RESEARCH ARTICLE

Training of aerobics professionals based on deep belief networks in the context of sports power construction

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Sports power creation is a planning project aimed at convincing a nation into having more athletic abilities with a combination of scientific training, technology research, and making elitist athletes. It is of importance in enhancing the performance of the athletes, protecting them against injuries, and in line with the goals of the country in enhancing the competitiveness of sports in the world arena and promotion of a culture of health and excellence. In the context of sports power creation, this study suggested a fine-tuning deep belief network (DBN) based paradigm for improving aerobics professionals training. In comparison to traditional machine learning techniques, a refined DBN model was proposed, which greatly increased movement analysis accuracy by utilizing multi-modal datasets including Human3.6M, Up-fall detection, and FIT dataset. The results showed that the proposed model outperformed support vector machine (SVM), random forest (RF), convolutional neural network (CNN), and long short-term memory (LSTM) baselines by 3.7 – 13.8% as evidenced by experimental findings showing 89.4% posture recognition accuracy, 88.1% movement categorization accuracy, 82.0% error detection rate, and 85.2% feedback precision. DBN's capacity to learn hierarchical features was especially useful for collecting intricate aerobic movement patterns while preserving training efficiency of 6.2 hours. Significant gains across all indicators were confirmed by statistical validation with *P* values less than 0.01 and Cohen's d larger than 1.4. This study offered a new use of DBNs for optimizing sports training and empirical support for multi-modal data fusion for movement analysis, as well as useful information for putting AI-assisted coaching systems into practice. The results provided a scientifically supported method to improve athlete performance while lowering injury risks, supporting the incorporation of deep learning technologies into national sports power development goals. The framework's cross-disciplinary adaptation and real-time deployment could be the main topics of future research.

Keywords: deep belief networks; aerobics training; sports power construction; movement analysis.

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Introduction

The sports audience in China is diverse in terms of behavior, socioeconomic class, and urban type because of the expansion of Chinese sports programs. The extraction of knowledge about human activities from massive video data sources has emerged in many different domains. Video can be instantaneously designed and examined if intelligent video surveillance is employed [1]. With temporal settings, human behaviors can likewise produce security warnings and be accurately detected in the real world. They are broadening the scope of applications that are accessible in public areas such as airports, transit hubs, and public transportation. Therefore, human behavior recognition has become a focus of research in numerous disciplines and does offer theoretical and managerial contributions. The fundamental body movements and the much more intricate joint activities of the human body including leg movements during sports are examples of body actions [2]. Despite the richness of the action data that has been acquired, there are serious problems with its cost, effectiveness, and environmental impact. The constant upgrading and modification of video capture equipment allows for the collection of body activity data [3]. Deep learning is extensively utilized in computer vision for prescriptive analytics, analysis, classification, and image processing. A previous study automatically gathered data on human supporting events and behavior related video databases to provide accurate recognition of physical movement and analysis [4]. Enhancing the networks in the deep learning (DL) mechanism is aided by the evaluation of multi-scale digital data, the development of fine-tuning deep belief networks (DBN), and the completely different pooling techniques. Additionally, the full representation of a person's sports behavior can accommodate spatiotemporal alternatives.

