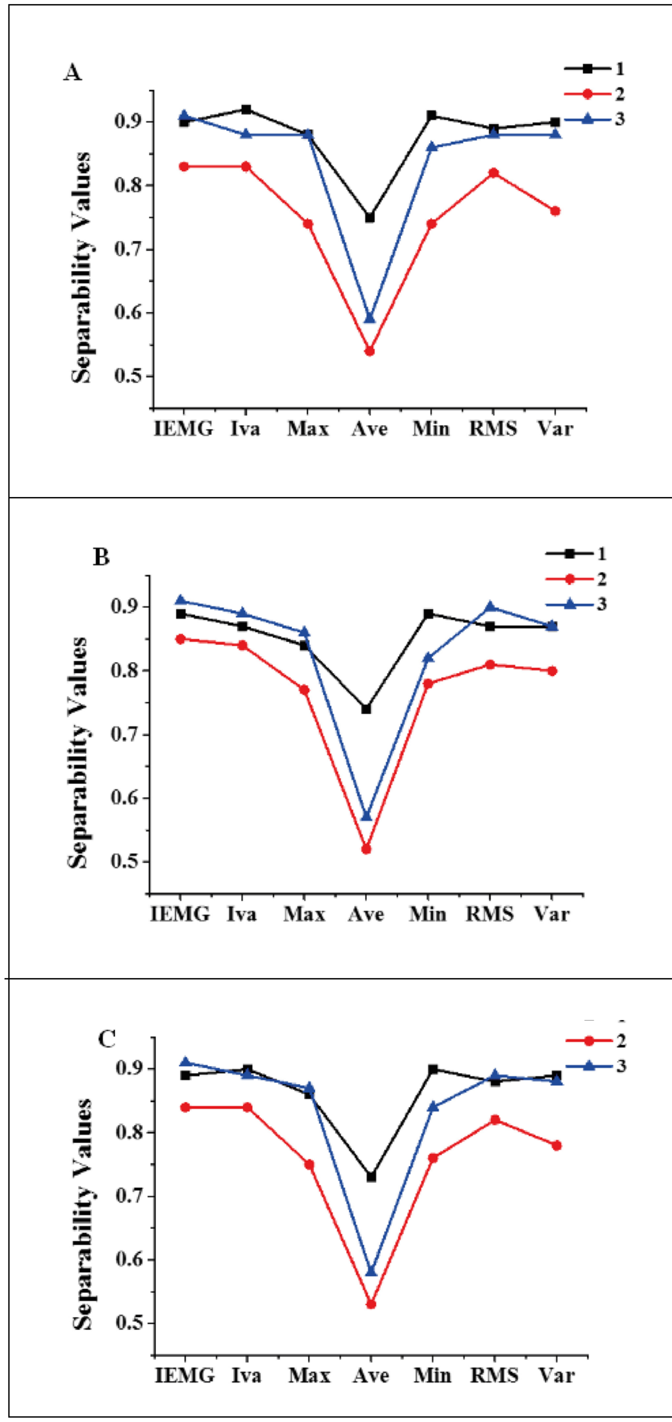

Figure 4. Comparison of classifier performance in different movements. A Precision rate, B Recall rate, C F1 value.

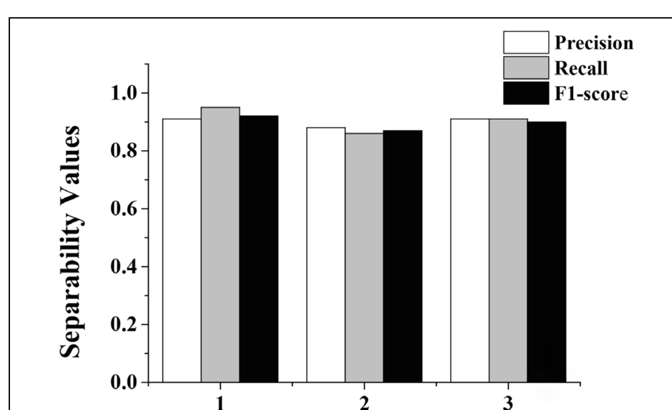

Figure 5. Classification results of the classifier in different movements.

