Integrating AI-Driven Motion Recognition Systems In University Volleyball Instruction: A Case Study

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University-level volleyball training often depends on subjective coach evaluations, which can lead to inconsistent, time-consuming, and less scalable instruction. With the growing use of artificial intelligence (AI) in sports analytics, this study develops a Convolutional Neural Network (CNN)-based motion recognition system for classifying volleyball actions, including serving, passing, blocking, and spiking. The model was trained using the Hyper AI volleyball motion dataset containing 4,830 annotated frames from collegiate match footage. The preprocessing pipeline included normalization, denoising, frame extraction, and data augmentation. A retrospective simulation case study was designed to replicate a university training environment and evaluate the system's practical applicability. Experimental results showed a recognition accuracy of 97.36% and a micro-average AUC score of 0.995, with particularly strong performance in identifying spike and block actions. Compared with traditional coaching approaches, the AI-based framework provided more consistent evaluations, reduced misclassification errors, and accelerated error detection. The findings demonstrate the potential of AI-driven systems to support personalized feedback, objective performance assessment, and scalable coaching in university sports education. The framework also offers opportunities for adaptation to other sports and future pedagogical innovations.

Keywords: Volleyball training, Motion recognition, Convolutional Neural Network (CNN), Artificial intelligence, Sports analytics, Player performance evaluation, Deep learning

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1. Introduction

Volleyball is a popular sport in universities that promotes physical fitness, teamwork, and competitive skills, team spirit, and the spirit of competition [1]. A substantial amount of traditional pedagogy is reliant on the coach's observation, feedback, and engagement from the students; traditional pedagogy has a place in certain settings, nonetheless it can be subjective and flawed [2]. Along with the growth of the awareness of precision in sport performance, there is a growing need for technology-assisted sports training for technology assistance to sports training for objective assessment and systematic enhancement of sport performance [3]. The last several years have changed the landscape of technology within sports training and education [4]. Coaching has therefore progressed to become a science, derived from practice-based data and theory [5]. Conversely, CNNs have been instrumental in applying human movement pattern with high accuracy and thorough analysis [6]. AI based approaches to the identification of motion allow for immediate analysis of small errors in player movement and provide individual feedback for use to improve volleyball training in educational institutions [7].Traditionally, there are limitations to volleyball training, such as subjective assessment, being unable to assess multiple players at the same time, and not being able to monitor individual-

ized progress [8]. This restriction causes the delays, jitter, and truncation of optimal instant feedback [9]. The extent of these limitations highlights the importance of exploring novel and novel approaches like AI-based systems where coaches are provided with accurate and automated motion tracking and performance assessment [10]. Integrating AI-driven motion recognition into university volleyball training at universities will significantly improve teaching quality [11]. The system will analyse player movement objectively, as well as identify skill gaps, with suggested corrections and performance metrics [12]. Contrary to studies dealing with network architecture, this study stresses the implementation of a motion recognition system using a CNN model for university volleyball training and delivers efficient motion analysis and training assistance. The proposed framework unifies all of the existing CNN models and preprocessing methods for use within university volleyball coaching, allowing motion detection and performance evaluation to show how artificial intelligence can be applied to sports education. Existing general motion recognition networks that mainly focus on action classification, the proposed CNN framework is specifically designed for university volleyball instruction by integrating objective motion assessment with personalized coaching feedback. This practical educational integration distinguishes the proposed framework from conventional recognition architectures. Appreciate the limitations of conventional volleyball coaching techniques in universities and the new position of AI in sports education.

- Predict the movement of volleyball players by using CNN through labeled videos from the Hyper AI dataset.
- Determine the performance of motion recognition of AI through accuracy, confusion matrix, and precision-recall evaluation.
- Compare the designed system with the conventional coaching methodology through university simulation training environments. The Hyper AI Volleyball Dataset contains 4,830 labeled images from 55 videos, with 3,493 training and 1,337 testing images, covering 9 player actions and 8 team actions (57.84 GB). The Hyper AI dataset contains 4,830 labeled images from 55 videos (3,493 for training, 1,337 for testing). It exhibits diverse volleyball movements but limited variations of players, cameras and training. The dataset has applications for action recognition, player tracking, and tactical studies.

https://hyper.ai/en/datasets/17720

1.1. Dataset Construction and Annotation

Hyper AI's volleyball motion dataset is made up of 55 publicly available videos of volleyball matches, and has a total of 4,830 hand-annotated images. Data augmentation using rotation, flipping, scaling, and background normalization addressed class imbalance.