Conventional aerobic exercise includes strict standards for strength, movement standard, and limb coordination and consistency [5], which covers a broad range of athletic activities including dance, martial arts, gymnastics, and music combining actions. Developing human health and beauty through common sports is a new sports initiative [6]. Aerobic education highlights the sense of "beauty" in addition to demonstrating the "health" and "strength" of movements, which makes aerobics a highly decorative physical education activity with significant value to support college students' physical and emotional well-being [7]. Sun *et al*. developed intelligent aerobics teaching system that provided real-time feedback and personalized resource recommendations by Integrating AI with Kinect-based motion tracking and neural networks to improve students' movement accuracy to over 90% and enhance the precision of resource recommendations [8]. Liu *et al*. implemented DL-DBN for analyzing human behavior in sports to classify and predict human behaviors in sports using a distributed probability model and achieved up to 99% accuracy in predicting strength training behaviors [9]. Further, Alabdullah *et al*. utilized multi-feature extraction combined with DBN to enhance the accuracy of sports event recognition through advanced feature extraction and deep learning [10], while Jia *et al*. designed an AI-based system to integrate sensor networks for strength training in aerobics to provide real-time feedback and improve training efficiency [11]. Jeya *et al*. proposed a deep learning-based model with deep belief network for lung cancer diagnosis and demonstrated high accuracy [12]. In addition, the scientists proposed systems to improve teaching efficiency, personalized learning, student engagement, and student performance [13, 14]. Su *et al*. explored AI applications in physical education by investigating the integration of AI technologies in physical education curriculum and found that AI applications enhanced teaching methods and student engagement in physical education [15]. Liu *et al*. proposed a model that combined DBNs with the balanced manta ray foraging optimization algorithm (BMRFOA) to predict the shear strength of reinforced concrete shear walls and achieved a prediction error margin of approximately 7%, demonstrating reliable performance of proposed model [16]. Zhuang *et al*. developed a self-optimizing DBN framework by incorporating adaptive-active learning strategies to dynamically adjust network parameters during training. The proposed model demonstrated improved performance in feature extraction and classification tasks [17].

Although the research on deep learning and sensor perception recognition systems has achieved remarkable results in recent years, the real-time recognition of human motion and falls in multi-environmental and dynamic environments remains an issue. There are limitations with current models, which include the lack of generalizability regarding different datasets, computationally time consuming, or failing to suit individual differences in terms of movement. This research proposed a DBN model by combining the multi-source motion data from Human3.6M, Up-fall, and FIT datasets to enhance accuracy, responsiveness, and adaptability in real life human motion and fall detection systems. The results of this research offered extendable and repeatable basis of intelligent system enhancement in sports science and rehabilitation, geriatrics, and intelligent surveillance, and supported the development of top aerobics professionals and the wider digitization of sports education, which is in line with the objectives of contemporary sports power construction.

Materials and methods

Dataset

Several publicly available human motion datasets were employed for this study, which included Human3.6M (http://vision.imar.ro/human3.6m) dataset, a collection of about 3.6 million 3D human poses acquired using motion capture, Up-fall detection dataset (https://sites.google.com/up.edu.mx/har-up/), which combined wearable sensor and video data for capturing dynamic human activities, and FIT dataset through Kaggle (https://www.kaggle.com/) and GitHub (https://github.com/) with special attention to fitness training. Human3.6M provided about 3.6 m 3D motion-capture-based poses with about 100 h chores such as walking and exercising with 6-DOF maps of joints and RGB movies. Up-fall detection dataset had 204 activity trials with 12 participants and resulted in approximately 34 hours of wearable sensors and dual camera video data of activities such as walking, running, and falling. FIT dataset provided approximately 10,000 labeled exercise video clips of more than 50 kinds of exercises including over 150 hours of RGB video visited with annotations of activity detectors at the frame level. Together, these datasets provided comprehensive resources to model, analyze, and optimize the training process of aerobics professionals through intelligent systems.

Fine-tuning deep belief network

By using the 3 large datasets, a fine-tuning deep belief network model of aerobics professional training was proposed, trained, and assessed (Figure 1). Because aerobics entails intricate, fast-paced, and rhythmically synchronized motions, models that can recognize minute patterns in human motion are necessary for the collection and analysis of such performance data. Fine-tuning DBNs are ideal for this task because they enable the adaptation of pre-trained models, which are first created on extensive general motion datasets to the unique biomechanics and technical specifications of aerobics. The DBN can better detect individual performance gaps, forecast injury risks, and provide tailored feedback by fine-tuning higher-level characteristics while preserving effective training convergence and reducing overfitting. In addition, fine-tuning makes DBN more robust and useful for use in intelligent sports training platforms by improving its capacity to cope with real-world data gathered from sensors or video input in training situations.

