Hybridized Hierarchical Deep Convolutional Neural Network for Sports Rehabilitation Exercises

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This work was supported by the Training Program for Young Backbone Teachers in Colleges and Universities of Henan Province, Research on the Reform of the Mode of Public Sports Teaching Club in Colleges and Universities, in 2018, under Grant 2018GJJS035.

ABSTRACT In recent years, rehabilitation has become a specialist field after a sports injury, and the evolution of rehabilitation has inevitably brought together a sports physiotherapist, sports doctor, and an orthopedic surgeon. For sports athletics, it is essential to determine the strategies to prevent injuries, optimize the rehabilitation, and improve performance. In the field of computer vision, deep learning has made a great success and the accuracy in image detection and image classification. Computer-aided physical rehabilitation evaluation involves assessing patient performance during the completion of prescribed rehabilitation exercises using sensory system data from the processing of movement. Since the rehabilitation assessment plays a vital role in improving patient outcomes and reducing healthcare costs, existing solutions lack versatility, robustness, and practical relevance. In this article, Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been introduced to enhance the accuracy, image segmentation of sports athletics exercise rehabilitation. The main components of the framework include measurements to quantify motion performance, scoring of performance measurement features into numerical quality scores, and deep convolutional neural network models to generate quality scores of input movements through supervised learning. Compared to many traditional neural network algorithms, the image segmentation algorithm enhances the convergence speed of the network, shortens training time, and improves the accuracy of sports athletics exercise rehabilitation, which is good practice for the reconstruction of the sports rehabilitation exercise.

INDEX TERMS Sports rehabilitation, deep convolutional neural network, segmentation.

I. INTRODUCTION
The ever-growing popularity of sports around the world has made the sports industry very competitive and financially profitable for sportspersons [1]. The emotional and physical burden of sports practice, training, and requirements have been improved [2]. In contemporary competitive sports, injured sportsperson are forced to re-compete as soon as possible, which is often demand both for the sportspersons and team leaders [3]. The highly competitive scenario will give athletes a chance to lose their place in the team, and of course, they will be under more significant pressure to return [4]. Thus, rehabilitation of sports injuries requires, compared to conventional rehabilitation after injuries, more exceptional care, a highly structured, sports-specific method, both athletes and injured tissues, who should prepare themselves for the next high level of physical and psychological requirements [5]. In the treatment of a wide variety of Musculoskeletal conditions, participation in physical therapy and rehabilitation programs is often compulsory and crucial [6]. However, for every rehabilitation session, the patient cannot be offered access to a clinician [7]. As a consequence, existing health care systems are organized around the world so that a fundamental part of the rehabilitation programs, followed by the second part in an outpatient environment, is done in a hospital facility under direct supervision by the clinician. Patients perform a series of prescribed exercises in their home [8].

With the continuous development in the machine learning approach, structural features are extracted from missing data, and existing lossless data is reconstructing one of the
main technologies of character animation driven by data [9]. Medical and physical therapies that may improve the benefits of exercise through pain control and muscle modifications are often combined by an active rehabilitation. Rehabilitation success relies on a sufficient dose of the most successful treatment at the right time.

The complicated non-linear structure between the stringent time-spatial and limb joints dependency makes it easy for a shallow machine to fully characterize the probable semantic system of human movement data as a distinctive use of motion capture technology [10]. With the development of deep learning, structural data modeling has come a breakthrough in recent years [11]. Human movement capture data contains complicated kinematic articulation relationships. The rigorous spatial and temporal structures of these joint data are a significant challenge for the efficient use of the deep learning model [12]. Deep learning technologies have been used in several areas [13]. From early simple applications of static imaging and text information processing to high dimensional applications like audio and video data processing, they have gradually developed [14]. Many approaches try to capture the motion while training, which supports sportspersons to improve and train physical function more accurately [15]. Figure 1 shows the Deep Convolutional Neural Network-based motion detection.