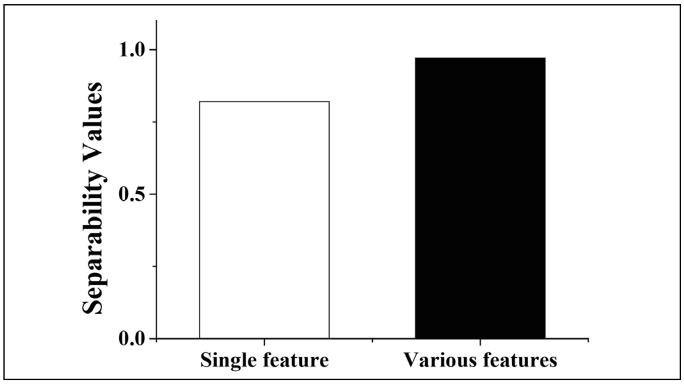

Figure 6. Comparison of classification effects between single and combined features.

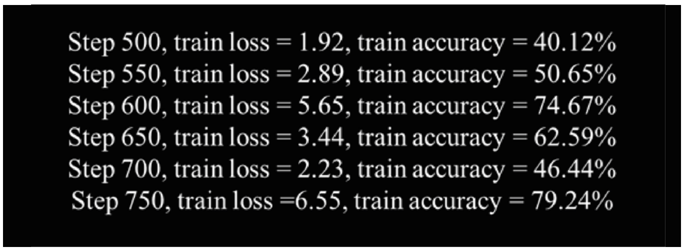

Figure 7. Classification results of CNN based on EMG spectrum.

DISCUSSION

After analysis, it is found taht among the 7 features, feature IEMG has higher accuracy in GBC than other features, and feature Ave performs the worst in classifier. This is largely due to the greater interference received by Ave, which makes the classification results prone to errors. This feature is also reflected in the accuracy rate, recall rate, and F1 score . After the analysis of the results of combined features and single features, it is not difficult to find that single features do not have a good classification ability for functional movements. However, by adding the feature dimension, the classification ability of classification model can

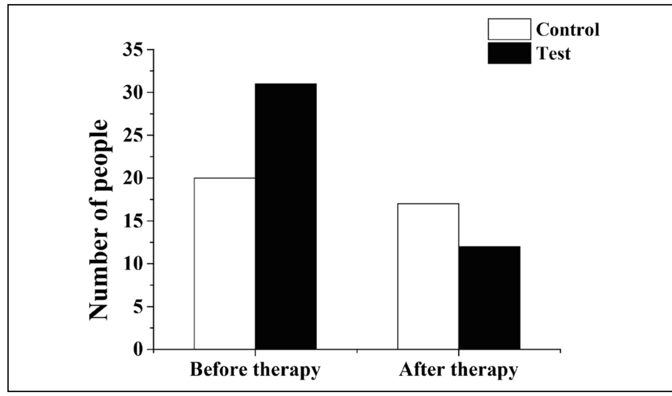

Figure 8. Sports injuries before and after rehabilitation training in different groups.

be significantly strengthened for different functional movements so as to obtain better classification effect . I. The signal noise in the original data is large, and the EMG signal itself is weak, which is easily affected by external interference. II. The spectrum mapping in the CNN is small, so that the CNN cannot be extracted from the image of the frequency spectrogram of the image. Iii. Sports itself has some disturbances of an irrelevant signal. The crouching involves a variety of muscles, such as Quadriceps, Hamstring, and Gluteus Maximus, which also participated in non-standard crouch.

CONCLUSION

In this study, the FMS method was proposed based on the EMG biorejectment. The experiment has innovated the traditional FMS of the EMG biological image to determine more objective, but since the number of samples of experimental training is too small, the experimental results still have a further improved space.

The author declare no potential conflict of interest related to this article

AUTHORS' CONTRIBUTIONS: Lian Duan analyzed and explained about taking squat as an example, using convolutional neural network (CNN) and EMG signals to determine whether the functional movement is a standard movement, and verifying it in the decision tree.