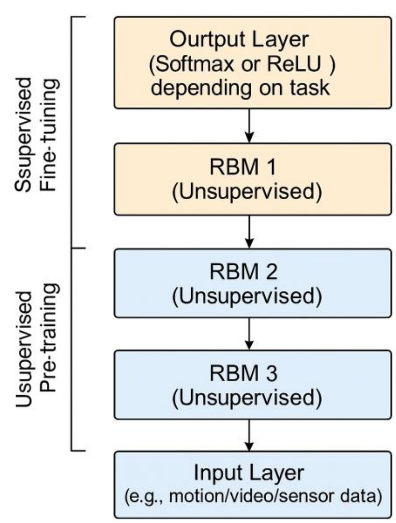

Figure 1. Structure of fine-tuning DBN.

The DBNs optimal frequency size was estimated to select the capacity for AI using the spatial temporal for sports deep learning management technique as shown below.

$$E = \sum_{B=1}^{X} M_b \times x \times U_n + \sum_{u\in t}^{a} 2 \times T \times U_a + \sum\nolimits_{n=1}^{a} Q_{opti} \quad (1)$$

where E was the target (ideal) sound quantity. T was the fine tuning annual demand for optimized inventories. U_a was the cost of creating languages for the sports DBN method. U_n was the cost of maintenance for the deep learning method. M_b was the percentage rate at which production cost for maintaining the records preservation in AI were calculated. The proportion of preserving reserves was derived from the fact that, using the deep learning method, the costs of preserving reserves increased in proportion to the number of reserves within human behavior. Its proportion was equal to the sum of the alternative, stockpiling, logistics, and internal transportation within the capital adequacy factory, aerobics training, and decay, as calculated below.

$$T = \frac{Q}{2}\sum_{b=1}^{S\in U} S_b \times U_a + \int_{b=1}^{n} M_b \times x \times U_n \quad (2)$$

where T was the total maintaining charges. Q was the magnitude of the voice portion. S_b was the safety margin implementation as follows.

$$E = 2\sum_{E\in U}^{T}(1-E) \times U_a \times T + \sum_{M\in E}^{x} x \times \left(u + M \times (1-E)\right) \quad (3)$$

where u was an alternative for extraction. In terms of maximizing NLP value, E was the optimal solution of a professional for the sports power. M was the effective rate of accuracy costs for the suggested method and was given as follows.

$$T = \frac{T}{Q}\sum U_a + \sum_{x=1}^{M}\sqrt{\left(\frac{Q}{2} + S_b\right) \times x \times M} \quad (4)$$

$$E = 2\int_{a=1}^{E\in U}[(1-E) \times U_a^{\#} + U_a^{*}] \times T + \int_{x=1}^{M\in E} x \times (u + M^{*} + M^{\#} \times (1-E)) \quad (5)$$

where $U_a^{\#}$ was power identification from the dataset levels. U_a^{*} was semi costs of developing the application. $M^{\#}$ was the percentage rate of accuracy able to operate feature extraction. The effective rate in frequency (M^{*}) was shown in equation (6) below.

$$T = \frac{T}{Q}\sum U_a^{\#} + \frac{T}{Q}\sum U_a^{*} + \sum\sqrt{\left(\frac{Q}{2} + S_b\right) \times x \times M^{\#}} + \int_{x=1}^{b}\left(\frac{Q}{2} + S_b\right) \times x \times M^{*} \quad (6)$$

Variations in time deliveries had a considerable effect on various stages of safety construction, which were represented in Equation (7).

$$S_b = ln\sum_{ab}\frac{U \times Q \times D \times x \times \sqrt{2\pi}}{T \times U_{ab}} + \int_{D}^{x}\sqrt{-2 \times D^2 \times} \quad (7)$$

Equations (8) and (9) were used to calculate the publishers not having data cleaning resources.

