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# Deep Learning Based Advanced Spatio-Temporal Extraction Model in Medical Sports Rehabilitation for Motion Analysis and Data Processing

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**ABSTRACT** Presently, A wide range of unlabeled and minimal style data significantly decreases the current motion sequence's reuse ability. An important method of data reuse has a successful classification and fragment separation, which has been discussed in this research. This paper focuses on these particular problems and the tremendous progress of deep learning in design and symbolic fields. A Limited Boltzmann Model (LBM) theory is based on the Advanced Spatio-Temporal Extraction Model (ASTEM), which has been used for analyzing the physiological motion of human skeletons. There are primarily three aspects to the results of the study. (1) For constructing a semi-combination model, the stack factor decomposition is used as a spatiotemporal model function and LBM discrimination. (2), Optimized algorithm used to create the three-channel generative LBM model using the weight decomposition idea and then extract the time and space-based abstract properties of the original motion series. (3) The unsupervised related model of frame detection is built using the perception of human interaction through 3D convolution LBM. A significant research direction of the medical analysis and extraction of sports data is used appropriately to interpret and gain valuable information and knowledge from motion analyses. Experimental outcomes show that this technique offers technical assistance and guidance for implementing a real cloud-based fusion system.

**INDEX TERMS** Sports medical data, limited Boltzmann model, advanced spatio-temporal extraction model.

## I. INTRODUCTION ABOUT SPORTS REHABILITATION

Today, digital technologies are introducing to the sports arena due to secure mobile networks, wearable, and artificial intelligence technology [1]. For coaching, tactical, or technological assessments, many professional sports clubs using sports analysis [2] to obtain a sense of their player's success [3]. The ProZone system for player movement analysis is developed at Old Trafford in Manchester as well as Reebok in Bolton. Live sports coverage, in addition to special teams, adopts sports analytics [4] to bring live game data to the public. With the next age of sports robots that have been created for rival people, sports analytics [5] will profit from predicting, determining, based on scheduled motion. Real-time analysis is essential in these applications. Besides, there is a growing trend for amateurs to use sports analytics on the popular playfield, where an inexpensive and easy-to-deploy program is preferred.

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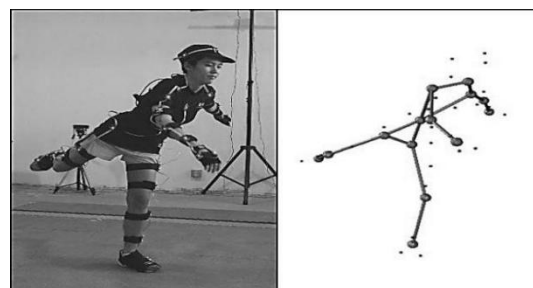


FIGURE 1. Example of motion analysis [13].

Consequently, a low-cost device performing real-time and precise sports analysis [6] is highly desirable and has many significant applications in real-world sports activities (Figure 1). Typically, the future conceptual context of human mobility data is difficult to fully define, by using a non-linear dynamic structure between limb relation and a strict time/space dependency [7]. The study points to the challenges

of establishing a direct connection between low-dimensional and human space and traditional algorithms [8]. Throughout the years, with the advent of simple computing, significant progress has been made with structured data modeling. The detailed spatial and time structure is a considerable challenge in successfully implementing a deep learning model [9].

Deep learning technology is implemented in a variety of fields, and it has been eventually extended to include high-level applications such as video and audio data processing from basic static image processing applications [5]. Through analyzing previous data with large numbers, the basic rule and past data can be easily retrieved from low-level data. Therefore, the main challenges are understanding the concepts of pre-processing and then developing new ideas. Many techniques are designed to accurately monitor movement in rehabilitation activities that promote and improve physical activity [10].

Only local dynamic constraints can be derived from a classical LBM model based on Markov restriction. The LBM used to eliminate compression distortion as an input of ALBM, and to achieve a simpler transition between different movements [11], the Comparison reconstructed the human spinal tract in five sections. Further, The Comparison used the encoder's ability to reconfigure the original information. It developed LBM training for each frame to obtain characteristics in storage structure and connect the hidden layer with the time information unit. The relationship assumed that through directional connections between the adjacent input frames, the entire motion series shared the same spatial transmission properties [12].

The scope for reuse of existing motion sequences [15] is substantially restricted by a large number of unlabeled or minimum design data [16], [17]. A successful way to reuse data has become an efficient way of classifying and fusing fragments. The paper focuses on the significant progress of deep graphics and iconography learning with a view to both issues.

The main contribution of this paper is discussed as follows: The Limited Boltzmann model (LBM) theory is used to establish a model of space extraction for medical sequences of human skeletons. The simulation method verifies the algorithm's superiority and efficiency, which is implemented successfully in rehabilitation training.