Patients are tasked with daily progress and visit the clinic regularly to evaluate their function [16]. However, many Medical Sources report low patient compliance with the recommended home rehabilitation exercise patterns, leading to extended treatment times and increased cost of health care [17]. While many factors that contribute to the low compliance rates have been identified, the significant impact is a lack of ongoing feedback and supervision of patient exercises by a health care provider [18]. The medical image segmentation is a crucial task for medical exercise rehabilitation processing, and numerous other related tasks require prior image segmentation in sports exercise rehabilitation image processing [19]. The segmentation algorithm for the rehabilitation image of sports exercise is, therefore, essential for medical image processing [20].

In this study, Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been suggested to enhance the accuracy, reliability, image segmentation of sports athletics exercise rehabilitation. A superpixel segmentation algorithm can segment the image into multiple superpixels. The classifier is trained to utilize the superpixels’ hierarchical features, and the classification outcomes are mapped to the pixel. In the end, a random field algorithm of a fully connected layer with paired potential energy and one potential energy is available. The energy function is utilized for smoothing the pixel classifying outcome and for enhancing the continuity and regional reliability of the pixel label.

The main contributions of this paper are

- To propose the Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been intended to enhance the accuracy, image segmentation of sports athletics exercise rehabilitation.
- Designing the image segmentation algorithm to sample the multi-layer convolution output in the convolutional neural network.
- The experimental results have been performed, and it enhances the convergence speed, reduces the training time, and enhances the segmentation accuracy.

The remainder of the paper articulated as follows: Section 1 and Section 2 discussed the introduction and signification of sports rehabilitation exercise. In section 3, the Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been proposed. In section 4, the numerical results have been illustrated. Finally, section 5 concludes the research paper.

II. RELATED WORKS

Nweke et al. [21] proposed mobile and wearable sensor-based human activity recognition (MWSHAR) using deep learning algorithms. Feature extraction affects the performance of the algorithm and decreases the time and difficulty of computing. Nevertheless, the instant recognition of human activity is based on handcrafted features that cannot handle complex operations, in particular with the current influx of multimodal and extensive sensor data. In addition, it offers diversity, higher generalization, and addresses challenges in human recognition by fusion of wearable sensors or mobile and deep learning methods for feature learning. This review is aimed at providing detailed summaries of deep learning
approaches for the recognition of human action by smartphone and available sensors.

Ravi et al. [22] introduced the feature learned with a deep learning approach (FL-DLA) for real-time activity classification. The implementation of this collective approach objective to come across some of the constraints in deep learning methods where the calculation of the node is necessary. Spectral-domain preprocessing is utilized to optimize the proposed method of in-node calculation in real-time, before transferring the data to the deep learning context. Our proposed deep learning approach is assessed with the precision of classification by state–methods, both in the laboratory and in real-world data sets. Their results demonstrate the validity and the performance of other approaches, involving the two strategies utilized in their combined pipeline for different human activities.

Ma and Pang [2] initialized the Convolutional Neural Network Algorithm (CNNA) in sports medical data. This article begins with an enhanced convolutional neural network deep learning methods to ensure efficient prediction and risk evaluation of diseases related to sports medicine. It adopts a self-adjusted algorithm, supplemented by the self-coding tensor convolution. The Neural Network model helps multi-dimensional sport medicine data analysis. Finally, this paper proposes a cloud-based simulation model of hardware on the loop to build a smart medical data platform for sports medicine. This method offers technical support and reference for implementing an accurate cloud-based fusion system, according to experiments. With the enormous increase in data, the traditional algorithm of deep learning is weak and inevitable in athletics health data mining.

Hannink et al. [23] introduced a deep convolutional neural network (DCNN) to map stride detailed inertial sensor data to an ensuing stride length. The proposed approach is not subjected to the methodology constraints which restrict the use of state–dual integrations methods, because of its independence from the stride definition. In addition, the accuracy of the benchmark dataset could be improved. New insights into the neurological progression conditions or the early signs can be increased by a more accurate motive stride length calculation. Because of the independence of the step statement, before unknown diseases can now, through retraining and the application of the proposed procedure, be studied in mobile gait analysis. The dataset used for training should, therefore, capture the most significant possible variability of the problem. Any application to a population different from the people used for training may otherwise lead to a lack of model validity.

