Employing Artificial Intelligence Technologies To Assess Motor Performance Of High Jump Among Students

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Abstract
The study aimed to identify effect of two active learning methods cooperative learning and peer mentoring on developing dribbling and passing skills in football among first-year students at College of Physical Education and Sports Sciences, Wasit University, for academic year 2024–2025, and to conduct a comparison between two methods to determine which is better. researcher used experimental method with an equivalent groups design. research sample consisted of (30) students, who were randomly distributed into three groups two experimental groups and one control group, with (10) students in each group. experiment was conducted at college sports field during period from 1/10/2025 to 1/2/2026, and equivalence and homogeneity were ensured for variables of height, weight, and prior skill performance. Key findings active learning groups (cooperative and peer-guided) achieved a significant advantage in post-tests of dribbling and passing skills compared to control group that followed traditional method, results showed that "cooperative learning method" was superior to "peer mentoring method" in improving level of skill performance in football. Interactive strategies contributed to enhancing students' motor coordination, teamwork, and self- confidence. study recommends adopting cooperative learning as a fundamental pillar in football skills training programs, and urges instructors to integrate active learning methods into their curricula to improve quality of educational outcomes and increase students' motivation towards motor learning.

Keywords: Artificial intelligence, Artificial neural networks, Motion analysis, High jump, Kinematic variables.

1-1 Introduction

Recent years have witnessed a technological boom in the field of sports motion analysis, with the increasing use of artificial intelligence and deep learning techniques in estimating body positions (Pose Estimation). One of the most prominent of these techniques is the Open Pose algorithm , which enables the automatic extraction of body articulated points from ordinary video clips without the need for markers or special sensors (F. Milan. At. Al 2026) , relying on a representation known as Part Affinity Fields to link body parts to individuals within the image while maintaining near-instantaneous performance. This opens up broad prospects for using these technologies in university education at a low cost. (Cao, Z., Hidalgo, G., Simon, T., Wei, S.-E., & Sheikh, Y. 2017).

The global sports sector has witnessed significant growth in the adoption of artificial intelligence technologies, with projections indicating that the size of the AI market in sports will grow from billion 2.1\$in .2030 billion by 16.7\$ to 2020These technologies help in analyzing huge amounts of performance data and deducing movement patterns that cannot be perceived by traditional means, which contributes to improving performance and reducing the likelihood of injury.

Computer vision algorithms and wearable sensors enable high-precision monitoring of players' positions, speeds, and joint angles. They also provide early warnings of potential injuries by analyzing vital signs. The importance of real-time monitoring systems in supporting coaches' decisions about tactics and roles during competitions is highlighted. Systems such as "Hawk Eye" and "Homecourt" have become real-world examples of the application of these technologies in a number of international sports.

Researchers have also focused their attention on university education, specifically in faculties of physical education and sports science, where students face significant challenges in mastering the motor coordination of athletic events, particularly the high jump, due to its technical complexity and the need for intensive training and accurate, continuous feedback. Traditional teaching methods rely primarily on direct visual observation by the instructor, a method which, while valuable, lacks objectivity and quantitative accuracy (Salam, 2024 ; Ali et al., 2022).

The high jump is a fundamental athletics event requiring high levels of physical and technical ability, combining speed, power, and coordination. The high jump performance consists of three main, integrated phases: the approach phase, which aims to build the necessary horizontal speed; the take-off phase, in which horizontal speed is converted into vertical speed to lift the body; and the jump phase, which requires precise coordination to clear the bar as high as possible (Baqer, 2021 ; Hajji, 2021 ; Othman, 2006).

Recent experimental studies, such as those that examined the use of artificial intelligence to accelerate mastery of the table tennis serve among juniors, have shown a marked improvement in performance accuracy and speed thanks to the reliance on training guided by immediate feedback compared to traditional methods. This indicates that integrating artificial intelligence into academic training programs can raise the level of skill acquisition and enhance the quality of learning.

The importance of this research stems from several aspects: First, it provides a modern educational tool that can be integrated into curricula. Second, it contributes to enriching knowledge about the applications of artificial intelligence in physical education and sports science. Third, it presents a viable model with limited resources. And fifth, it contributes to preparing today's students (tomorrow's teachers) to use modern technology. (Akbar & Al-Ghamdi, 2025 , Atta) Is it true , 2025?