## II. RELATED WORKS

Mirabella *et al.*, [17] provided a motion capture method that offers both precise measurements of the human arm's motion parameters and a virtual model for the graphical reconstruction of the motion. The hardware uses several MEMS inertial sensors whose data is processed using quaternion based mathematical methods. The Measures on a prototype have proven the device to be very precise; hence, it is possible to obtain a video motion very faithful to the actual sensors mounted on the joints of the arms.

Ling *et al.*, [18] compared to the first time where the traditional method of development of technology for virtual

reality, it develops a realistic system of lower limb rehabilitation, creates a more accurate human lower limb rehabilitation model, studies the lower limb rehabilitation movement with passive mode and simulates the improvements to human musculoskeletal enhancements in the second stage of rehabilitation. Second, analysis is being carried out on a robust omnidirectional mobile based on a low limb rehabilitation control system based on medical big data and artificial intelligence. It defines the Omni-directional moving with lower limb recovery system error based on dynamic models and analyzes the technical problems of standard design, dissipation, and value. The nonlinear robust control system is built for omnidirectional lower limb rehabilitation motions by constructing the storage mechanism using the reverse push process. The consistency of the control policy is discussed in the theorem of Lyapunov.

Karg *et al.*, [19] described the use of the parametrically concealed model of Markov (PHMM) to estimate the exercise fatigue induced by observing dramatic changes. Here, the linear regression, along with the PHMM model, has been analyzed, and a top-level Markov hidden model with variable state transitions provides details about fatigue improvement during exercise and the initial condition. The solution is checked in an optical motion-captured squat database. The exhaustion figures for one squat, several squats, and a whole exercise are strongly related to subjective scores.

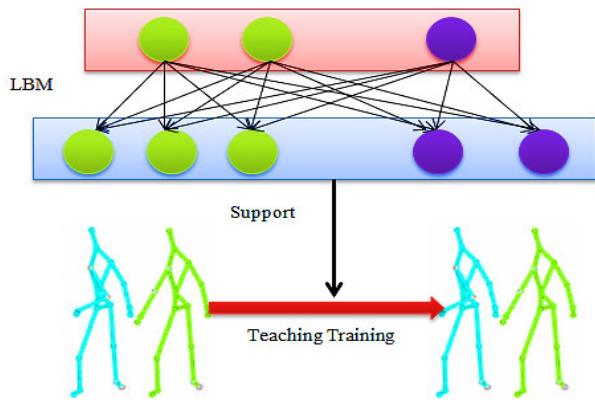
A movement risk assessment approach based on the big data analysis was introduced by Zhang *et al.*, [20]. A Risk Assessment Model for large-scale sports, for the multi-level overlay and multi-factor mediation variance scheme, has the analysis of risk data on sport and the use of the Neural Big Data Framework (NBDF) are used as risk assessments. This paper focuses on risk factor research. The test results show the proposed methodology, in Comparison with the traditional risk assessment method, can achieve high efficiency and reliable motion risk assessments, which can apply to large-scale risk assessments. The approach is focused on big data analyses. The theory and practice of Big Data-driven health/disposal management, the promotion, and enhancement of Sports Health Management and the growth of Big Data healthcare Industry have the theoretical and practical importance in this framework. Based on the above survey the proposed method has better accuracy and prediction ratio in motion analysis and data processing when compared to other existing ways which has been represented as follows,

## III. DEEP LEARNING APPLICATION IN MEDICAL SPORTS REHABILITATION

As the basis of deep learning theory, Deep Neural Networks (DNN) has minimized gradient diffusion and gradient explosion issues with the incorporation of multi-computing units into the conventional backpropagation algorithm. Advanced human motion-modeling mainly involves four types of specific learning systems and their application for movement generation, according to DNN's topological structure [21].

**A. LIMITED BOLTZMANN MODEL**

Limited Boltzmann (LBM) model [22] is a stochastic network that can learn how input data sets distribute probability. Specific Boltzmann system for reduction measurements, classification, collaborative filtration, feature learning, and modeling has been applied. Limited Boltzmann machines can be equipped through supervised learning or unsupervised learning according to the mission. LBM model using the weight decomposition idea and then extract the time and space-based abstract properties of the original motion series. The LBM training and recovery system is demonstrated in Figure 2.



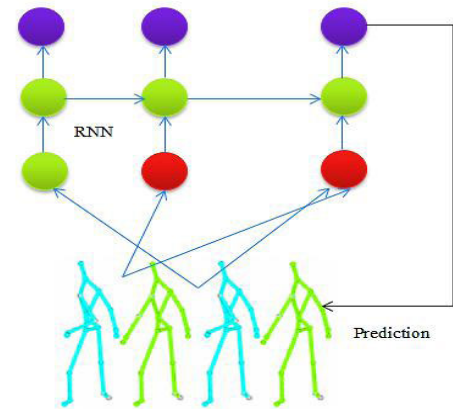
**FIGURE 2.** The training and rehabilitation system based on the LBM.