Xia et al. [24] proposed dual-modal attention enhanced deep learning model (DMAEDL) for quantification of Parkinson’s disease features. A convolutional neural network (CNN) is modeled separately on the right and left gait, followed by an LSTM. The right and left samples were sequentially separated from the several 1-Dimensional vertical ground reaction (VGRF) signaling to the detection of the gait cycle for model training and testing. Experimental results show that our model can deliver cutting-edge classification accuracy performance. The suggested method is expected to be a helpful guide for the quantitative evaluation of PD gait that are adequately trained to ensure high confidence and precision.

Frank et al., introduced a Dynamic Neuromuscular Stabilization (DNS) approach for analyzing the sufficient abdominal, vertebral, gluteal or other musculature strength; the central nervous system ensures heart stability by precise alignment of these muscles and regulation of the intra-abdominal pressure [25]. Recognizing the developmental exercise physiology offers a framework for understanding the inter-relationship and interdependence of the body, the joints, the muscles when traveling and the significance of complex and stabilizing exercise of the muscles in the kinetic chain.

To overcome these issues, in this paper, Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been suggested to enhance the accuracy, image segmentation of sports athletics exercise rehabilitation. The article offers a new framework with a segmentation algorithm for evaluating rehabilitation, which comprises the formulation of metrics for quantifying movement performance, numerical movement quality scores, and deep learning end–models to encode the relation between movement data and quality scores. The performance measurement is based on probabilistic modeling of the Gaussian mixture model skeletal joints, and therefore the log-like nature of the model is used to perform performance assessment.

III. HYBRIDIZED HIERARCHICAL DEEP CONVOLUTIONAL NEURAL NETWORK (HHDCNN)

In this paper, Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been initialized to enhance the accuracy of motion capture, image segmentation of sports athletics exercise rehabilitation. The multi-layer convolutional network neural architecture has chosen, and a fully connected layer and readout layer have been selected. Figure 2 demonstrates the proposed Hierarchical Hybridized Convolutional Neural Network architecture.

The primary aim for this selection is the locality of the feature of this type of framework, which forces the network to take into consideration and preserve its temporal input data as a multi-channel synchronous time sequence. It only takes into account associations and does not connect the data in the input signal from temporarily far away regions.

In the initial convolutional layer, $y_{j,i}$ feature maps are built by convolution with $l = 1,\ldots,M_l$ kernels $\varphi_{j,i}^{(1)}$ of size $j = 1,\ldots,K_j$ and $i \in [1,M_0]$. The preprocessed inertial sensor information $y_{j,i}$ with $j = 1,\ldots,K_0$ samples and $i = 1,\ldots,M_0$ channels serve as input to the network. A bias term $a_j^{(1)}$ is summed up to every feature map before a Rectified Linear Unit activation function generates the activation of first convolutional layer output,

$$b_j^{(1)} = \text{ReLU} \left( \sum_{i} \varphi_{j,i}^{(1)} \ast y_i + a_j^{(1)} \right)$$  

(1)
As derived in equation (1) where \( l \in [1, M_1] \) and \( \text{ReLU} (z) = \max(0, z) \).

Subsequently, every convolutional layer let’s add a max-pooling layer that downsamples the feature maps by compelling the extreme in non-over fitting length windows denoted as \( d \). The factor of downsampling \( 1/d \). The initial max-pooling layer output is known as \( q^{(1)}_{j, i} \) with \( j \in [1, K_0/d] \) and \( i \in [1, M_1] \).

In the following convolutional layer, a similar method is iterated with various kernels and bias. Assumed the input data \( q^{(2)}_{j, i} \), feature map is built by convolution with \( l = 1, \ldots, M_2 \) kernels \( q^{(2)}_{j, i} \) of length \( j = 1, \ldots, K_2 \) and \( i \in [1, M_1] \). A bias terms \( a^{(2)}_i \) is summed up before a Rectified Linear Unit activation function generates the node output,

\[
b^{(2)}_i = \text{ReLU} \left( \sum_{j} q^{(2)}_{j, i} \ast q^{(2)}_i + a^{(2)}_i \right)
\]

As discussed in equation (2) where \( l \in [1, M_2] \). Subsequently max-pooling the output \( q^{(2)}_i \) is of size \( j \in [1, K_0/d^2] \) and \( i \in [1, M_2] \). Similarly, up to \( \log_d K_0 \) convolutional layer succeeded by max-pooling can be weighted before the input data is downsampled to size one.