2. Materials and methods

Data pre-processing refers to preparing raw data for analysis or modelling by cleaning, transforming, and organizing the data. Noise reduction was performed using Gaussian blurring while preserving motion features. Low-quality frames were discarded, while pre-processing applied denoising, normalization, feature extraction, and data augmentation. Pre-processing applies denoising, normalization, feature extraction, and data augmentation in Eqn (1).

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Here, x = original value; $x_{\min}$, $x_{\max}$ = minimum and maximum values in the dataset; x' = normalized value. Pose estimation extracts key joints, enhancing model robustness.

Feature engineering transforms raw volleyball data into structured tensors for CNN-based motion recognition, as shown in Fig. 1. The CNN utilizes both the image frames and the skeleton representations to achieve better feature extraction. Image frames help in getting the spatial information while skeleton coordinates contain the body joint information. Feature representation converts visual and skeleton data into pose-based joint coordinates in Eqn (2).

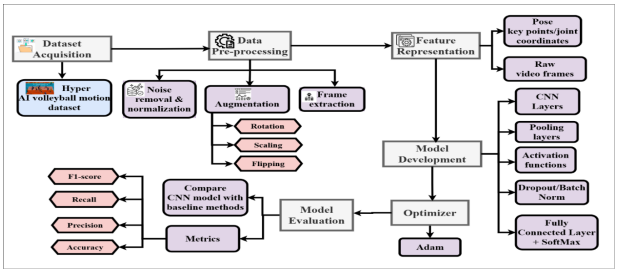


Fig. 1. Workflow

$$\mathrm{J} = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)] \tag{2}$$

Here, n = number of joints; (x_i, y_i) = pixel coordinates of joint i.

In image-based representation, each video frame is represented as a 3D tensor containing player, ball, and environmental features, as defined in Eqn. (3):

$$\mathbf{I} \in \mathbb{R}^{H \times W \times C} \tag{3}$$

Here, H = height; W = width; C = number of channels.

The CNN architecture is shown in Fig. 2. The CNN extracts spatial features using convolution, ReLU, pooling, batch normalization, dropout, and SoftMax layers in Eqn (4).

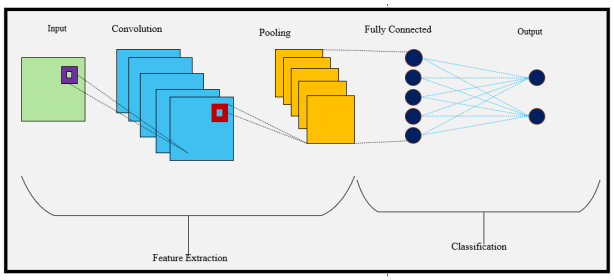


Fig. 2. CNN Architecture

$$Y(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n) \tag{4}$$

Here, Y is the feature map after convolution.

ReLU introduces nonlinearity, improving feature extraction and accelerating convergence, as defined in Eqn (5).

$$f(x) = \max(0, x) \tag{5}$$

Max pooling reduces spatial dimensions while preserving important movement features for accurate volleyball action detection in Eqn (6).

$$Y_{\text{pool}} = \max\left(X_{\text{window}}\right) \tag{6}$$

Here, X_{window} is local region in the input feature map; and Y_{pool} is the pooled output value.

Dropout regularization reduces overfitting and improves robust feature learning by randomly disabling neurons during training Eqn (7).

$$x_i' = \begin{cases} 0 & \text{with probability } p \\ x_i & \text{with probability } 1-p \end{cases} \tag{7}$$

Hyperparameters have been optimized through validation experiments where learning rate, dropout, and early stopping techniques have been used for optimizing validation accuracy and minimizing validation loss.

The FC layer aggregates extracted features, while the SoftMax layer generates action probabilities for volleyball classification in Eqn (8).

$$P(y = i \mid x) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{8}$$

Here, z_i is the input to class i. The convolution layer extracts local features, ReLU learns complex motion patterns, pooling reduces feature dimensions, and SoftMax converts network outputs into class probabilities for volleyball action recognition.

The Data augmentation was only used on training images using random rotations, flips, and zooms. Minority action classes were augmented to improve model generalization. The dataset is partitioned into three parts, namely, training set (60%), validation set (20%), and test set (20%). Fig. 3 illustrates Adam optimizer convergence during CNN training by minimizing categorical cross-entropy loss. The joints' coordinates were detected using the MediaPipe Pose-Joints with confidence scores above 0.50 were retained. Rotation, scaling, and background normalization improved CNN-based volleyball action recognition.