**B. RECURRENT NEURAL NETWORK (RNN)**

Compared to an LBM model, the RNN is a graphic model that is designed to model long-term concept dependence. The recurrent structure of the time axis is identical to LBM and can be applied feedback weights between the hidden layers. RNN is equated with a specific neuron called the Memory Cell, a classic time series modeling approach that carries hidden autoregressive layer connections to the historical information feedback. The hidden layer entry does not contain information about the input layer, and information about the new use of the hidden layer has semantic recognition and text generation. The use of LBM is empty concerning human motion collection data. As shown in Figure 3, a new motion sequence can be generated with the decoding level, by using the LBM structure for the extraction and extrapolation of the characteristic of two different motion types are described as follows,

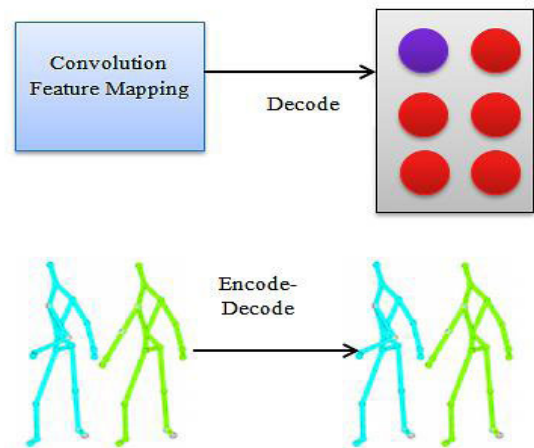
**C. DEEP CONVOLUTIONAL NEURAL NETWORK**

Traditional neural network architectures are entirely connected, which can easily result in “dimensional disaster” and other serious problems. The local processing of information, parameter sharing, and invariance of transmission of specific convolution kernels at CNN are incredibly useful in computer vision. In the coordination of the human joint problem



**FIGURE 3.** RNN-based sequential motion frame extension.

reconstruction, the capacity of 3D convolution is expressed in all these respects. It can model the overall configuration and timing of the skeleton. Due to the monotony of gathering data sets, it is not more challenging to create motion, such as interacting with multiplayer scenarios that remain in the synthesis of necessary motion Specified based on customer retention and other activities. Figure 4 displays the complex structure diagram of sports fitness.



**FIGURE 4.** CNN-based sequence motion frame expansion.

**D. REINFORCEMENT LEARNING**

Reinforcement learning has low modeling capability for high-human movement data. Furthermore, DRL is essential for the production of roles in complex and constrained scenes in real-time. In the course of medical recovery, it is crucial for us to communicate with the community and to help people improve as quickly as possible.

**IV. PROPOSED METHODOLOGY (ADVANCED SPATIO-TEMPORAL EXTRACTION MODEL)**

This paper focuses on the significant progress of deep graphics and iconography learning. A Limited Boltzmann Model

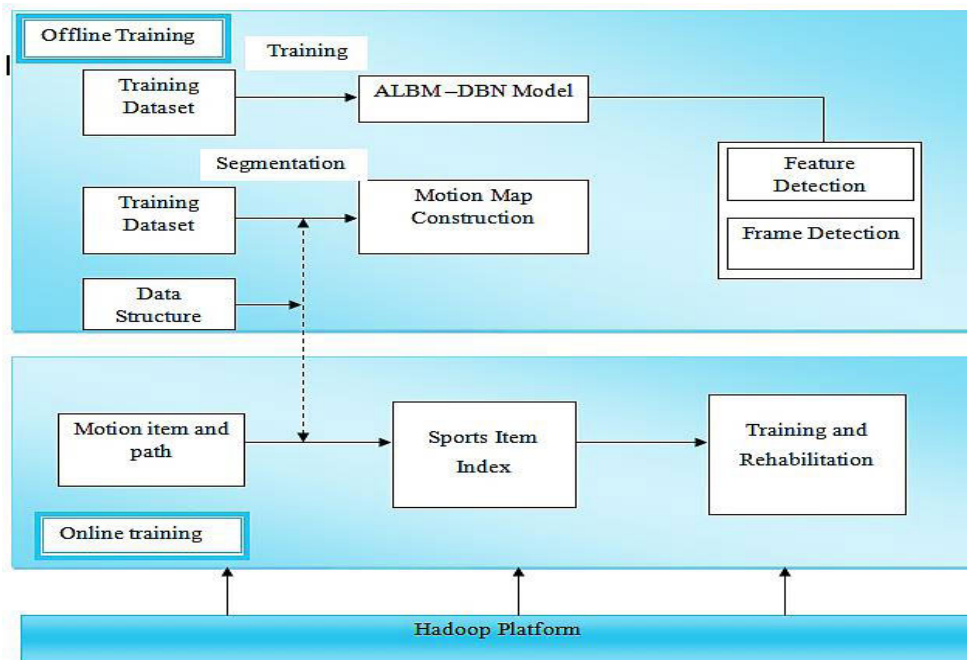


FIGURE 5. The framework of the ALBM Model.