The output from the final max-pooling layer is the fully connected layer \( q^{(2)}_i \) is flattened to a 1-D vector \( q^{(*)}_i \) with \( j = 1, \ldots, (M_2K_0/d^2) \) and \( i = 1, \ldots, M_{fc} \). A bias term \( a^{(*)}_i \) is summed up before a Rectified Linear Unit activation function generates the fully connected layer output

\[
q^{(*)}_i = \text{ReLU} \left( \sum_{j} S^{(*)}_{j, i} q^{(*)}_j + a^{(*)}_i \right)
\]

With \( i \in [1, M_{fc}] \).

To end, an output layer compresses the \( M_{fc} \) hidden layer output nodes to the distinct target parameter motion frame. It is accomplished by multiplication with a weight vector \( S^{(*)}_{j, i} \) with \( j \in [1, M_{fc}] \). A final bias \( d^{(*)} \) is summed up to reach the evaluation of the target parameter.

\[
x = \sum_{j} S^{(*)}_{j, i} q^{(*)}_j + d^{(*)}
\]

Similarly, a target variable \((x_1, \ldots, x_m)\) denoting a set of motion features can be calculated by fluctuating the dimensionality of bias and weights and in the layer.

As shown in algorithm 1, the threshold Segmentation algorithm is an effective and simple image segmentation algorithm. It separates the gray image from the gray level to be divided into many portions with one or many thresholds and a similar type of pixels as the gray levels are the same, and it discussed in figure 3. For optimum thresholding peak 1 and peak, 2 values of the image have been taken to resulting in inaccurate segmentation. The selection of the threshold expression is as follows,

\[
R = r[y, x, f(y, x), p(y, x)]
\]

As inferred from equation (5) where \( p(y, x) \) local feature elements in the region nearby the change point are and \( f(y, x) \) is the gray value at the pixel \((y, x)\) of the picture. \( R \) Is the function of point \((y, x)\) and \( p(y, x) \).
Algorithm 1 Threshold Segmentation Algorithm

| Input: x, y, I, j |
| Output: R |

For (j = 0)

\[ R = r[y, x, f(y, x), p(y, x)] \]

For (i = 0)

\[
I(\theta) = -\frac{1}{n} \left[ \sum_{j=1}^{n} \sum_{i=1}^{l} k \{ x^{(j)} = i \} \log \frac{e^{\theta_{R,y}^{(j)}}}{\sum_{k=1}^{l} e^{\theta_{R,y}^{(j)}}} \right] + \lambda \frac{1}{2} \sum_{j=1}^{l} \sum_{i=0}^{m} \theta_{ji}^2
\]

For (i < j)

\[ h_{W_i,o} = e^{x_i,o} / \sum_{a \in \text{classes}} e^{x_i,a} \]

End for

End for

End for

End

Return

FIGURE 3. Optimum Thresholding.

Figure 4 shows the extracting superpixels feature from the input image. The feature depiction of the superpixel is determined, and the training process is employed for a softmax classifier. The loss function is expressed as,

\[
I(\theta) = -\frac{1}{n} \left[ \sum_{j=1}^{n} \sum_{i=1}^{l} k \{ x^{(j)} = i \} \log \frac{e^{\theta_{R,y}^{(j)}}}{\sum_{k=1}^{l} e^{\theta_{R,y}^{(j)}}} \right] + \lambda \frac{1}{2} \sum_{j=1}^{l} \sum_{i=0}^{m} \theta_{ji}^2
\]  

(6)