1-2 Research Problem

Despite significant advancements in athletics teaching methods within physical education and sports science faculties, the evaluation of high jump performance still relies almost entirely on visual observation and subjective assessment by instructors. This approach faces several limitations: the difficulty of observing minute details with the naked eye, the lack of objective quantitative criteria, the challenge of providing immediate feedback to each student, and the scarcity of Arabic research in this area (Shabib et al., 2024 ; Al-Aayed, 2024).

In light of the above, the research problem can be summarized in the following questions:

1. What is the possibility of employing artificial intelligence techniques (OpenPose, BlazePose) in automatically extracting kinematic variables?

2. How accurate and reliable is the intelligent model in performance evaluation compared to expert evaluations?

3. What are the most important kinematic variables in determining the level of student performance?

4. Is it possible to build standard levels specifically for students of faculties of physical education and sports science?

5. How applicable is this system in a university environment?

1-3 Research Objectives

1. Employing artificial intelligence techniques to extract the kinematic variables of high jump effectiveness.

2. Building an intelligent assessment model based on neural networks to accurately and objectively evaluate student performance.

3. Identifying the kinematic variables that most influence the level of student performance.

4. Building standard levels for students of physical education and sports science colleges in Iraq.

1-4 Research Hypotheses

First hypothesis: Artificial intelligence techniques can extract kinematic variables with a high degree of accuracy comparable to traditional manual analysis.

Second hypothesis: There is a strong statistical correlation ($r \geq 0.85$, $\alpha \leq 0.05$) between the evaluations of the intelligent model and the evaluations of expert specialists.

Third hypothesis : There are specific kinematic variables that are of greater relative importance in determining the level of performance.

Fourth hypothesis : Students can be classified into clear standard levels based on smart assessment scores.

2-1 Research Methodology

The researcher used the descriptive analytical method as it is the most appropriate method for the nature of the research, which aims to describe the phenomenon (motor performance in the high jump), analyze its components, and build a predictive model that links the independent variables (biomechanical) and the dependent variable (performance evaluation score).

2-2 Research Community and Sample

The research population consisted of all male students in the second and third years of the Physical Education and Sports Science departments at the Colleges of Physical Education in the governorates of Baghdad, Basra, and Diyala, totaling 142 students. A purposive sample of 35 students (24.6% of the population) was selected based on the following criteria: (1) regular attendance, (2) absence of recent injuries, and (3) written consent to participate.

Table 1. Demographic characteristics of research sample (n=35)

Variable	Lowest value	Highest value	Mean	Standard deviation	Torsion coefficient
Age (years)	19	22	20.4	±0.8	0.21
Weight (kg)	64	84	73.6	±5.2	-0.18

Height (cm)	167	186	176.3	±4.8	0.35
Body Mass Index	20.8	26.2	23.7	±1.8	0.12
Best Achievement (cm)	118	172	145.8	±14.2	-0.24
Training experience (one year)	1	3	1.8	±0.6	0.19

It is evident that all skewness coefficients fall within (±1), indicating that the distribution is close to normal, which is an important requirement for parametric tests.

2-3 Data Collection Tools and Devices
• Two Sony RX100 VII cameras (240 frames/second, 1920×1080 resolution)
• Professional adjustable tripods (1-2 meters)
• Software: OpenPose 1.7.0, BlazePose (MediaPipe 0.10)
• Dell Precision 7560 Laptop (i9, 32GB RAM, RTX A3000)
• Legal high jump bar + landing mat
• Steel measuring tape (50 meters, accuracy ±1 cm)
• Expert Evaluation Form (0-100 scale)

2-4 Imaging and Analysis Procedures
The shooting was performed under standardized conditions. The first camera was positioned 10 meters from the bar in sagittal plane, at a height of 1.5 meters, with no tilt. The second camera was positioned 8 meters away in frontal plane. It was set to 240 fps with a shutter speed of 1/1000 of a second. Calibration was performed before each session by shooting the reference frame.