REFERENCES

1. Liu CL, Feng YN, Zhang HQ, Li YP, Zhu Y, Zhang ZJ. Assessing the viscoelastic properties of upper trapezius muscle: Intra- and inter-tester reliability and the effect of shoulder elevation. J Electromyogr Kinesiol. 2018;43:226-229.
2. Shaofei W. Internet public information text data mining and intelligence influence analysis for user intent understanding. Journal of Intelligent & Fuzzy Systems. 2020;38:487-94.
3. Xi X, Tang M, Miran SM, Luo Z. Evaluation of feature extraction and recognition for activity monitoring and fall detection based on wearable sEMG sensors. Sensors (Basel). 2017;17(6):1229.
4. Zhang S, Guo S, Gao B, Huang Q, Pang M, Hirata H, et al. Muscle strength assessment system using sEMG-based force prediction method for wrist joint. Journal of Medical and Biological Engineering. 2016;6(1):121-31.
5. He M, Feng L, Qu J. Denoising algorithm of Φ_OTDR signal based on clear iterative EMD interval-thresholding. Optics Communications. 2019;453;124352.
6. Wu S, Liu J, Liu L. Modeling method of internet public information data mining based on probabilistic topic model. The Journal of Supercomputing. 2019;75(4):5882-97.
7. Stromberg KA, Agyemang AA, Graham KM, Walker WC, Sima AP, Marwitz JH, Harrison-Felix C, Hoffman JM, Brown AW, Kreutzer JS, Merchant R. Using Decision Tree Methodology to Predict Employment After Moderate to Severe Traumatic Brain Injury. J Head Trauma Rehabil. 2019;34(3):E64-E74. Erratum in: J Head Trauma Rehabil. 2019;34(6):401.
8. Karthick PA, Ghosh DM, Ramakrishnan S. Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms. Comput Methods Programs Biomed. 2018;154:45-56.
9. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, et al. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Trans Med Imaging. 2016;35(5):1285-98.
10. Mokha M, Sprague PA, Gatens DR. Predicting Musculoskeletal Injury in National Collegiate Athletic Association Division II Athletes From Asymmetries and Individual-Test Versus Composite Functional Movement Screen Scores. J Athl Train. 2016;51(4):276-82.
11. Moran RW, Schneiders AG, Mason J, Sullivan SJ. Do Functional Movement Screen (FMS) composite scores predict subsequent injury? A systematic review with meta-analysis. Br J Sports Med. 2017;51(23):1661-9.
12. Lewis V, Douglas JL, Edwards T, Dumbell L. A preliminary study investigating functional movement screen test scores in female collegiate age horse-riders. Comparative Exercise Physiology. 2019;15(2):105-12.
13. Wu S. Nonlinear information data mining based on time series for fractional differential operators. Chaos. 2019;29:013114.
14. Bonazza NA, Smuin D, Onks CA, Silvis ML, Dhawan A. Reliability, validity, and injury predictive value of the functional movement screen: a systematic review and meta-analysis. Am J Sports Med. 2017;45(3):725-732.
15. Lisman P, Nadelen M, Hildebrand E, Leppert K, de la Motte S. Functional movement screen and Y-Balance test scores across levels of American football players. Biol Sport. 2018;35(3):253-60.
16. Bond CW, Dorman JC, Odney TO, Roggenbuck SJ, Young SW, Munce TA. Evaluation of the functional movement screen and a novel basketball mobility test as an injury prediction tool for collegiate basketball players. J Strength Cond Res. 2019;33(6):1589-600.
17. Tee JC, Klingbiel JF, Collins R, Lambert MI, Coopoo Y. Preseason functional movement screen component tests predict severe contact injuries in professional rugby union players. J Strength Cond Res. 2016;30(11):3194-203.
18. Leeder JE, Horsley IG, Herrington LC. The Inter-rater Reliability of the Functional Movement Screen Within an Athletic Population Using Untrained Raters. J Strength Cond Res. 2016;30(9):2591-9.
19. Ke Q, Wu S, Wang M, Zou Y. Evaluation of developer efficiency based on improved DEA Model. Wireless Personal Communications. 2018;102(4);3843-9.
20. Margraf NG, Rogalski M, Deuschl G, Kuhtz-Buschbeck JP. Trunk muscle activation pattern in parkinsonian camptocormia as revealed with surface electromyography. Parkinsonism Relat Disord. 2017;44:44-50.