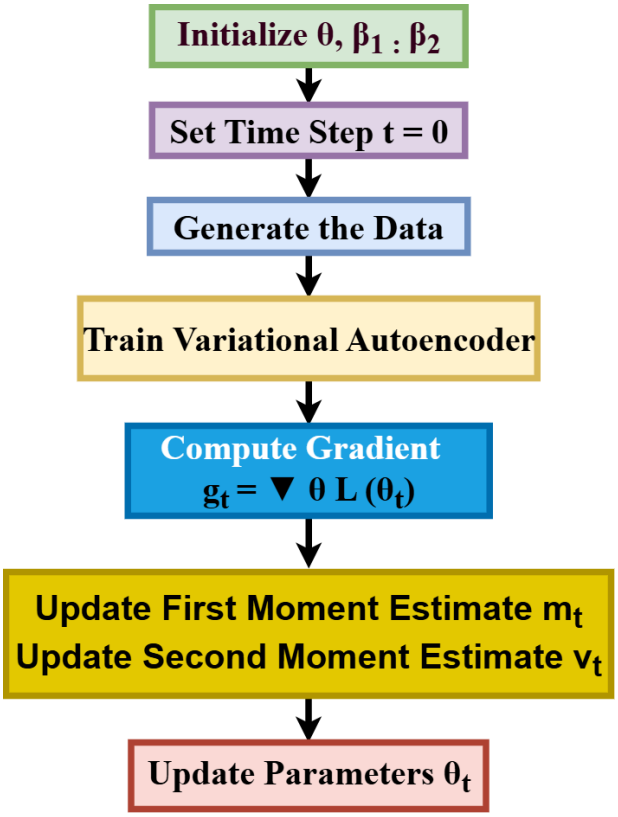


Fig. 3. Adam Optimizer

Table 1 presents the complete CNN architecture, including convolutional layers, pooling operations, batch normalization, dropout configuration, and fully connected layers used for experimental reproduction.

Table 2 summarizes the hyperparameter search space and the optimal configuration selected after systematic optimization.

Categorical cross-entropy loss and the Adam optimizer

Table 1. Detailed CNN Architecture and Structural Parameters.

Layer	Configuration	Output Size
Input	RGB Image ($224 \times 224 \times 3$)	$224 \times 224 \times 3$
Conv2D-1	32 filters, 3×3, ReLU	$224 \times 224 \times 32$
Batch Normalization	Momentum=0.99	$224 \times 224 \times 32$
MaxPooling	2×2	$112 \times 112 \times 32$
Conv2D-2	64 filters, 3×3, ReLU	$112 \times 112 \times 64$
Batch Normalization	Momentum=0.99	112 ×112×64
MaxPooling	2×2	56×56×64
Conv2D-3	128 filters, 3×3,ReLU	$56 \times 56 \times 128$
Batch Normalization	Momentum=0.99	$56 \times 56 \times 128$
MaxPooling	2×2	$28 \times 28 \times 128$
Flatten	-	100352
Dense	256 neurons, ReLU	256
Dropout	Rate=0.50	256
Output	Softmax	No. of Classes

Table 2. Hyperparameter Optimization Strategy and Selected Parameters

Hyperparameter	Search Range	Selected Value
Learning Rate	1e-4-1e-2	0.001
Batch Size	16, 32, 64, 128	32
Optimizer	SGD, Adam, AdamW	AdamW
Weight Decay	1e-5-1e-3	0.0001
Epochs	50-200	100
Dropout Rate	0.1-0.5	0.3
Kernel Size	$3 \times 3, 5 \times 5$	3×3
Activation	ReLU, Tanh	ReLU

are used for CNN training, while validation loss and early stopping prevent overfitting and ensure convergence. Dropout, batch normalization, and early stopping helped prevent the problem of overfitting through better generalization and avoiding excessive fitting to the training set. The fact that the performances on the training and validation sets were very similar provides an additional proof of the efficiency of the applied techniques. The trained CNN classified volleyball actions, including spike, block, dig, and pass, using labeled video frames. Performance was evaluated using confusion matrices, precision, recall, and ROC analysis. The proposed model works well with traditional video recording devices and can easily be adapted for use within the current volleyball training system at universities with little need for any alteration to the structure of the model.