(LBM) theory is based on the Advanced Spatio-Temporal Extract Model (ASTEM), which has been used for analyzing the physiological motion of human skeletons. Here the deep learning based advanced LBM algorithm has been used to provide better superiority and efficiency in rehabilitation training when compared to existing methods.

**A. ADVANCED LBM ALGORITHM**

Given the incorrect recognition and inadequate correlation of trace segments in current movement graph design methods, the design of movement maps with unsupervised contextual learning and with a decay-movement segmentation approach is proposed. For a spatial structure of the skeleton movement, the Boltzmann machine, which limits its convolution, is used to extract the spatial characteristics from the time axis automatically, and detect the candidate’s transition point. The results show that it is easier to use fast matrix interpolation to generate the natural movement transition sequence than with traditional movement graphics structures in the primary position derived from the approach. However, distorted angle restriction combination improves the re-usability of original movement data and has no flexibility to control position concerning the speed of movement generation. The results show that it is preferable to use quick matrix interpolation to construct the natural movement sequence as opposed to the traditional movement graph structures since the key position obtained from this method.

Furthermore, distorted angular limit balancing improves the re-usability of the original motions and does not lose stability in position regulation provided with the speed of

motion formation. Figure 5 shows that an offline phase has the ALBM model, which trains a large number of sample data, that allows user data sets to identify the points in motion diagrams in transition. During online segmentation and style recovery, the quadrupling environmentally dependent structure meets the constraints between the online and offline Input motion. A lot of computation is involved in deep learning analysis. In this study, the Hadoop cloud platform supports deep learning. The performance of the platform can be improved significantly.

**1) COMPONENT DETECTION OF TRANSITION FRAMES BASED ON CONVOLUTION-ALBM**

DNN Preprocessing is standard, as all details about the human body inside each frame should be taken. To remove the linkage of each element, it relates to the whole connection layer. The local skeleton association and the joint details of the limb joint are not included in these methods.

The human skeleton is reorganized to solve this problem by using the following three adjacent connections, which each describe the local perception region of the convolution mechanism so that the contribution to any movement style is automatically calculated. The value kernel is focused on preliminary knowledge in conventional methods to prevent the sensitive functioning of decarbonization, which is calculated by the weight of each joint.

This paper proposes a stacked 3D- ALBM / DBN network for unsupervised training based on the spatial structure of motion capture data to completely leverage the advantages of DNN for automated feature removal (Figure 6).

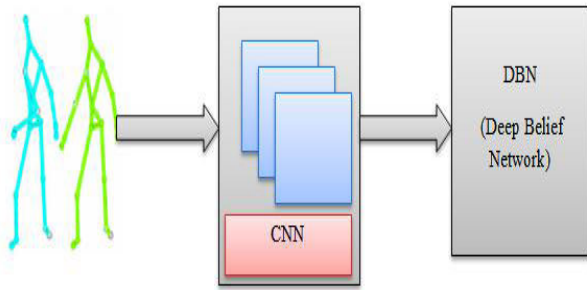


FIGURE 6. The internal structure of the model for detecting transition frames.

### 2) THE CONVOLUTION-ALBM ALGORITHM CONCEPT

For both implementations, the benefits of convolution ALBM are specifically illustrated for unsupervised learning of local structures and temporal characteristics. The Convolution-ALBM is extended, based on the intrinsic human skeleton spatial structure in each frame, to eliminate spatial and temporal data and candidate points of change in implied space based on the euclidean space between frame segments. The Convolution-ALBM is extended for enabling the three-dimensional data to be extracted. As 3D Conv-ALBM still includes an ALBM training divergence algorithm for motion capture data expansion and its control function can be defined accordingly and varies in the same coordinates from local information sharing (weight) and biases.

$$R(X, H, \theta) = - \sum_p \sum_\beta \sum_q \frac{X_\beta^p}{\vartheta} \otimes G_{p,q} \otimes P_\beta^q - \sum_d \sum_\beta \frac{(X_\beta^p - b_p)^2}{2\vartheta_p^2} - \sum_d \sum_\beta P_\beta^q - b_q \quad (1)$$

where  $X_\beta^p$  indicates the alpha block perceptual range for the dimension  $P \in (a, b, c)$  of input data;  $X_\beta^p$  represent a local time, a convergence block spatial element, where  $G_{p,q}$  is the weight that connects the input data with the output unit. Delta is a training variance setting. The value is always set to 1, because of the presence of the normalization operation. Necessarily, a small, LBM structure can form with some neurons in the winding layer of the 3D-model in each local sensing region. The signal value from the lower to the top layer is given according to sampling carried out by Gibbs as:

$$P_\beta^q = \sum_{P \in (a,b,c)} \frac{X_\beta^p}{\vartheta} \otimes G_{p,q} + b_q \quad (2)$$