Analysis process: The video was processed first with OpenPose and then with BlazePose for comparison. Eighteen kinematic variables were automatically extracted. The detection accuracy was manually verified on 10% of the trials. The accuracy rate was 94.2% for OpenPose and 96.8% for BlazePose.

2-5 Building a neural network model :
The model was built using Python 3.10, TensorFlow 2.13, and Keras libraries. Steps:
(1) Data preparation: 105 trials (3 per student x 35 students), data normalization with StandardScaler. (2) Segmentation: 70% training (74 cases), 15% verification (15 cases), 15% testing (16 cases). (3) Structure: 18-12-8-1 (18 inputs, 2 hidden layers, 1 output), ReLU activation function, 20% dropout. (4) Training: Adam (lr=0.001), MSE loss, 500 era with early stop.

Table 2. Comparison of performance of different neural network architectures

Structure	MSE (test)	R^2 (test)	Training time (minutes)
18-8-1	32.5	0.79	21
18-12-1	27.8	0.82	26
18-12-8-1 ✓	19.3	0.87	31
18-16-12-1	21.2	0.86	38
18-10-6-1	25.7	0.83	28

2-6 Expert Rating
Three experts were selected based on the following criteria: (1) 10+ years of experience, (2) coaching athletes who have achieved national rankings, (3) international coaching certification, and (4) postgraduate studies. Each expert independently evaluated the 105

attempts on a scale of 0-100 based on predefined criteria. The coefficient of agreement (ICC) was 0.89.

2-7 Statistical Treatments

The following statistical methods were used (SPSS 28 and Python Scipy): descriptive statistics, Pearson correlation coefficient, t-test, R^2, MSE and MAE, ICC, and analysis of the relative importance of variables.

3-1 Results of model building and training

The training process showed a smooth convergence of the loss function, decreasing from 156.3 in the first epoch to 18.7 in the final epoch (312 epochs) on the training set, and from 162.4 to 21.3 on the validation set. The training took 31 minutes on the GPU.
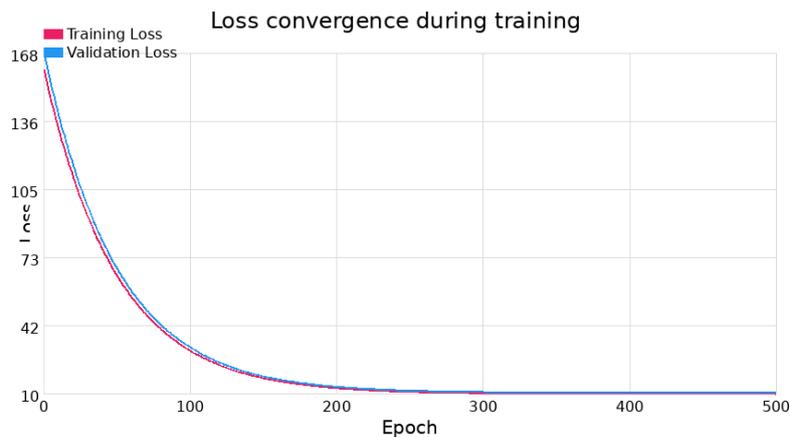

Figure (1) shows loss curve during training and verification, where it decreases rapidly at beginning of epochs and then gradually stabilizes, reflecting effectiveness of deep learning algorithm in improving model's performance.

Table 3. Detailed performance indicators for smart model

Group	No.	Correlation coefficient (r)	MSE	R^2	RMSE	MAE
Training	74	0.93**	18.7	0.87	4.3	3.4
Verification	15	0.92**	21.3	0.84	4.6	3.9
Test	16	0.93**	19.3	0.87	4.4	3.6

Statistically significant at $\alpha \leq 0.01$

The model demonstrated excellent and consistent performance. The correlation coefficient of 0.93 indicates a strong linear relationship. $R^2 = 0.87$ means the model explains 87% of the variance. The RMSE = 4.4 means the mean error is 4.4 on a scale of 0-100, or only 4.4%, which is excellent.