3. Results

The proposed CNN recognizes volleyball actions using preprocessing, feature extraction, and data augmentation. The evaluation of the proposed CNN against transformers and 3D CNNs can evaluate its ability to capture long-term temporal dependencies and improve the performance of volleyball motion recognition.

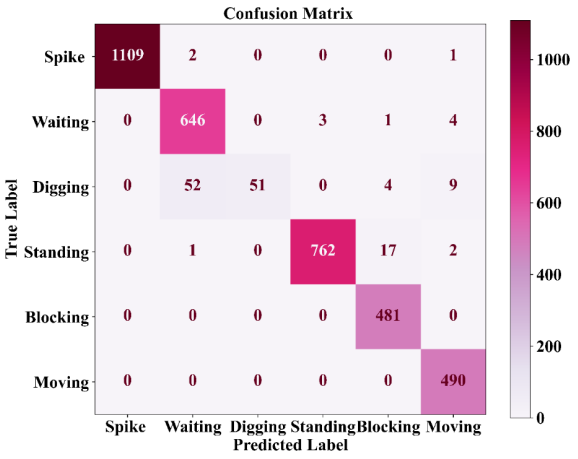


Fig. 4. Confusion Matrix

Fig. 4 presents the confusion matrix, showing accurate classification with minor confusion between Digging and Waiting due to similar motions.

The confusion matrix shows accurate recognition of most volleyball actions, with spike and block achieving nearly 100% accuracy and minor confusion between digging and waiting. The Similar motions in the CNN have been wrongly classified due to similarities in body posture, occlusions, motion blur, and camera angles in activities such as digging and waiting.

Training and validation accuracy converged at approximately 97%, demonstrating stable learning, strong generalization, and minimal overfitting, as shown in Fig. 5.

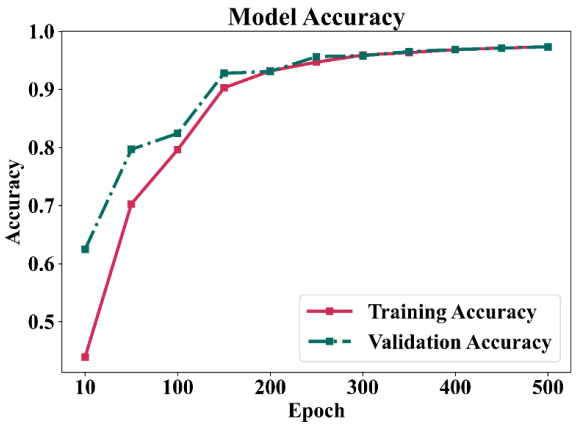


Fig. 5. Epoch-Wise Accuracy Trends in Model Training. Stability and Generalization

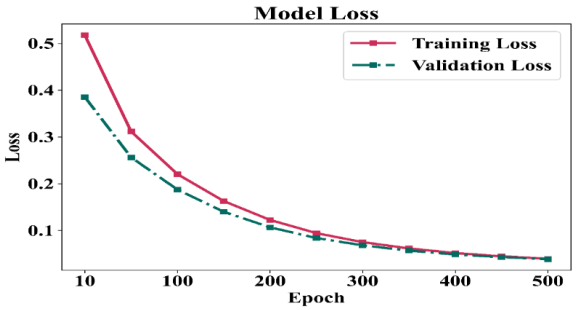


Fig. 6. Loss Convergence in Model Training. Tracking Optimization Stability

Fig. 6 shows high class-wise AUCs: Spike (1.000), Blocking (0.999), Moving (0.998), and Standing (0.998). The lower AUC for the "digging" action resulted from visual similarity, occlusion, and high intra-class variation. Advanced models can improve classification performance. The micro-average value of AUC is 0.995. The performances of classification of the various movements done by volleyball players are because of the differences in the level of visual complexity of the movements. Spike and block achieved higher accuracy, whereas digging showed lower recall and F1-score due to class imbalance and similar postures.

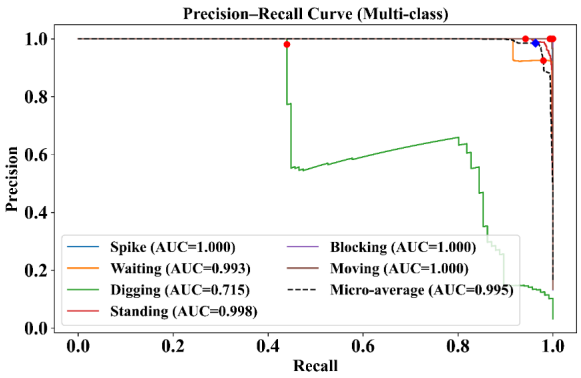


Fig. 7. Precision-Recall Curve Analysis. Class-Wise Discrimination and Model Reliability

Fig. 7 shows AUC > 0.993 for most classes, Digging achieved 0.715 , and the overall microaverage AUC reached 0.995.