As discussed in equation (6) where \( \theta_i \) is the vector weight that needs the training to acquire, and \( m \) is the respective dimension. The parameter \( l \) is the category in all samples in the training set and \( n \) is the training set samples. When \( x^{(j)} = i \), the outcome is 1, otherwise 0. To prevent overlapping, a specific term is summed up, and \( \lambda \) is the normalization variable. The expression \( kx^{(j)} = i \) is the indicator function. The weight vector can be determined once training is completed. The likelihood distribution of superpixel \( W_i, j \in \{1, \ldots, l\} \) can be calculated as \( h_{W_i,o} \). The specific estimation procedure is as follows,

\[
x_i = \theta_{R,y}^{(j)}
\]  

(7)

As shown in the above equation (7) and (8) \( l \) is the categories. The parameter \( o \) denotes the category to which the superpixel appears that the likelihood that every pixel refers to every class is determined. To identify the pixel’s likelihood distribution, the superpixel refers to the pixels that every type can be mapped, and it comprises. The definite mapping relations are as follow,

\[
V_D^{PL} = V_D^{WI(\varphi(j)=i)}
\]  

(9)

As inferred from equation (9) where \( V_D^{WI} \) the likelihood is that superpixel \( W_i \) refers to category D, and \( V_D^{PL} \) is the likelihood that pixels in superpixels refer to category D. The expression \( \varphi(j) = i \) denotes that the superpixels category is mapped to the pixel it comprises. Subsequently, map the pixel’s likelihood distribution has been identified as belonging to every class. There are two hidden layers has been used. These hidden layers are used to reduce the complexity. Figure 5 shows the data preprocessing flow diagram.

A unit energy potential stated in an image surface or pixel and a potential energy pair indicated between adjacent pixels or neighboring regions are the main random field conditional...
algorithm. Poor ability causes the boundaries between different image objects to smooth excessively. Thus, the issue that various object boundaries are extremely smooth can be improved, if it is possible to enhance the ability to prompt paired potential energy to long-term spatial relations between picture areas and pixels. The concentrated variance between paired potential energy to long-term spatial relations between the color similarity degree and pixels correspondingly. In the following kernel function, the pixel position data utilized to eliminate certain isolated areas and play a smoothing role is used only to provide position information. The algorithm converts the message process into the function space. The kernel function can reduce the time complexity of message transmission from the second to the first energy, thereby enhancing the algorithm’s efficacy.

The Gibbs sampling algorithm is still used at the reverse reconstruction stage. To overcome the inconsistency in the dimension caused by the pooling operation, the zero operation will be performed in de-convolution. The visible layer is a real value unit is contrary to the forward inference process. The assessment can be sampled from the given Gaussian distribution:

$$U'_\beta \sim M \left[ \sum_r D'_\beta \otimes \text{rot} \left( L_{d,r}, 180^\circ \right) + c_d, \gamma^2 \right]$$

Determination of the parameters of the network architecture already defined, that is, the weights/ kernels and biases of every layer, with a training data set, has been considered. Neural network training is usually a problem with scalar error (implicitly) optimization based on network attributes. This error develops a difference between the reference to the ground truth of the training dataset and the prediction output. Weights and biases of every layer are changed to minimize the error with back-propagation. The only way to accelerate the learning phase (stochastic learning) is in practice to show only the training dataset random subsets, called miniatures, in one iteration of the training learning.

The relative error distribution can be expressed as,

$$\epsilon_j = \frac{x_j - x_{j,\text{ref}}}{x_{j,\text{ref}}} \text{ with } j \in [1, M_{\text{batch}}]$$

As shown in equation (15) where $M_{\text{batch}}$ denotes the mini-batch size, the discrepancy measure to minimize can be defined as $G(\epsilon) = \text{rmsq}(\epsilon)$. The term $\text{rmsq}(\epsilon)$ is the RMSE on the mini-batch.

The employment of a deep learning algorithm is driven by the accessibility of high-performance computing. The threshold segmentation algorithm high accuracy in image segmentation and classifies the motion categories to prevent injuries from the wrong position. Data sets are generalized by classification and efficiency metrics with a range of various validation methods. The following section discussed the experimental results and discussion.