Therefore, when the binary implicit state is applied, the activation unit's energy contribution to the model is:

$$P_\beta^q = S \left( P_\beta^q = 1 \mid X_\beta^p, \theta \right) = \frac{e^{P_\beta^q}}{1 + \sum_q e^{P_\beta^q}} \quad (3)$$

In the image processing process, neural network architecture only reduces the advantage of weight-parameters and improves the noise protection of the model. The role includes data obtained through technology for movement capture vulnerable to environmental deficiency. However, its reliability lacks theoretical and experimental support. This paper thus reflects the standard approach to high probability pooling:

$$S_{ab} = \max(P_\beta^q)_{2 \times 2} \quad (4)$$

$(\cdot)_{2 \times 2}$  represents the surrounding region selected in the convolution layer  $P_\beta^q$  by the pooling process. In the reverse stage of reconstruction, the Gibbs sample algorithm is only being used. In the deconvolution, the null operation can be performed to solve the inconsistency dimensions induced by the pooling method. A visible layer is a real unit of value, and it can be sampled out of the Gauss distribution, in contrast to the forward inference method:

$$X_\beta^p \sim M \left[ \sum_q P_\beta^q \otimes n^t (G_{p,q}, 180^\circ) + b_p, \vartheta^2 \right] \quad (5)$$

Equation (3) and (5) demonstrate the method of the reverse data recovery and forward extraction using convolution LBM, respectively:

$$b_p = Q_\beta^q - (X_\beta^p)^{(G)} \quad (6)$$

$$b_q = P_\beta^q - (C_\beta^q)^{(G)} \quad (7)$$

$$G_{p,q} = Q_\beta^q \times P_\beta^q - (C_\beta^q)^{(G)} \times (X_\beta^p)^{(G)} \quad (8)$$

LBM is challenging to learn the features of real data with less variation in the actual training process. Therefore the layer standardization approach proposed in recent years when connecting Convolution-ALBM to DBN model is used to avoid the covariable offset phenomenon. This fundamental algorithm is described as follows:

$$\rho = \frac{1}{H} \sum_{i=1}^1 S, \quad D_1 = \sqrt{\frac{1}{H} \sum_{i=1}^1 (S - \rho)^2} \quad (9)$$

$\rho$  is the mean value for all pooling layer connecting units, and  $D_1$  is the Convolution-ALBM to DBN connecting node. Because Convolution-LBM extracts feature from multiple convolution cores, its size typically exceeds the input size when its grouped neurons are entirely interconnected. The key to promoting the fast recovery of identical frames is the efficient method of data dimension reduction.

### 3) FRAGMENTATION AND SEGMENTATION

The Motion Graph provides a kind of efficient way of evaluating data reuse and tracking existing motion databases. The Comparison showed that the construction of a motion graph mainly comprises three phases: movement segment division, transit point identification, and intermediate transition frame growth. The key evaluation for the graphical structure is always functional, which provided that the user satisfies the specified input limitations.

It implies that the long motion sequences are immediately segmented based on the four-structure of decay. A deep learning function extraction system detects candidate transition frames between segments.

The graph model can be connected continuously more closely, but the complexity of the process would be increased as well. A useful motion graph has been combined to restrict the time and graph connectivity intelligently.

Continuing pairs of frames have a wide area based on a suitable transmitting point. The decision for a deep-fragment for the segment is given in Figure 7. However, the movement series has a scenario of regression, since the left picture direction is opposite to the direction of motion.

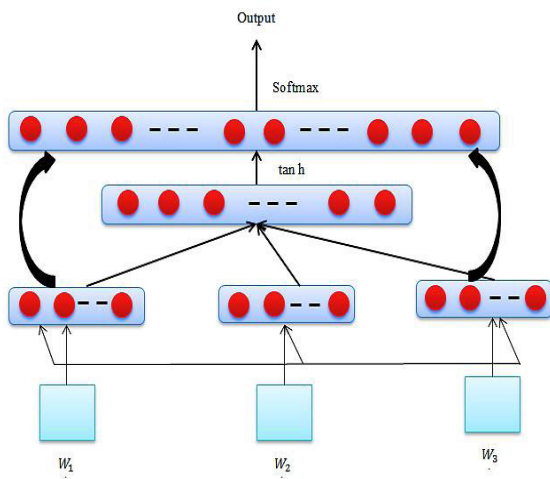


FIGURE 7. The decision of the transitional fragment segment is based on a deep neural network.