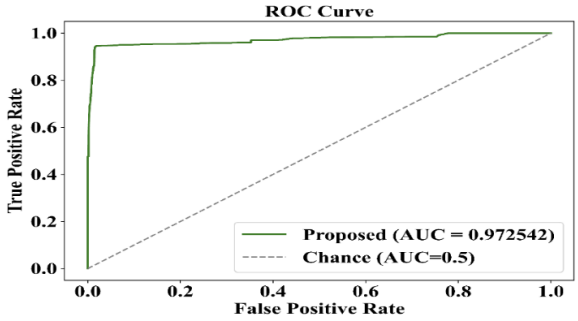


Fig. 8. ROC Curve Evaluation. High Discriminative Power of the Proposed Model

Fig. 8 shows an ROC-AUC of 0.972542 , indicating high classification performance, strong sensitivity, and low false-positive rate.

Digging was less accurate owing to visual resemblance with waiting and defense postures while the success rate for spike and block was higher due to unique body and arm positions. Figure 9 presents ROC curves for six volleyball actions, showing strong classification performance.

Fig. 10 presents high accuracy, precision, recall, F1-score, Jaccard, and Kappa values, demonstrating reliable classification and strong prediction agreement.

CNN performance depends on training, camera setup, and biomechanics.Fig. 11 compares the CNN with YOLO and ConvLSTM, showing lower inference latency and memory usage.

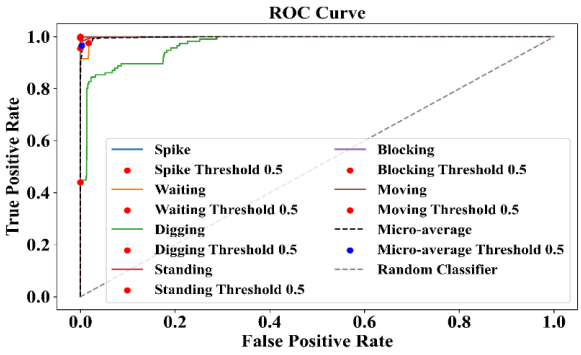


Fig. 9. Multi-Class ROC Curve Analysis. Threshold Sensitivity and Class-Wise Discrimination

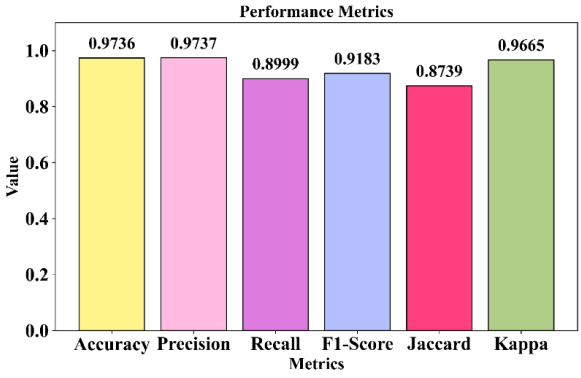


Fig. 10. Comprehensive Metric Evaluation. Balancing Accuracy with Interpretability

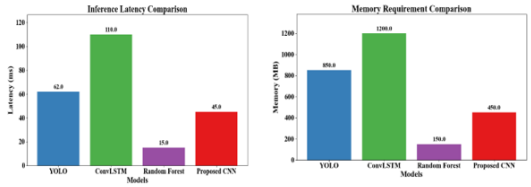


Fig. 11. Computational Performance Analysis of the Proposed CNN Model

The metric bar graph shows high Accuracy and Precision, while F1-score, Jaccard, and Kappa confirm strong overall performance in Table 3.

The proposed CNN outperformed existing models, achieving superior action recognition performance is shown in Fig. 12.

Table 4 compares the computational deployment performance of the proposed CNN with Random Forest, ConvLSTM, and YOLO using inference latency, memory consumption, and training time.