**IV. EXPERIMENTAL RESULTS AND CONCLUSION**

**A. PERFORMANCE RATIO EVALUATION**

The recovery of the optimal form (anatomy) and function (physiology) is rehabilitation. The rehabilitation plan should take into consideration the fact that the patient’s objective (the sportsman) is a return to the same action and the same surroundings in which the injury took place. The final goal in a rehabilitation process is to reduce the level of the injury, to reduce or reverse impairments and functional losses and to avoid, correct, or neglect the unconscious person. The technical capacity should be the same, and the proposed Hierarchical hybridized deep convolutional neural network (HHDCNN) method enhances the performance of
the sports rehabilitation when compared to other conventional approaches. Figure 7 demonstrates the performance ratio of the suggested HHDCNN system.

Table 1 demonstrates the performance ratio evaluation of the introduced HHDCNN model. Utilizing a deep learning algorithm, the capacity to perform movements in a smoothly, accurately, and controlled manner can be defined as coordination. The techniques of rehabilitation refer to neuromuscular re-increasingly. Improved coordination depends upon the repetition of the different sports and correct training positions and movements. Simple activities must start, be performed slowly and correctly, increasing in speed and complexity gradually. The 1900 training and testing data has been taken for analysis.

### B. AVERAGE RECOGNITION ACCURACY

The suggested HHDCNN system achieves high overall recognition accuracy because the movement trajectories of the image captured from the side views are the same. Jumping jacket with an average accuracy of 98.9 percent is the easiest to identify. The accurate use of the combined features for most source combinations inside views has improved. This is because of the similar appearance of those views. Both metrics are highly correlated for the wrist or combined datasets and show the logarithmic growth trend, asymptotically limited as the window size approaches sixty. The pocket dataset is very well correlated with both metrics; there is a more significant gap between them. The proposed Deep learning algorithm increases the recognition accuracy of the sportsperson motion to avoid the injuries. Figure 8 demonstrates the average recognition accuracy of the introduced HHDCNN model.

### C. PREDICTION RATIO ANALYSIS

The prediction of human movement from motion capture data is a classic computer-vision problem, and the human body is taken up by conventional approaches. As the auxiliary information for prediction, this classification provides the action group, and the predictor preserves more detailed data for accurate self-supervision recognition. The hierarchical hybridized deep convolutional network (HHDCNN) which manages action recognition and motion prediction in accordance to collect action patterns using graph-based operations. Our model is a backbone, head of the action, and head of motion prediction, in which both heads are reinforced. Figure 9 demonstrates the prediction ratio analysis of the suggested HHDCNN approach.
D. TRAINING EFFICIENCY RATIO

Local features are usually motion specific, restricting the ability of arbitrary spatial-changes within movement data to be handled efficiently. The results proposed to confirm our hypothesis that effective motion assessment is firmly based on human movement models. Probabilistic approaches, like the Gaussian kernel function, have improved the ability in comparison with model less approaches to address the inherent variability and measurement uncertainty in human motion data. The training efficiency can be developed using the proposed HHDCNN method. Figure 10 shows the training efficiency ratio of the proposed HHDCNN method.

E. ERROR RATE

Figure 11 illustrates the evolution of the train and test error for all data sets. Training errors improve over time in all cases. In some cases, training error can increase from epoch to epoch, due to two reasons: the use of micro batching instead of the complete training set and the establishment of a high rate of education. The second reason is solved by adjusting these hyperparameters during the training process, ensuring convergence as the number of times increases. In the event of a test error, its evolution is considerable noise; it does not converge to the combined dataset can be fixed through a more significant number of epochs through the training process. The proposed deep learning method has less error rate. Figure 11 demonstrates the error rate of the proposed HHDCNN method.

F. F-MEASURE AND ROC

The use of an algorithm for deep learning is motivated by high-efficiency computational accessibility. The algorithm of threshold segmentation is strong in image segmentation and categorizes the motions for the avoidance of injury from the wrong position. Data sets with different testing methods are simplified through grouping and F-Measure performance. Figure 12(a) shows the F-measure value of proposed HHDCNN method. Figure 12(b) shows the Receiver Operating characteristics of proposed HHDCNN method. It have high better function in F-Measure and ROC.