**B. SPORTS MEDICAL MOTION DATA PROCESSING**

The following are the cloud, big data, and internet technology for the advancement of the digital integration model, enhancement of the sports medical information system, compliance with intelligent sports health surveillance requirements, and the variety and complexity of sport health data. For data processing in the model, the enhanced deep learning algorithm is used.

Data is produced from the cloud data center (Figure 8). The information is first sent to the control layer during the acquisition, and the correct application data is subsequently sent to the control layer. The data is passed on to the appropriate application layer by the control layer.

The following three core equations (9,10,11), as shown in should be followed at the data transmission level based on net jitter. At data transmission level: Equation 9 is the delay form, D is the time delay, Equation 10 corresponds to network jitter formula RTT which is the trace delay, N corresponds to the number of nodes, Equation 11 corresponds to the formula of delays, where Q corresponds to a value of total and D is the

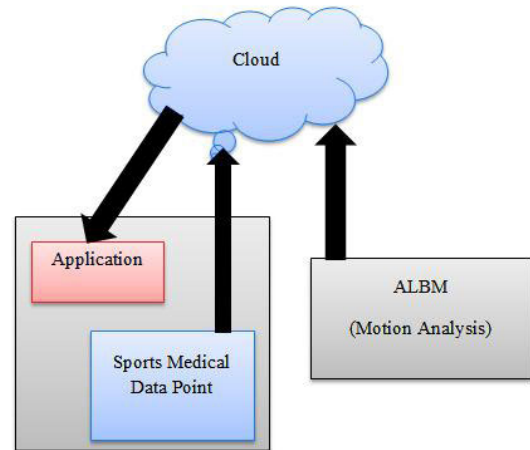


FIGURE 8. Data processing.

value of the time of corresponding duration.

$$\begin{cases} D = D_p + D_j + D_q \\ RRT = 2D \end{cases} \tag{10}$$

$$I = \frac{\sum_{j=2}^{\pi} RRT_j - RRT_{j-1}}{m - 1} \tag{11}$$

$$B = \frac{Q}{D} \tag{12}$$

The enhanced neural network proposed as a data processing center in this paper is used for this framework. The appropriate data training flow of the enhanced steps of the neural network is defined as follows:

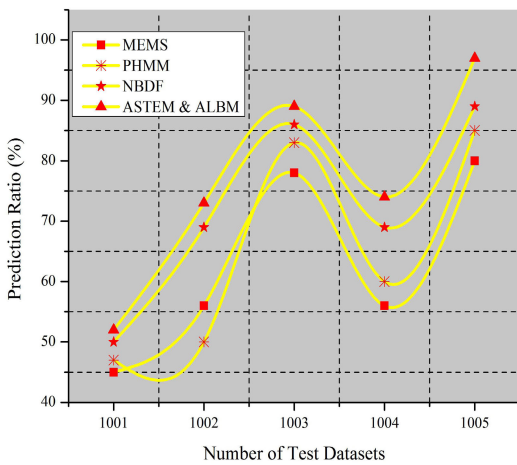
| Steps -1 for Enhanced Neural Network |   |
|--------------------------------------|---|
| 1.                                   | Enable data nodes and the correct selection areas.  |
| 2.                                   | Reduce complex data dimensions and save them in the network layer data storage area.                                  |
| 3.                                   | Copy data and related data models by sorting operations into separate partitions.                                     |
| 4.                                   | Training nodes are placed on a network parameter for a convolutional neural network.                                  |
| 5.                                   | The new parameter is spread into various classification areas if the training data is pre-heated to a certain amount. |
| 6.                                   | Open the training node and set the data delay function.   |
| 7.                                   | The epoch deadline for the training is set, and the model of the data parameter is saved.                             |

The results show that it is easier to use fast matrix interpolation to generate the natural movement transition sequence than traditional movement graphics structures in the primary position derived from the approach. The performance of the proposed method is evaluated as follows in the results and discussion section.

**V. RESULTS AND DISCUSSIONS**

**A. PREDICTION ANALYSIS**

The coherence of the frame segments used for design transformation directly affects the quality of the entire motion chain. Adjacent nodes that represent identical frames and moving edges that reflect linear interpolations on the sphere are based on the concept of a smoother transfer between high-similarity structures. The experiment chooses 40 frames for the duration of the windows of the linear synthesis algorithm. The first and final frames can be divided into the beginning and end frames of the combined section. The two kinds of LBM motion-synthesis style transition use Gauss noise to direct the development into hidden form. The interpolation algorithm can be used directly on the other hand side of the map to create intermediate frames that are identical to the primary machine interpolation in the open-source Ogre engine System based on the calculated length of a train. Two ends-(left to the left) has the transmission paths as the basis for evaluating the quality of the moving sequences created by various methods. The pathways generated by different ways contain various narrative characteristics and visual effects, as shown in Figure 9. In reality, human movement is often accompanied by a tumbling of the small body, particularly during movement capture; stress affects data quality directly in patients. To this effect, the typical trace in the motion series includes a certain amount of noise based on the movement map generated by the initial motion segment.