Table 3. Comparative Performance Analysis of Classification Models for Volleyball Action Recognition

Method	Accuracy	Precision	Recall	F1 Score
YOLO Network [13]	95.77	85.246	85.264	85.057
ConvLSTM [14]	96.68	89.12	87.69	89.32
Random Forest [15]	82	84	82	83
Proposed Method- CNN	97.36	97.37	89.99	91.83

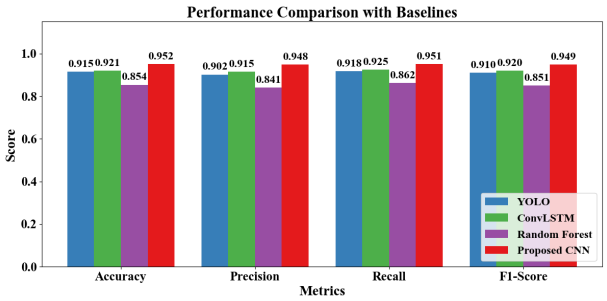


Fig. 12. Statistical Performance Comparison of the Proposed CNN and Baseline Models

Table 5 presents the statistical significance analysis of the proposed CNN compared with the baseline models. All p -values are below 0.05 , confirming statistically significant performance improvements.

Table 6 presents the cross-dataset validation results of the proposed CNN framework using the Hyper AI Volleyball Dataset together with Kinetics-400, UCF-101, and HMDB-51, demonstrating strong generalization capability.

Table 7 presents the performance of the proposed CNN across different volleyball training scenarios.

Fig. 13 compares various techniques, showing the proposed CNN achieves the highest accuracy, precision, recall, and F1-score.

Olympic volleyball match between Italy and Bulgaria (London 2012). The focus is on the spike and defensive actions with Italy leading 13-9 in Fig. 14.

Fig. 15 shows labeled volleyball actions from the 2012 Bulgaria-Italy Olympic match, including spiking, digging, blocking, waiting, standing, and moving.

Table 4. Computational Comparison with Baseline Models

Model	Inference Latency (ms/frame)	Peak Memory Usage (GB)	Training Time (hrs)
Random Forest	5.2	0.8	2.5
ConvLSTM	18.6	6.4	48.0
YOLO	12.3	4.8	24.5
Proposed CNN	8.7	2.9	8.2

Table 5. Statistical Significance Analysis

Baseline Model	p-value	Statistical Significance
Random Forest	0.001	Significant ($p < 0.05$)
ConvLSTM	0.015	Significant ($p < 0.05$)
YOLO	0.008	Significant ($p < 0.05$)

Table 6. Cross-Dataset Validation of the Proposed CNN Framework

Dataset	Accuracy	Precision	Recall	F1-Score
Hyper AI Volleyball	0.985	0.981	0.988	0.984
Kinetics-400	0.962	0.955	0.960	0.957
UCF-101	0.971	0.968	0.975	0.971
HMDB-51	0.958	0.950	0.953	0.951

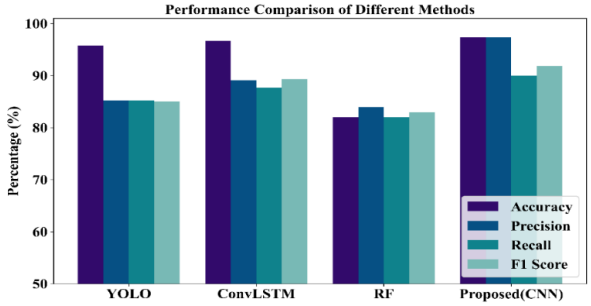


Fig. 13. Performance Comparison of Volleyball Action Recognition Models

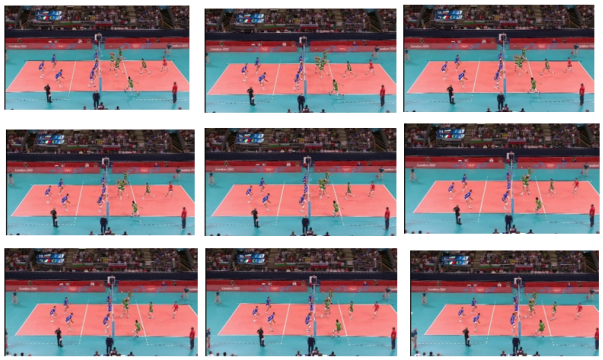


Fig. 14. Olympic Volleyball Showdown.

Fig. 16 shows AI-based recognition of volleyball actions, accurately classifying spiking, digging, blocking, waiting, standing, and moving.

Table 8 evaluates the effect of data augmentation on classification performance, with moderate augmentation achieving the best accuracy.