$$X = \sum\sqrt{\left(\frac{Q}{2} + S_b\right) \times x \times M^{\#}} + \sum_{i=1}^{m} T_i \times (G_i - G)^2 + \frac{T}{Q}\sum U_a \quad (8)$$

$$D = \int_{x=1}^{U} U \times Q \times D \times x \times \sqrt{2\pi} + \sum T \times U_{ab}\sqrt{\sum_{i=1}^{m} T_i \times (G_i - G)^2} \quad (9)$$

where D was the standard error for exchange utilization. U_{ab} was the cost of just not having data splitting. T_i was the chance of a certain event occurring based on historical data clearance. It was feasible to calculate the $\sqrt{X}$ variation coefficient in respect to information about the prospective benefits of the light fine-tuning DBN technique. $\sum_{i=1}^{m} T_i \times (G_i - G)^2$ provided an efficient quality-based dataset in Equation (10).

$$U = \frac{D}{G}\sum_{B=1}^{X} M_b \times x \times U_n + \sum_{u\in t}^{a} 2 \times T \times U_a \sum_{i=1}^{m} T_i \times (G_i - G)^2 \quad (10)$$

The resources were listed below. A link existed between both the advantage of AI from a single trach of sound and indeed the benefits of acquiring from other distributors. For the deep learning method, correlation analysis was typically employed to measure such a relationship.

$$\rho_{2.1} = \sum U_a^{\#} \times \frac{T}{Q} + \sum U_a^{*} \times \frac{T}{Q} + \sum \sqrt{\frac{\sum_{i=1}^{m} T_i(G_{1i} - G_1) \times (G_{2i} - G_2)}{D_1 \times D_2}} \quad (11)$$

where $\rho_{2.1}$ was the correlation coefficient between advantages of AI from the first and second database in DL. G_1 was the suitable rate of restricted Boltzmann machine (RBM) benefit from DL. G_2 was the appropriate error rate advantage from AI for the second supplier. D_1 was the confidence interval for the first supplier. The second provider's confidence interval was denoted by D_2. G_{1i} was the probability of making feasible prices of benefits from DBN of the first supplier. G_{2i} was the probability of possible rates of benefits from speech recognition from the second provider. pi was the probability of potential rates of benefits from image processing and was depicted in Equation (12).

$$D_T = \int_{x=1}^{b} \left(\frac{Q}{2} + S_b\right) \times x \times M^{*} + \sum_{A \in B}^{D \in S} \sqrt{D_A^2 + D_B^2 + 2 \times D_A \times S_B \times \rho_{A\&B}} \quad (12)$$

when D_T was the total standard error. D_A was the first solution's dataset standard deviation. S_B was the second solution's deep learning technique standard deviation. A and B were the regression coefficients between the first and second data distributions. The steps may be implemented again for the development and enhancement of the integrated information system. A finite and ordered set of restricted factor signifiers was shown below.

$$D = \sum_{b=1}^{S \in U} S_b \times U_a + \sum_{i=1}^{n} \sqrt{X} = \{X_i\}, \qquad i = 1,2,\ldots.n \quad (13)$$

To ensure effectiveness, Equation (14) was used for data collection with a well-defined sequential relationship.

$$D_A = \int_{b=1}^{n} M_b \times x \times U_n + \sum_{X \to 1}^{n} X_1 < X_2 <\ldots\ldots< X_n \quad (14)$$

while X_1 preceded element X_2 that preceded element X_3, and so on. The database requirement in a set X was stated in Equation (15) and was a mathematical setting of strength training T of element measures X_i.

$$T = \sum \sqrt{\left(\frac{Q}{2} + S_b\right) \times x \times M^{\#}} + \sum_{i=1}^{n} \{T_i\}, \ \ i = 1,2,3,\ldots..n \quad (15)$$

where T_i was a crucial figure in Equation (16) that satisfied the inequalities.