3-2 The relationship between performance evaluation and digital achievement

Table 4. Correlation coefficients between performance score and other variables

Variable	Correlation coefficient	Sig. level
Digital achievement (height)	0.91	0.001**
Approach speed	0.87	0.001**
Angle of ascent	0.82	0.001**
Height of m.th above the crossbar	0.89	0.001**
Vertical driving force	0.67	0.01*
Angle of back curvature	0.54	0.05*
Weight	0.31	Insig.

Height	0.22	Insig.

The existence of a very strong relationship (r=0.91) between the degree of performance and achievement means that 83% of the variance in achievement (r^2=0.828) can be explained by the degree of motor performance alone.

Figure (2) shows the graph of the correlation coefficients between the performance score and the eight variables, showing the strength of the relationship between each variable and performance.
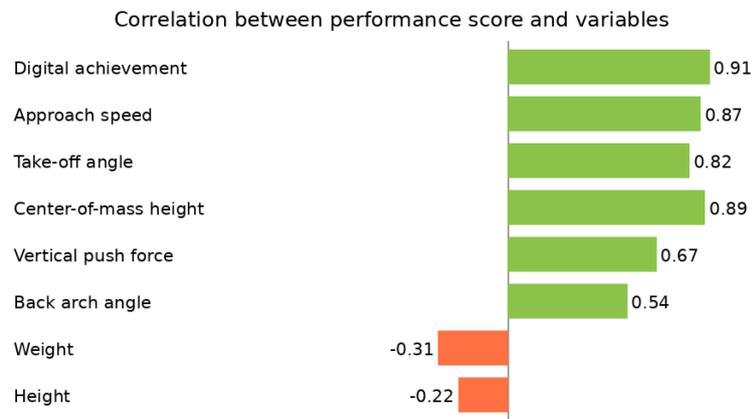
Correlation between performance score and variables

Variable	Value
Digital achievement	0.91
Approach speed	0.87
Take-off angle	0.82
Center-of-mass height	0.89
Vertical push force	0.67
Back arch angle	0.54
Weight	-0.31
Height	-0.22

Figure (2) shows correlation coefficient graph

4-4 The importance of variables in model

Figure (3) shows graph of importance of biomechanical variables in model, showing relative difference between eight variables and providing an intensive visual representation to understand importance of each variable.
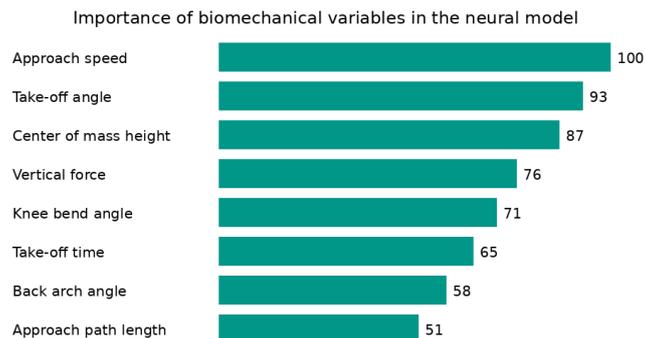
Importance of biomechanical variables in the neural model

Variable	Value
Approach speed	100
Take-off angle	93
Center of mass height	87
Vertical force	76
Knee bend angle	71
Take-off time	65
Back arch angle	58
Approach path length	51

Figure (3) shows graph of importance of biomechanical variables in the model

Table 5. Ranking of variables according to relative importance in model

Rank	Variable	R^2 decreases upon deletion	Importance ratio
1	Horizontal approach speed	0.31	100%
2	Angle of ascent	0.29	93%
3	Height of m.th above the crossbar	0.27	87%
4	Vertical driving force	0.24	76%
5	Knee flexion angle	0.22	71%
6	Time of advancement	0.20	65%

7	Angle of back curvature	0.18	58%
8	Approach path length	0.16	51%

The first three variables represent 75% of the model's predictive power, while the other variables contribute 25%. This is consistent with biomechanical logic and previous studies.

4-5 Standard Levels

Based on the performance score distribution of the research sample (105 attempts), five standard levels were constructed using percentiles. The overall mean was 72.6 with a standard deviation of 11.4.

