AI-DRIVEN MOTOR ASSESSMENT IN SPORTS EDUCATION: CLASSIFYING BASKETBALL PLAYERS THROUGH DROP JUMP PERFORMANCE

VALUTAZIONE MOTORIA NELL'EDUCAZIONE SPORTIVA BASATA SULL'IA: CLASSIFICAZIONE DEI GIOCATORI DI BASKET ATTRAVERSO LA PERFORMANCE NEL DROP JUMP

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ABSTRACT
The use of artificial intelligence (AI) in motor and sports contexts promises improvements in performance enhancement, and psychophysical wellbeing of both athletes and educators. This study used AI to classify amateur and professional basketball players through drop jump performance, using a support vector machine to joint smoothness data. The model reached 80% accuracy, with key differences in knee movement. Results show that AI may support educators within motor and sports education contexts.

L'intelligenza artificiale (IA) nei contesti motori e sportivi può migliorare performance e benessere psicofisico di atleti ed educatori. Questo studio ha utilizzato una support vector machine per classificare giocatori di basket amatoriali e professionisti in base alla fluidità del drop jump. Il modello ha raggiunto un'accuratezza dell'80%, evidenziando differenze nei movimenti del ginocchio. I risultati indicano il potenziale dell'IA a supporto dell'educazione motoria e sportiva.

KEYWORDS
Artificial Intelligence, Basketball, Movement analysis
Intelligenza Artificiale, Basketball, Analisi del movimento

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1. Introduction

The use of technology and artificial intelligence (AI) contributed in assisting professionals from numerous fields, enhancing possibilities a future frontiers in healthcare, education and sports science (Al Kuwaiti et al., 2023; Chen et al., 2020). Within the sports education context, in particular, AI technology represents a significant advancement, integrating traditional pedagogical methodologies and offering innovative strategies to achieve accurate, detailed, and objective assessments of athletic performance (Araújo et al., 2021). Traditionally, sports educators and coaches were mainly dependent on subjective methods of evaluation. Such methods can be typically influenced by individual biases, prior experiences, and personal preferences (Osório, 2020). This makes such evaluations often inconsistent, provided with limited reliability and compromised accuracy, hence reducing the development and the progression of athletes. Technological advancements have partially solved this issue (Kos et al., 2018). Indeed, the use of technology in sports is now extremely widespread and enables objective measurement and identification of details that would otherwise be undetectable. This has allowed many sectors, including physical education and sports, to rely on increasingly accurate and useful information to correctly evaluate individuals' motor characteristics (Carissimo et al., 2023; Fujimura & Sugihara, 2005). Such an approach enables precise assessments and objective long-term monitoring, which are valuable in evaluating the outcomes of motor learning pathways, consistently relying on objective and shareable data.

In addition to traditional technology, AI-based systems offer an even greater level of support for motor and sports education, as well as for movement assessment (Zago et al., 2021). By processing large volumes of data and identifying complex patterns, AI can provide personalized feedback, detect subtle asymmetries or inefficiencies in movement, and predict performance trends or injury risks with high accuracy (Arac, 2020). These systems enhance the educational process by adapting learning paths to the individual needs of each student or athlete, making instruction more effective and engaging. Furthermore, AI allows for real-time analysis and continuous improvement, offering teachers, coaches, and researchers a powerful tool to refine their methods and base their decisions on a deeper, data-driven understanding of human movement (Caramiaux et al., 2020). Recent advancements in AI technology have filled this gap by enabling detailed quantitative analyses that enhance the reliability, validity, and objectivity of athlete evaluations. The capacity of AI-driven systems to systematically collect extensive datasets, meticulously analyze athletic performance metrics, and produce detailed interpretations has dramatically elevated the standards and effectiveness of sports training programs. As a result, AI technology can facilitate evidence-based decision-making processes, significantly improving the precision and personalization of training interventions (Duan et al., 2019). These advances align well with contemporary educational aims, which require evidence-based methodologies. Furthermore, modern sport educational context prioritizes tailoring instructional and training strategies to meet the unique physiological, biomechanical, and psychological needs of individual athletes. By incorporating AI-driven analysis, educators may be better equipped to develop personalized training protocols that precisely address each athlete’s specific requirements, hence optimizing skill acquisition, maximizing training efficiency, and ultimately enhancing overall athletic performance. This individualized approach has proven to foster higher levels of athlete engagement, motivation, and sustained improvement over the long term (Leckey et al., 2025; Me¸żyk & Unold, 2011).