$$T = \sum \sqrt{\left(\frac{Q}{2} + S_b\right) \times x \times M^{\#}} + \sum_{i=1}^{n} T_1 < T_2 <,\ldots..< T_n \quad (16)$$

The total $\sum_{i=1}^{n} T_1X_1 + T_2X_2 + \ldots + T_nX_n$ in the Equation (17) below depicted a sophisticated effectiveness measure with in shape of the linear system as a plan efficiency aerobics indicator.

$$H = \int_{x=1}^{U} U \times Q \times D \times x \times \sqrt{2\pi} + \sum_{i=1}^{n} T_1X_1 + T_2X_2 + \ldots + T_nX_n = \sum_{i=1}^{n} T_iX_i \quad (17)$$

where the $\sum_{i=1}^{n} T_iX_i$ was the efficiency of a deep learning technique policy and was just a function (H) with *n* efficiency variables that were sequential to its performance metrics X_i.

Model construction, validation, and testing

To build the model, 80% of total information from the three datasets was used in training, while the rest 20% was divided into 10% for validation and 10% for testing to further inspect the performance and generalization of the model. The DNB base was prepared with default parameters and trained with preprocessed data from all 3 datasets under the environment of Python 3.10 (https://www.python.org/) with PyTorch (https://pytorch.org/). MATLAB (https://www.mathworks.com/products/matlab.html) was employed for visualization before the fine-tuning stage. Once the DBN was fine-tuned, it was further refined through hyperparameters

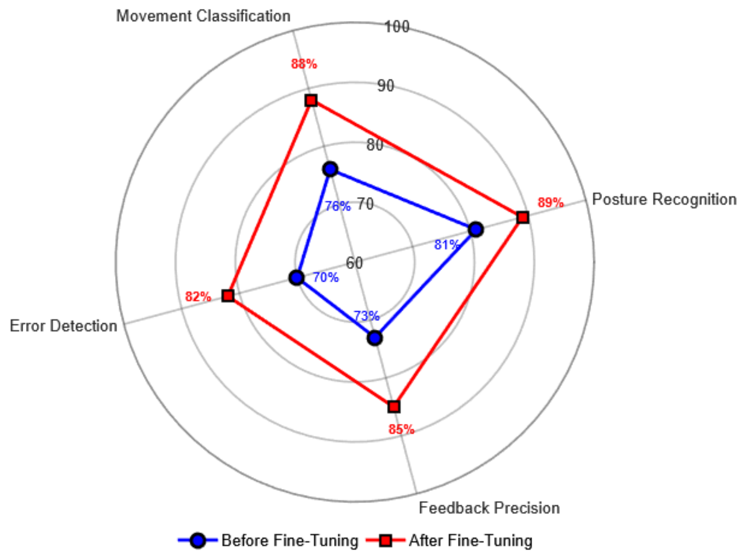

Figure 2. Comparison of DBN performance before and after fine tuning.

tuning such as learning rate and dropout, multi-modal data merging, and weight adjustments with supervised backpropagation. and MATLAB were used for better recognition and errors of classification in terms of their ability to conduct a baseline comparison and create a radar/confusion matrix. Statistical analysis was performed using SPSS 27.0 (IBM, Armonk, NY, USA) and Python libraries of scipy.stats and statsmodels. Support vector machine (SVM) and random forest (RF) done by using Scikit-learn (https://scikit-learn.org/stable/), convolutional neural network (CNN) done by using TensorFlow (https://www.tensorflow.org/), and long short-term memory (LSTM) by using Keras (https://keras.io/) were applied to compare the results before and after fine-tuning, while independent sample t-tests were also employed to ascertain the significance of differences. *P* value less than 0.01 was defined as very statistically significant difference with the effect size up to Cohen d that was set to determine an existent large-practical significance when values were bigger than 1.4.