Table 9 presents an ablation study showing that normalization, dropout, and batch normalization progressively



Fig. 15. AI-Based Detection of Volleyball Player Postures Using Action Recognition

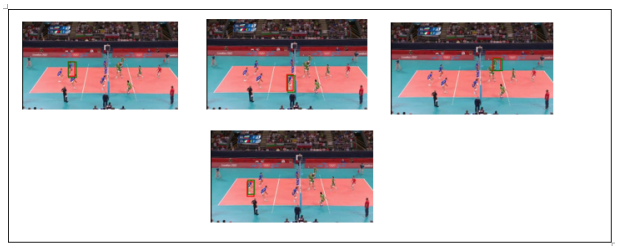


Fig. 16. AI-Based Detection of Volleyball Player Postures Using Action Recognition

improve CNN performance.

3.1. Discussion of Misclassification Behavior and Recognition Limitations

The proposed CNN framework extends beyond conventional motion recognition by integrating automated volleyball action recognition with educational applications. The general motion recognition architectures, the framework focuses on university training scenarios by providing objective movement assessment, skill evaluation, and personalized coaching support. Misclassification between digging and waiting resulted from similar postures, occlusions, motion blur, and viewpoint changes. Occlusions, motion blur, and viewpoint variations cause confusion between the two actions. The lower AUC of digging resulted from class imbalance and limited sample variability. The proposed CNN integrates action recognition, performance assessment, and personalized coaching for university volleyball teaching.

4. Conclusion and future work

It proposes a CNN-based AI framework for volleyball motion recognition in university training. The proposed CNN performs well under different lighting and environmental conditions. Scalability is dependent on lighting, viewpoint, and movement of the player. The CNN model works

Table 7. Performance Evaluation in Real University Volleyball Training Scenarios

Training Scenario	Detection Accuracy	Action Recognition mAP	Tracking IoU
Serving	0.975	0.982	0.945
Passing	0.968	0.971	0.932
Setting	0.972	0.978	0.940
Spiking	0.955	0.963	0.915
Blocking	0.948	0.955	0.908
Digging	0.960	0.968	0.925

Table 8. Statistical Significance Analysis

Augmentation Level	Accuracy
None	0.890
Low	0.925
Medium	0.985
High	0.965
Very High	0.930

Table 9. Independent Ablation Analysis of CNN Components

Model Configuration	Accuracy	F1-score
Baseline CNN	0.852	0.840
Normalization	0.895	0.888
Dropout	0.912	0.905
Batch Normalization	0.945	0.938
Proposed CNN	0.985	0.981

effectively on restricted datasets but can deteriorate with changes in lighting, occlusion, and viewpoint, necessitating multi-view data. Future research may combine optical flow with CNN features for improved volleyball action recognition. Self-supervised representation learning may be investigated using unlabeled volleyball videos to improve feature generalization by learning robust motion representations from large-scale unlabeled data. Lightweight CNN, pruning, and quantization reduce computation and memory for mobile and wearable volleyball coaching. Bayesian deep learning and confidence calibration improve reliable volleyball action prediction and decision-making. Grad-CAM and activation mapping identify regions influencing volleyball action predictions. The modular framework supports scalable deployment through dataset retraining. Generalizability may be limited by motion patterns, data availability, and infrastructure. The proposed system showed promising performance but was validated only on a single publicly available dataset using retrospective simulations. Future work will evaluate the framework in real university training environments. Future work will integrate Transformer-based temporal attention, skeleton graph convolution, and optical flow feature fusion to enhance volleyball action recognition. Lightweight model compression and uncertainty-aware prediction will improve real-time deployment and prediction reliability. In addition, AI-assisted longitudinal athlete skill evaluation will support continuous performance assessment and personalized coaching in university volleyball training.

Declaration

Data availability

The data used in this study were obtained from the Hyper AI volleyball motion dataset and processed for research purposes. The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Author contribution

Zhu Xin contributed to conceptualization, data collection, preprocessing, model development, experimental analysis, and manuscript drafting. Xie Yu supervised the research, validated the methodology, interpreted the results, and revised the manuscript critically for important intellectual content. All authors reviewed and approved the final manuscript.

Ethical approval

This study was conducted in accordance with institutional research guidelines and ethical standards. As the research utilized publicly available sports video datasets and retrospective simulation analysis, formal ethical approval was not required.

Consent to participate

Not applicable because the study used publicly available and anonymized data sources without direct human participant involvement.