The suggested hybridized hierarchical deep convolutional neural network (HHDCNN) method achieves high accuracy.
in image segmentation, reliability, performance, less error rate in predicting athletics motion and rehabilitation process. The threshold segmentation algorithm has been performed for accurate image prediction of movement.

V. CONCLUSION AND FUTURE WORK

This paper presents the Hybridized Hierarchical Deep Convolutional Neural Network (HHDCNN) has been proposed to enhance the accuracy of motion capture, image segmentation of sports athletics exercise rehabilitation. The accurate and useful diagnostic processes of doctors are supported by deep learning algorithms, particularly image registration image recognition, classification, lesion segmentation, image location and detection, fusion, and microscopic imaging analyses. The sports rehabilitation image segmentation algorithm can relatively precisely identify the position and category of objects on the picture. To address the shortcomings of conventional methods of image detection, an image segmentation algorithm for sports exercise rehabilitation is proposed based on the Hybridized hierarchical DCNN. Superpixels are utilized for extracting the feature of the image through a deep learning approach. Finally, a random field condition of a fully connected layer is designed to enhance the continuity and consistency of local pixel markers with the fully detailed condition classification results. The results show that the method suggested not only improves segmentation accuracy significantly, and reduces algorithm running time, reduces doctors’ tasks, and reduces the error rate. In future the advanced deep learning methods will be used to achieve better reliability.

REFERENCES

[1] Y. Su, “Implementation and rehabilitation application of sports medical deep learning model driven by big data,” IEEE Access, vol. 7, pp. 156338–156348, 2019.

[2] H. Ma and X. Pang, “Research and analysis of sport medical data processing algorithms based on deep learning and Internet of Things,” IEEE Access, vol. 7, pp. 118839–118849, 2019.

[3] M. M. Hassan, S. Huda, M. Z. Uddin, A. Almogren, and M. Alrajabai, “Human activity recognition from body sensor data using deep learning,” J. Med. Syst., vol. 42, no. 6, p. 99, Jun. 2018.

[4] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, “A robust human activity recognition system using smartphone sensors and deep learning,” Future Gener. Comput. Syst., vol. 81, pp. 307–313, Apr. 2018.

[5] P. Vyass, “Pose estimation and action recognition in sports and fitness,” San Jose State Univ., San Jose, CA, USA, Tech. Rep. 695, 2019.

[6] K.-R. Mun, G. Song, S. Chan, and J. Kim, “Gait estimation from anatomical foot parameters measured by a foot feature measurement system using a deep neural network model,” Sci. Rep., vol. 8, no. 1, pp. 1–10, Dec. 2018.

[7] A. D. Vigotsky, I. Halperin, G. J. Lehman, G. S. Trajano, and T. M. Vieira, “Interpreting signal amplitudes in surface electromyography studies in sport and rehabilitation sciences,” Frontiers Physiol., vol. 8, p. 985, Jan. 2018.

[8] M. Panwar, D. Biswas, H. Bajaj, M. Jobges, R. Turk, K. Maharatta, and A. Acharya, “Rehab-net: Deep learning framework for arm movement classification using wearable sensors for stroke rehabilitation,” IEEE Trans. Biomed. Eng., vol. 66, no. 11, pp. 3026–3037, Nov. 2019.

[9] Y. Liao, A. Vakanski, and M. Xian, “A deep learning framework for assessing physical rehabilitation exercises,” 2019, arXiv:1901.10435. [Online]. Available: http://arxiv.org/abs/1901.10435

[10] J. Law, “Evaluation of sport rehabilitation students’ value of communication skills to enhance the summative assessment of musculoskeletal injuries,” J. Learn. Student Exp., vol. 1, p. 17, Dec. 2018.

[11] Y. Liao, A. Vakanski, and M. Xian, “A deep learning framework for assessing physical rehabilitation exercises,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 2, pp. 468–477, Feb. 2020.