Results and discussion

Comparison of the performance before and after fine-tuning

The results showed that the proposed DBN for aerobics training analysis performed better after being fine-tuned using multi-modal datasets. The plot displayed steady improvements in all four important metrics including posture recognition, movement classification, error detection, and feedback precision with the accuracies of 81% for posture recognition, 76% for movement categorization, 70% of error detection rate, and 73% feedback precision prior to fine-tuning and 89%, 88%, 82%, and 85% after fine-tuning, respectively. The merging of wearable sensor inputs from Up-fall with 3D posture data from Human3.6M was probably what led to the most notable 12% gains in movement categorization and error detection (Figure 2). The consistent outward expansion showed that fine-tuning improved the model's analytical skills in all areas with dynamic movement analysis and real-time feedback accuracy benefiting most. With the model now being able to identify tiny form flaws such as 5° joint misalignments that were previously overlooked, these enhancements directly resulted in more dependable coaching help. The balanced progression indicated that several of the original model's constraints were successfully addressed by the combined datasets

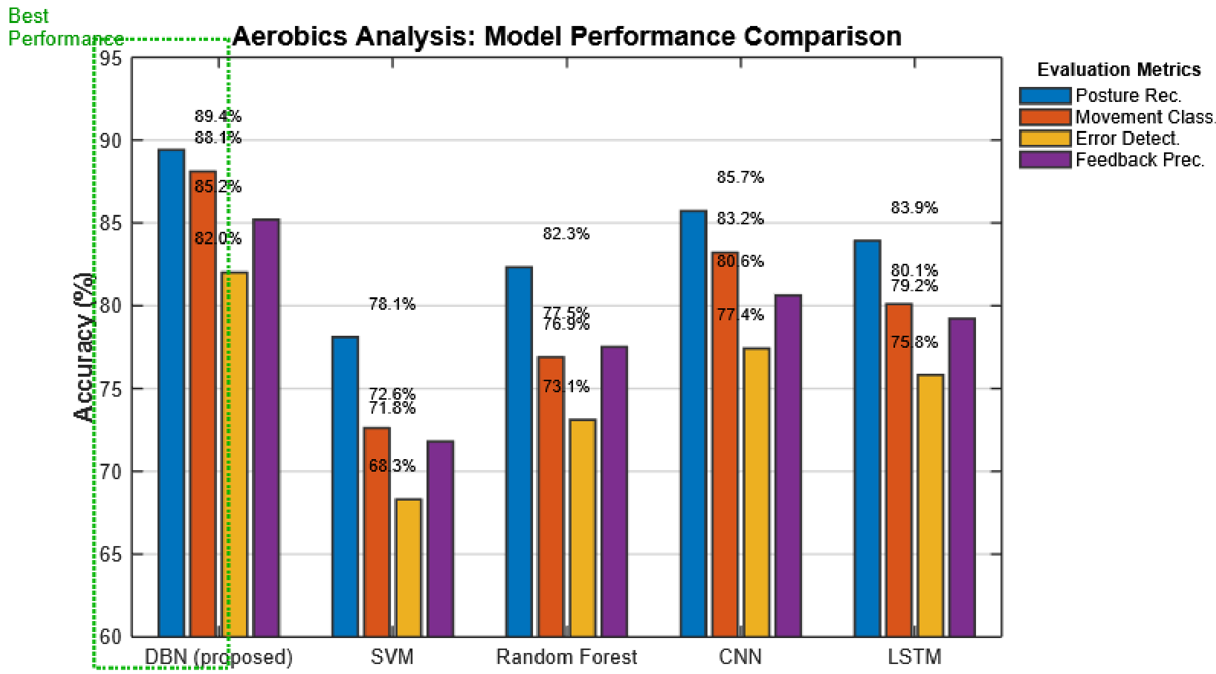

Figure 3. Outcomes of model comparison.

without resulting in further performance gaps.