In the specific context of basketball, the integration of AI-based analytical tools has been widely used to assess jumping abilities and their characteristics, also for injury prevention purposes (Shah et al., 2025). Specifically, the analysis of the drop jump resulted in a key evaluative procedure designed to assess crucial performance indicators such as explosive strength, neuromuscular coordination, motor control, and biomechanical efficiency (Kawaguchi et al., 2021; Tan et al., 2024). The drop jump test involves athletes dropping from a defined height and immediately performing an explosive vertical jump upon landing. This procedure captures numerous critical metrics, including jump height, ground reaction forces, contact time, and kinematic smoothness. Kinematic smoothness, commonly quantified through the jerk ratio is a measurement reflecting the rate of change in limb segment acceleration during dynamic movements, and has emerged as a particularly insightful performance indicator (Buckley et al., 2017). Lower jerk ratio values signify smoother and more efficient motion, hence superior motor control, effective neuromuscular coordination, and enhanced performance efficiency (Koop et al., 2018). The integration of this metric within AI-driven evaluations may provide coaches and educators with robust and actionable insights, directly informing training regimens and athlete-specific interventions. Extensive biomechanical research underscores the importance of smooth, fluid movements in minimizing mechanical stresses placed on joints and musculature, thereby reducing susceptibility to injuries and enhancing overall athletic effectiveness (Kiely et al., 2019). This relationship suggests the idea for sports education programs to integrate detailed biomechanical assessments into their curricula. Implementing comprehensive biomechanical evaluations enables educators to substantiate training practices with empirical evidence, aligning with best practices for enhancing athletic performance while safeguarding athlete health and longevity in sport. A useful analytical tool should help the educators and coaches in accurately understanding the skill level or competence of individuals performing specific athletic exercises. The drop jump, a plyometric exercise frequently utilized to assess lower limb explosive power and neuromuscular coordination, presents varied biomechanical profiles depending on an athlete's experience and skill (Troisi Lopez, Limone, et al., 2025). Precisely identifying the level of proficiency can guide trainers to implement tailored and more effective training interventions, ultimately enhancing athletic performance and reducing injury risk. To facilitate precise analysis and classification of athletic performance, machine learning techniques such as the Support Vector Machine (SVM) have become increasingly valuable (Hearst et al., 1998). SVM is a supervised learning algorithm primarily utilized for classification tasks. It operates by finding the hyperplane that best separates distinct classes within a feature space. This optimal hyperplane is determined by maximizing the margin between the nearest data points of each class, known as support vectors, thus ensuring robust generalization to new, unseen data. Within the broader scope of artificial intelligence, SVMs stand out due to their efficiency, accuracy, and effectiveness, particularly in scenarios involving complex datasets and multidimensional spaces. The application of SVM algorithms has become widespread in biomechanical analyses and sports science research (Toledo-Pérez et al., 2019; Troisi Lopez, Minino, et al., 2025). Specifically, SVM has frequently been applied to classify various performance levels based on detailed movement analyses. Researchers and sports scientists commonly leverage this algorithm to objectively differentiate athletes based on biomechanical efficiency, precision, and overall quality of movements (Taha et al., 2018).

Consequently, our aim is to employ the SVM algorithm to classify professional basketball athletes and amateur basketball practitioners based on biomechanical smoothness features extracted from lower limb joint movements during the drop jump. Smoothness, a critical indicator of motor control and neuromuscular efficiency, represents the fluidity and coordinated nature of joint motion. By analysing smoothness features, we aim to objectively distinguish between athletes of different skill levels. Our hypothesis is that the SVM classifier, using smoothness-derived features, will successfully classify professional and amateur athletes at a rate exceeding random chance, demonstrating the algorithm's practical applicability and effectiveness in sports education and performance assessment.