[12] W. R. Johnson, A. Mian, M. A. Robinson, J. Verheul, D. G. Lloyd, and J. A. Alderson, “Multidimensional ground reaction forces and moments from wearable sensor accelerations via deep learning,” 2019, arXiv:1903.07221. [Online]. Available: http://arxiv.org/abs/1903.07221

[13] D. M. Jia, C. F. Yuan, S. Guo, Z. Z. Jiang, D. Xu, and D. A. Wang, “Application of artificial intelligence and big data,” in Proc. Int. Conf. Artif. Intell. Adv. Manuf. Sports Rehabil. Chin. Judicial Administ. Drug Addict, Oct. 2019, pp. 1–5.

[14] J. J. Winslow, M. Jackson, A. Getzin, and M. Costello, “Rehabilitation of a young athlete with extension-based low back pain addressing motor-control impairments and central sensitization,” J. Athletic Training, vol. 53, no. 2, pp. 168–173, Feb. 2018.

[15] D. Kim, J. Kwon, S. Han, Y.-L. Park, and S. Jo, “Deep full-body motion network for a soft wearable motion sensing suit,” IEEE/ASME Trans. Mechatronics, vol. 24, no. 1, pp. 56–66, Feb. 2019.

[16] J. D. Runsohoh, A. Nikfarjam, E. Jones, B. Loew, B. Y. Kwong, K. Y. Sarin, and N. H. Shah, “Detecting chemotherapeutic skin adverse reactions in social health networks using deep learning,” J. Amer. Med. Assoc. Oncol., vol. 4, no. 4, pp. 581–583, 2018.

[17] Y. Liang, D. Wu, D. Ledesma, C. Davis, R. Slaughter, and Z. Guo, “Virtual Tai-Chi system: A smart-connected modality for rehabilitation,” Smart Health, vol. 9, pp. 232–249, Dec. 2018.

[18] K. B. Gunter, C. J. Shields, S. D. Ott, and R. A. Coronado, “Rehabilitation of an adolescent equestrian athlete with a history of multiple concussions: A case report describing an adapted Return-to-Sport protocol,” J. Orthopaedic Sports Phys. Therapy, vol. 48, no. 12, pp. 934–942, Dec. 2018.

[19] K. A. Weber, A. C. Smith, M. Wasielewski, K. Eghtesad, P. A. Upadhyayula, M. Wintermark, T. J. Hastie, T. B. Parrish, S. Mackey, and J. M. Elliott, “Deep learning convolutional neural networks for the automatic quantification of muscle fat infiltration following whiplash injury,” Sci. Rep., vol. 9, no. 1, pp. 1–8, Dec. 2019.

[20] J. Mosele, “Artificial intelligence in the sport industry,” M.S. thesis, Politecnico di Milano, Milan, Italy, 2018.

[21] H. F. Nweke, Y. W. Teh, M. A. Al-garadi, and U. R. Alw, “Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges,” Expert Syst. Appl., vol. 105, pp. 233–261, Sep. 2018.

[22] D. Ravi, C. Wong, B. Lo, and G.-Z. Yang, “A deep learning approach to on-node sensor data analytics for mobile or wearable devices,” IEEE J. Biomed. Health Inform., vol. 21, no. 1, pp. 56–64, Jan. 2017.

[23] J. Hannink, T. Kautz, C. F. Paslaosta, J. Barth, S. Schulein, K.-G. Gassmann, J. Klucken, and B. M. Eskofier, “Mobile stride length estimation with deep convolutional neural networks,” IEEE J. Biomed. Health Inform., vol. 22, no. 2, pp. 354–362, Mar. 2018.

[24] Y. Xia, Z. Yao, Q. Ye, and N. Cheng, “A dual-modal attention-enhanced deep learning network for quantification of Parkinson’s disease characteristics,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 1, pp. 42–51, Jan. 2020.

[25] C. Frank, A. Kobesova, and P. Kolar, “Dynamic neuromuscular stabilization & sports rehabilitation,” Int. J. Sports Phys. Therapy, vol. 8, no. 1, p. 62, 2013.

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