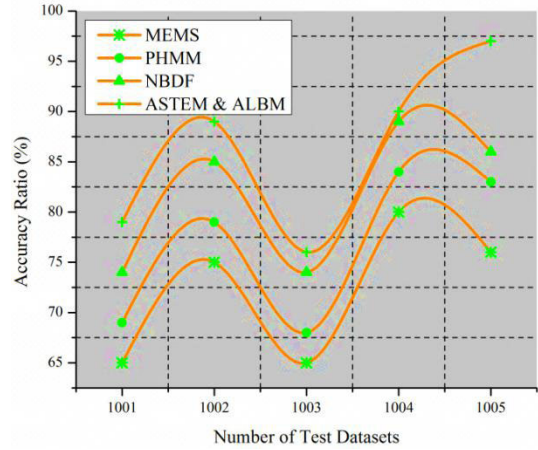


**FIGURE 9. Prediction ratio.**

**B. ACCURACY RATIO**

The main aim of the analysis is to investigate the effect of the input and the angle of Euler on the quality of motion generation. The first is the extraction by a focal distance vector, the relative location for each joint, corresponding to the root joint, as the data management method for absolute skeleton positioning coordinates within the 3D space. Furthermore, input data as mutual rotation information should be used. To prevent universal locks, the Euler angle data must first be

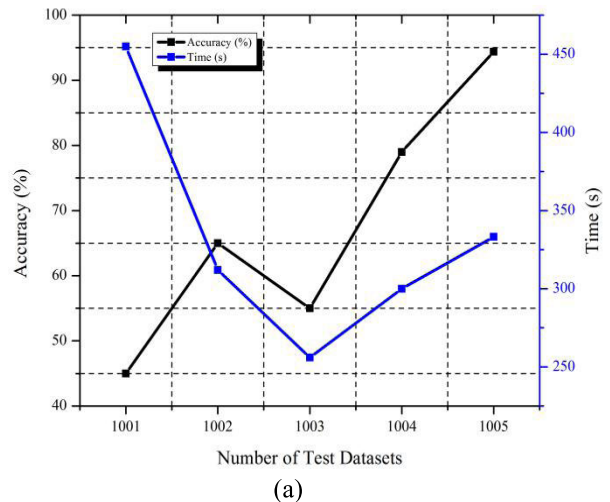
converted into an exponential mapping form. In the current position, the total area of core knowledge is replaced with the direction and forward differential vectors of the human body. Figure 10 shows the comparative findings between the proposed algorithm with the MEMS, PHMM, NBDF.



**FIGURE 10. Accuracy ratio.**

Figure 10 provides almost 97 percent accuracy with the proposed deep network model. In Comparison, the algorithm is nearly 10 times larger than conventional neural networks. It can make a higher assumption based on the quality of the moving frame produced by two data types. The quantity of space transmission created by different methods of communication in the graph model also differs in the super-efficient choice of the model, which directly impacts on the quality of the rehabilitation of the data.

However, the data of co-centralization implicitly incorporates the configuration of the body of the sports athlete in a learning process, thereby enhancing the transition between the skeletal structures and redirecting the movements. The