2. Methods

2.1. Participants

For our study, we used a dataset published by Zhao et al., including kinematic time series recorded through a stereophotogrammetric system (Zhao et al., 2023). From this dataset we extracted the drop jump movement performed by basketball players and analysed a total of 30 players. Then, we divided the sample according to their basketball skill level, creating two groups. The first group consisted of 13 amateur players (AP), while the second group consisted of 17 professional players (PP). More details about the acquisition system, sample population, and specific movements are available in the original paper.

2.2. Procedure

We used data from Zhao et al. published dataset, focusing on the execution drop jump exercise performed by professional and amateur basketball players. The authors collected the data using a stereophotogrammetric camera system. All the details on the recording procedures and the instruction given to the participant are available in the original paper (Zhao et al., 2023).

2.2.1. Data processing

For our analysis, we focused on the kinematic data of joint excursion angles related to lower limbs: neck, trunk, and both left and right shoulders, elbows, hips, knees, and ankles. Three-dimensional time series (anteroposterior, mediolateral, and vertical) were available for each joint. The data were individually inspected to identify label errors, lost values, anomalies, and control their internal consistency (e.g., same order of the data). Interpolation was used to fill missing data using MATLAB's 'fillmissing' function with the 'spline' method if the gap was under 0.1 seconds; if the gap was greater, we excluded the participant's data (The MathWorks Inc, 2022). Data from six (out of twenty-three) professional athletes and four (out of seventeen) amateur athletes were excluded for poor reliability.

2.2.2. Smoothness evaluation

Jerk represents the first derivative of acceleration and is commonly employed to assess gait parameters related to movement smoothness. A typical method involves calculating the root mean square (RMS) of the jerk across the three-dimensional space — specifically along the anteroposterior (AP), vertical (V), and mediolateral (ML) axes — to derive a single value for each axis that reflects smoothness (Troisi Lopez et al., 2022). To further condense this information into a dimensionless parameter, the Jerk Ratio (JR) is calculated by taking the logarithmic ratio of ML to V RMS jerk and AP to V RMS jerk, with the results expressed in decibels (dB).

$$JR_{\frac{AP}{V}} = 10log_{10}\left(\frac{RMS\ AP\ Jerk}{RMS\ V\ Jerk}\right)$$

$$JR_{\frac{ML}{V}} = 10log_{10}\left(\frac{RMS\ ML\ Jerk}{RMS\ V\ Jerk}\right)$$

Each measure was calculated for each joint of each participant of each group.

2.2.3. Level classification

An AI-based algorithm, the SVM, was used to perform supervised classification of the data. The algorithm, analysing the joints' smoothness of the drop jump of each athlete was able to provide a binary classification output and classify the athletes as "professional" or "amateur". 10-fold cross validation was used during the analysis to ensure robustness and generalizability of the classification model (Varoquaux et al., 2017).

2.2.4. Statistical comparison

To individuate which joint mainly showed significant difference between amateur and professional athletes, we performed permutation tests with 10,000 iterations, with significance defined at $p < 0.05$. The permutation test, chosen for its minimal assumptions about data distribution, provided a robust statistical framework for analysing differences between groups (Nichols & Holmes, 2002).

3. Results

The SVM model effectively discriminated between amateur and professional basketball players, achieving an overall classification accuracy of 80%, as reported in Figure 1. Furthermore, the results were the same with both AP/V Jerk ratio and ML/V Jerk ratio. Specifically, ten out of thirteen amateur athletes were correctly recognized as amateur, while three were mistakenly labeled as professional athletes. Concerning the seventeen professional athletes, fourteen of them were labeled correctly while three of them were recognized as amateur basketball players.