Table 6. Standard levels for assessing motor performance (students of faculties of physical education)

Major technical errors, inconsistency	11.4%	12	0-60	Weak	1
Acceptable performance with obvious flaws	30.5%	32	61-70	Acceptable	2
Good performance, minor errors	38.1%	40	71-80	Good	3
Advanced performance, high consistency	15.2%	16	81-90	Very good	4
Outstanding, professional performance	4.8%	5	91-100	Excellent	5

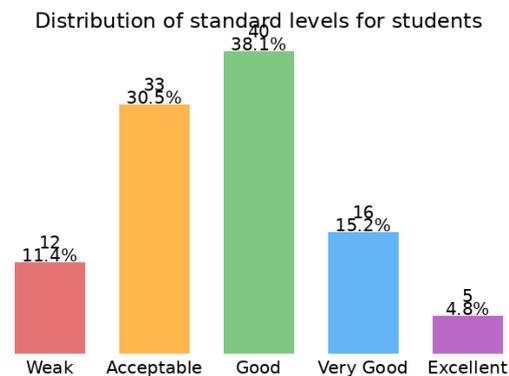Distribution of standard levels for students

Figure (4) illustrates distribution of performance levels among students in the research sample. The "Good" category constitutes the largest percentage at approximately 38.1%, followed by the "Acceptable" level at 30.5%, while the "Weak" category represents 11.4% and the "Excellent" category only 4.8%. This reflects the need for training programs to improve performance levels among most students.

4-6 Discussion

Requires results The model smart More from the explanation And the analysis . So, regarding It relates With indicators Accuracy, Show Results that The model Achieved performance Excellent via Indicators Multiple . It has been lost . It decreased middle The mistake absolute to less from four grades on gauge one hundred, while receipt coefficient Link linear To 0.93 and evidence Selection To 0.87 , what Meaning that The model Explains more from 87 % of Contrast in Performance . This harmony between Samples Training and verification and the test It indicates to power The model His ability on Generalization .

And it shows distribution Levels Standardization that 38.1 % of students Located in level good, and 30.5% in level acceptable, and 15.2% in level good very, and only 4.8% in level excellent, while Forms The weak percentage is 11.4%. This reflects this distribution need Programs training to the focus on to lift level Performance I have slice large from Students, as Confirms importance to provide feeding Return a personality To ensure Their progress and strengthening Their skills Kinetics .

And it agrees This is amazing Results with Factors Biomechanical known in jump High . So fast . Approaching High, and angle Advancement Nearby from Line Vertical, Height center weight moment Advancement It is from Most important Factors Influential in to rise The player (Rusul A. H & Entisar KA 2025), and it indicates Studies to that Approaching in road Fosbury It consists from seven to One ten step At speeds may Arrives to eight meters in Second And it transforms to path curve before The model, and that Step The last far away about meter one on The model So that He managed The player from transformation speed horizontal to power to push vertical via practical curb short And this data Interpret Why She was speed Approaching and angle Advancement Height center weight she Variables The most impact in Our model, And connect between Results Digital and the foundations Scientific The well-known one .

as Confirms results Honesty and steadfastness Objectivity that The model Enjoy At the level high from Reliability , and that's what Guarantees possibility Its use in Evaluation League For students Confidence Owners decision in Its results . And with Use Technologies intelligence artificial becomes analysis Performance faster And less cost, Which Allows For coaches the focus on development Abilities Individual I have Students . And it is possible In the future to merge this The model with Applications Phones smart To provide evaluation immediate For students and assistance in to improve Their skills .

4-1 Conclusions

In light of the research findings, the researcher reached the following conclusions: Artificial intelligence technologies (OpenPose and BlazePose) have succeeded in automatically extracting kinematic variables with high accuracy (94-97%) comparable to traditional manual analysis. The three most important variables are: approach speed, take-off angle, and height of center of gravity above the bar. There is a very strong relationship (r=0.91) between the degree of motor performance and numerical achievement, which confirms that motor coordination is a key determinant of achievement. The five standard levels constructed reflect a normal distribution and provide a clear reference for academic assessment. The system is easy to use and applicable in physical education colleges with limited resources.