**FIGURE 11. Accuracy and Time (a) ASTEM & ALBM, (b) MEMS (c) PHMM (d) NBDF.**

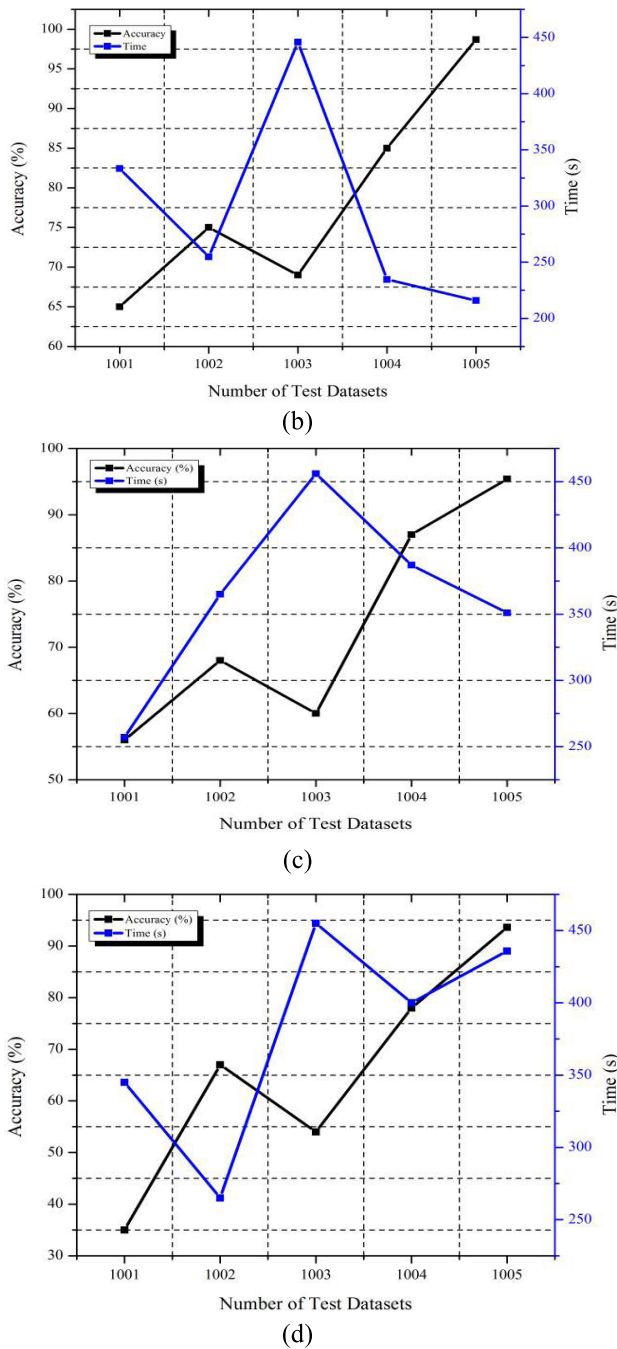


FIGURE 11. (Continued.) Accuracy and Time (a) ASTEM & ALBM, (b) MEMS (c) PHMM (d) NBDF.

TABLE 1. Comparison of different results.

| Model       | MEMS   | PHMM   | NBDF   | ASTEM & ALBM |
|-------------|--------|--------|--------|--------------|
| Time        | 333.27 | 435.78 | 350.89 | 215.9        |
| Accuracy(%) | 94.4   | 93.6   | 95.4   | 98.7         |

motion frames generated from rotation data input are of higher data quality and are appropriate for people who use the original skeleton data. Table 1 shows the comprehen-

sive effects of Comparison. As seen, our model consumes less than other deep neural networks in terms of time and precision.

The central distance curves of the apex end-electors are shown in Figure 11(a,b,c,d) with the root relationship of series moving movements produced in four models with two data entering to understand the smoothness of the restructured movement in the time-axis. The intensity of the movement depends on the dimensions and length of the jitter.

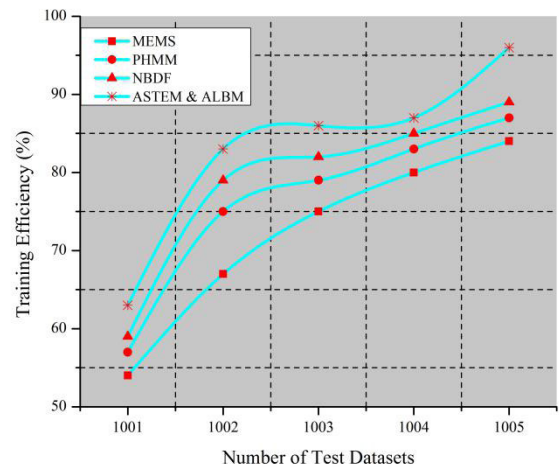


FIGURE 12. Training efficiency.

The comparison figure indicates that the motion model has a lower variability of the central distance vector. In this paper, it contrasts other methods for evaluation of convergence speed and algorithm training performance, such as MEMS, PHMM, and NBDF. A better and faster convergence may occur in the original model, as shown in figure 12. In addition, the convergence efficiency is much higher than the other two network models. Experiments demonstrate the effectiveness of our algorithm.

## VI. CONCLUSION

Many unlabeled and minimal form data minimize the reuse of current sequences of motion. Extensive reuse of data has developed into a standard and separate classification of data. A Spatiotime extraction method is designed for the medical sequences of motion on the human skeleton based on the Limited Boltzmann Machine Theory (LBM). The results of the research are shown in three aspects. (1) To construct a semi-supervised combination pattern, the stack factor decomposition Space-time Model and the discriminatory LBM function are used in this paper. (2) Next, the underlying model uses an assumption of weight decomposition for a three-channel LBM model with a generator active and then extracts the general tempo-space characteristics of the initial motion series. It defines the current input segment's behavior style at the top using the discriminating LBM template. In the voting space, finally, perform stylistic statistics on the entire motion sequence. Candidate frames are obtained for the creation of graphic model nodes. Control for the direction and design



is based on requirements for similarity testing attitude. The extraction of sports data is how a large number of sports medical data and cases are used to interpret correctly and to gain valuable data and knowledge from motion analyses. The simulation method verifies the algorithm's superiority and efficiency and is commonly used in recovery training.

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