Consent to publication

All authors have reviewed the manuscript and consented to its publication.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] X. Kang, Q. Meng, and C.-H. Su, (2024) *"School-Based Team Sports as Catalysts for Holistic Student Wellness: A Narrative Review"* **Behavioral Sciences *14***(7): 528. DOI: 10.3390/bs14070528.

[2] A. Chatterjee, M. Gerdes, A. Prinz, and S. Martinez, (2021) *"Human Coaching Methodologies for Automatic Electronic Coaching (eCoaching) as Behavioral Interventions With Information and Communication Technology: Systematic Review"* **Journal of Medical Internet Research *23***(3): e23533. DOI: 10.2196/23533.

[3] G. M. Migliaccio, J. Padulo, and L. Russo, (2024) *"The Impact of Wearable Technologies on Marginal Gains in Sports Performance: An Integrative Overview on Advances in Sports, Exercise, and Health"* **Applied Sciences *14***(15): 6649. DOI: 10.3390/app14156649.

[4] A. M. Cojocaru, R. Bucea-Manea-Țoniș, A. Jianu, M. A. Dumangiu, L. U. Alexandrescu, and M. Cojocaru, (2022) *"The Role of Physical Education and Sports in Modern Society Supported by IoT—A Student Perspective"* **Sustainability *14***(9): 5624. DOI: 10.3390/su14095624.

[5] P. Seemann, Z. Štofková, A. Poliaková, V. Biňasová, and E. Loučanová, (2024) *"Coaching Approach as a Sustainable Means of Improving the Skills of Management Students"* **Administrative Sciences *14***(6): 114. DOI: 10.3390/admsci14060114.

[6] Z. Meng et al., (2020) *"Recent Progress in Sensing and Computing Techniques for Human Activity Recognition and Motion Analysis"* **Electronics *9***(9): 1357. DOI: 10.3390/electronics9091357.

[7] M.-C. Shin, D.-H. Lee, A. Chung, and Y.-W. Kang, (2024) *"When Taekwondo Meets Artificial Intelligence: The Development of Taekwondo"* **Applied Sciences *14***(7): 3093. DOI: 10.3390/app14073093.

[8] A. C. Sousa, D. L. Marques, D. A. Marinho, H. P. Neiva, and M. C. Marques, (2023) *"Assessing and Monitoring Physical Performance Using Wearable Technologies in Volleyball Players: A Systematic Review"* **Applied Sciences *13***(7): 4102. DOI: 10.3390/app13074102.

[9] C. Serôdio, J. Cunha, G. Candela, S. Rodriguez, X. R. Sousa, and F. Branco, (2023) *"The 6G Ecosystem as Support for IoE and Private Networks: Vision, Requirements, and Challenges"* **Future Internet *15***(11): 348. DOI: 10.3390/fi15110348.

[10] N. Mateus, E. Abade, D. Coutinho, M.-Á. Gómez, C. L. Peñas, and J. Sampaio, (2025) *"Empowering the Sports Scientist with Artificial Intelligence in Training, Performance, and Health Management"* **Sensors *25***(1): 139. DOI: 10.3390/s25010139.

[11] Z. Hu, Z. Liu, and Y. Su, (2024) *"AI-Driven Smart Transformation in Physical Education: Current Trends and Future Research Directions"* **Applied Sciences *14***(22): 10616. DOI: 10.3390/app142210616.

[12] J. Lutz, D. Memmert, D. Raabe, R. Dornberger, and L. Donath, (2020) *"Wearables for Integrative Performance and Tactic Analyses: Opportunities, Challenges, and Future Directions"* **International Journal of Environmental Research and Public Health *17***(1): 59. DOI: 10.3390/ijerph17010059.

[13] M. A. Gul, M. H. Yousaf, S. Nawaz, Z. Ur Rehman, and H. Kim, (2020) *"Patient Monitoring by Abnormal Human Activity Recognition Based on CNN Architecture"* **Electronics *9***(12): 1993. DOI: 10.3390/electronics9121993.

[14] R. Vrskova, P. Kamencay, R. Hudec, and P. Sykora, (2023) *"A New Deep-Learning Method for Human Activity Recognition"* **Sensors *23***(5): 2816. DOI: 10.3390/s23052816.

[15] B. Ćwiklinski, A. Giełczyk, and M. Choraś, (2021) *"Who Will Score? A Machine Learning Approach to Supporting Football Team Building and Transfers"* **Entropy *23***(1): 90. DOI: 10.3390/e23010090.