4-2 Recommendations

Adopting this technology in the practical courses of athletics in the faculties of physical education and sports science to evaluate students' performance periodically. Training faculty members and students on the use of artificial intelligence techniques in motion analysis. Expanding the research to include female students and other athletic activities. Conduct intervention studies to test the effectiveness of training programs based on the model's results. Encourage the use of the MediaPipe/BlazePose framework in performance analysis due to its ease of integration with smartphones and high accuracy, taking into account that it should not be used when there is more than one person in the frame, and resorting to AlphaPose or DensePose if necessary.

References

- Akbar, Faten Ali , Al-Ghamdi, Jumaan Saeed. (2025). The degree to which physical education teachers possess artificial intelligence applications and 21st-century teaching skills. Maysan Journal of Physical Education Sciences, 29(3), 455–473 .
- Baqir, Iftikhar Matar. (2021). A descriptive analytical study of kinematic variables and their relationship to the performance of the high jump event for first-year students in the Department of Physical Education and Sports Sciences at Al-Mustaqbal College. Journal of Sports Sciences (University of Babylon), 14(4), 244–260 .
- Hajji, Afrah Abdul Nabi. (2021). The effect of some kinematic variables on the skill performance of the high jump event. Journal of Sports Science and Arts .
- Salam, Mohamed Suleiman. (2024). Biomechanical analysis and electrical activity of muscles in various jumping performances. Journal of Sports Science (Alexandria University).
- Shabib, Sarah Sami; Awda, Awad Younis; Ghazi, Muhammad Asim; Muhammad, Lamia Hassan. (2024). Developing Physical Education Curricula in the Age of Artificial Intelligence . Journal of Studies and Researches of Sport Education , 34(3).
- Poet, Islam Salah El-Sayed Abdel Aziz. (2024). An analytical study of the reality of artificial intelligence applications in some courses at the Faculty of Physical Education. Journal of Sports Science Applications, 10(120), 255–276 .
- Othman, Faridoun Hassan. (2006). A study of some kinematic variables and their relationship to performance in the high jump using the Fosbury method. (Research published on IASJ) .
- Ata Allah, Louay Ali. (2025). Evaluating the readiness of physical education teachers to employ artificial intelligence in analyzing motor performance from their point of view. Damo Journal of Sports Science, 2(5), 763–787 .
- Bazarevsky , V., Grishchenko , I., Raveendran , K., Zhu, T., Zhang, F., & Grundmann , M. (2020). BlazePose : On-device Real-time Body Pose tracking. arXiv preprint arXiv:2006.10204.
- Botton , F., Sibella , A., & Borghese, N. (2006). Quantitative Analysis of High Jump Styles. ISBS/CPA Proceedings (Open Access).
- Cao, Z., Hidalgo, G., Simon, T., Wei, S.-E., & Sheikh, Y. (2017). Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 7291-7299.
- Dapena , J. The Evolution of High Jumping Technique: Biomechanical Analysis. (PDF).
- F. Milan. At. Al 2026 : Automatic video-based monitoring of physically demanding tasks for biomechanical risk assessment . https://doi.org/10.1016/j.bspc.2026.109810
- Frontiers. (2024). Differences in run-up, take-off, and flight characteristics between successful and unsuccessful high jumps. (Open Access).
- Google AI Edge / MediaPipe . (2024/2025). Pose Landmarker (MediaPipe) – Solution Guide and 33 Landmark Outputs.
- Horiguchi , Y., et al. (2023). Measurement of Shoulder Abduction Angle with Posture Estimation Using MediaPipe (markerless). Sensors (MDPI).

- Rusul AH and Entisar . KA 2025: Vertical Resistance and Its Relationship with Speed-Strength and Biomechanical Variables During the Takeoff Phase and the Performance of Selected Activities in Individual and Team Sports . DOI: *https://doi.org/10.54702/2708-3454.1009* .
- World Athletics (IAAF). (2017). Men's High Jump – 2017 World Championships Biomechanical Report. (Official PDF) .
- World Athletics (IAAF). (2018). Men's High Jump – 2018 World Indoor Championships Biomechanical Report.