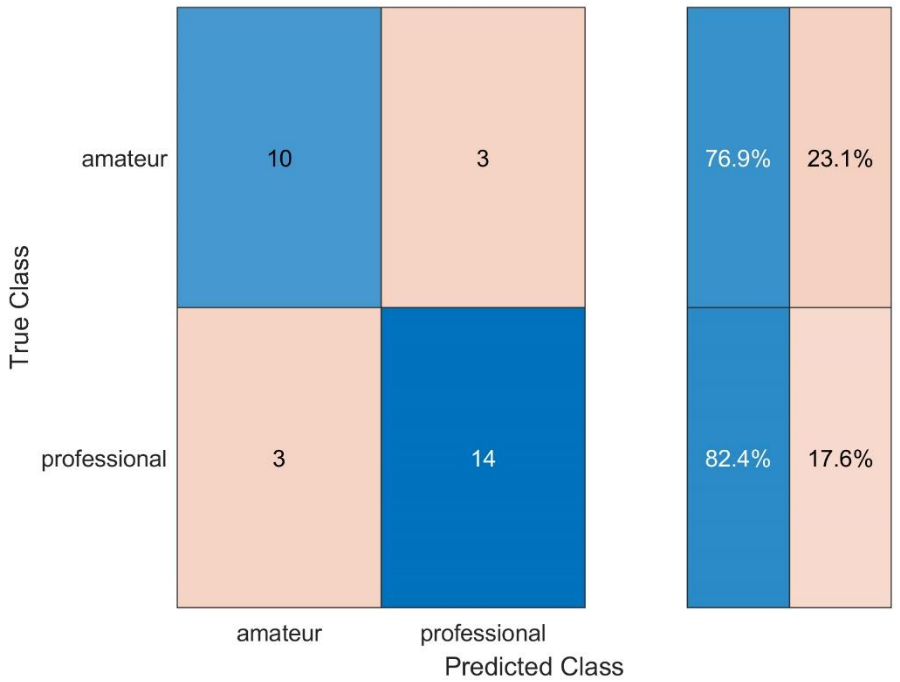

Figure 1. The figure shows the confusion matrix resulting from the classification. The vertical axis represents the true level of the basketball players, while the horizontal axis shows the level predicted by the artificial intelligence. The diagonal cells (blue boxes) indicate the number of players correctly classified at each level, whereas the other cells (red boxes) represent misclassifications. On the right, the percentages of correct (blue boxes) and incorrect (red boxes) classifications are shown for each level.

With regard to the analysis of the differences in smoothness between the two groups, jerk ratio analysis indicated significant differences in movement smoothness, at both the left and right knees in AP/V jerk ratio and ML/V jerk ratio. Specifically, the ML/V jerk ratio was significantly lower in professional athletes at both left ($p = 0.025$) and right knees ($p = 0.009$). The results showed the same pattern in the AP/V jerk ratio, resulting lower in professional athletes at both left ($p = 0.014$) and right knees ($p = 0.018$). These results are displayed in Figure 2.