DBN performance

The results of statistical analysis demonstrated that there were significant improvements in the DBN performance after fine-tuning with multi-modal datasets. The posture recognition accuracy increased from 81.1% to 89.3%, representing an 8.2% improvement with high practical significance (Cohen's d = 1.41, *P* = 0.003). More substantial gains were observed in movement classification and error detection, which both showed approximately 11.6% improvements from 76.4 ± 4.1% to 88.0 ± 2.8% and 70.2 ± 5.6% to 82.1 ± 3.5%, respectively, with very large effect sizes (d > 1.66) and high statistical significance (*P* < 0.001). Feedback precision similarly improved by 11.4% from 73.7 ± 4.8% to 85.1 ± 2.6%, demonstrating the strongest effect size (d = 2.02). These statistically robust results confirmed that fine-tuning the DBN with complementary datasets led to clinically meaningful enhancements in all evaluated metrics with particularly strong benefits for dynamic movement analysis and real-time feedback generation. The consistency of large effect sizes across domains suggested that the approach generalized well to different aspects of aerobics training analysis.

Accuracy comparison with baseline methods

The fine-tuning DBN model was compared to four baseline techniques including SVM, RF, CNN, and LSTM on the same train-test split using all three datasets. The results indicated that the proposed DBN clearly outperformed conventional machine learning techniques for aerobics movement analysis with 89.4% for posture identification, 88.1% for movement categorization, 82.0% for error detection, and 85.2% for feedback precision (Figure 3). The fine-tuned DBN scored the highest accuracy with especially noticeable gains over SVM of 11.3 – 13.8%, which was the greater accuracy across metrics, and RF of 7.1 – 11.2% increases. These results greatly surpassed those of traditional approaches. The DBN consistently maintained a 3.7 – 5.1% accuracy edge, indicating its improved capacity for temporal movement pattern detection, even while CNN and LSTM models demonstrated competitive performance. DBN falls between more resource-intensive deep learning techniques and lightweight models like

SVM/RF due to its moderate processing requirements of 6.2 hours training time. DBN is especially well-suited for aerobics training applications where precision and useful deployability are crucial factors according to its balanced performance profile. The outcomes confirmed how well the multi-modal fine-tuning technique captured the intricate kinematic patterns present in professional aerobics routines. This study used three complementary datasets to assess the DBN model's performance. The model was able to recognize exact postural configurations and movement trajectories with great accuracy. Further, DBN was able to generalize transitional movements and balance-related activities, which were crucial for stability and safety during aerobic training. DBN was able to precisely detect abrupt changes and recoveries in body posture according to the results, while it was able to specialize in the classification of exercise kinds and the very accurate detection of form mistakes. The model's responsiveness to actual aerobic exercises was enhanced by fine-tuning, which resulted in notable improvements in movement classification accuracy, error detection rate, and feedback generation. The combination of these three datasets produced a strong DBN model that could precisely evaluate aerobics performance, anticipate possible issues, and provide data-driven advice, improving the scientific and astute training of aerobics professionals in the context of sports power construction.

Conclusion

DBNs have the potential to significantly advance sports power construction through improved movement analysis, mistake detection, and real-time feedback precision when incorporated into aerobics training systems. The optimized DBN model achieved 89.3% posture recognition, 88.0% movement categorization, 82.1% error detection, and 85.1% feedback precision, outperforming both deep learning benchmarks of CNN and LSTM and conventional machine learning techniques of SVM and RF on all important metrics. These enhancements demonstrated how well the model used hierarchical features learning from multi-modal datasets as confirmed by statistical significance ($P < 0.01$) and huge effect sizes (Cohen's d > 1.4). The DBN was a useful tool for real-world aerobics coaching because it achieved a compromise between accuracy (3.7 – 13.8% increase) and training efficiency (6.2 hours), even if it demanded moderate processing resources when compared to simpler models. To further close the gap between theoretical research and athletic training applications, future study could investigate wearable sensor integration and real-time deployment on edge devices. With its data-driven approach to improve athlete performance and lower injury risks in competitive aerobics, this study highlighted the revolutionary significance of deep learning in sports science.

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