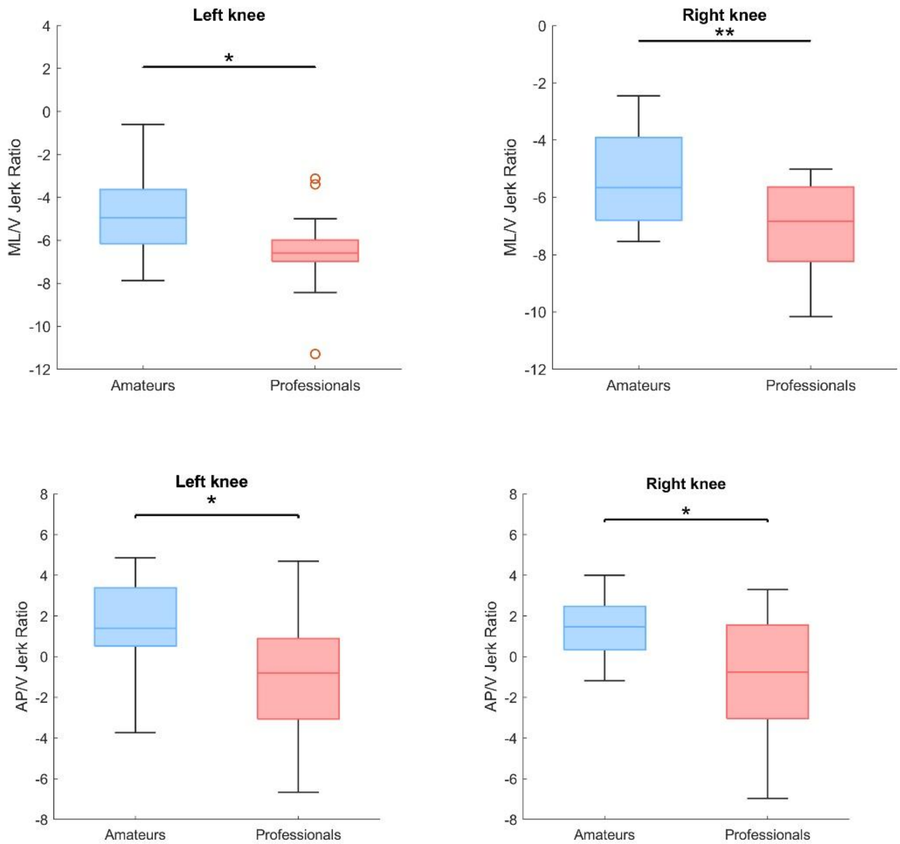

Figure 2. The figure shows the results of the comparison between the ML/V (mediolateral/vertical) and AP/V (anteroposterior/vertical) jerk ratios of the right and left knees in amateur and professional basketball players. All comparisons are significant and indicate greater movement smoothness during the drop jump in favor of professional athletes. * $p < 0.05$; ** $p < 0.01$

4. Discussion

In this study, we aimed to evaluate the ability of artificial intelligence-based systems to provide support to educators and coaches in the motor and sports fields. Specifically, we measured the AI's capability to classify and distinguish between amateur and professional basketball players. For the evaluation, we chose to assess movement fluidity during the drop jump, a plyometric exercise used to improve vertical jump ability and explosive power. The results are consistent with our hypothesis that the AI would be able to perform a correct classification, although it should be noted that the classification accuracy in our sample reached only 80%. Furthermore, additional analyses showed that the main difference between amateur and professional athletes during the execution of the drop jump lies in knee control.

Starting from this very last finding, it is our opinion that the outcome of our analysis may be considered relevant both for training AI systems, which could prioritize knee movement fluidity when evaluating performance, and for coaches, who can target knee-specific strength and mobility work (Malfait et al., 2016). Integrating AI into sports assessment could thus improve the accuracy and objectivity of athlete evaluation and training strategies. Our results also suggest that, beyond strength or explosiveness, the quality of joint movement, particularly at the knee, is crucial for distinguishing higher-level athletes. This aligns with previous studies regarding drop jump in basketball players. For instance, Zagatto et al. showed that drop jumps enhance neuromuscular readiness in basketball players (Zagatto et al., 2022), while Rouis et al. linked knee extensor strength to vertical jump performance (Rouis et al., 2015). Theoharopoulos et al. further emphasized the importance of muscular adaptations around the knee in professional players (Theoharopoulos et al., 2000). Altogether, these findings suggest that both strength and smooth, coordinated joint control are essential for superior athletic performance.

For what concerns the main aim of the study (i.e., AI-based athletes level classification), our findings underscore the potential impact of incorporating artificial intelligence methodologies within sports education field, underlining their utility along with a detailed biomechanical evaluation such as smoothness (i.e., jerk ratio) analysis (Araújo et al., 2021). Indeed, the finding that an AI-based analysis was able to distinguish between professional and amateur basketball players with an accuracy of 80% can be of interest for both educational and sports contexts. Such a result suggests that AI can capture subtle feature of motor characteristics that might be difficult for the human eye to systematically and consistently detect, particularly when evaluating large numbers of individuals. On the contrary, AI can offer an objective evaluation tool that could aid the educators or the trainers in their evaluations. In educational environments, especially physical education classes or youth sports academies, this capability could serve as a powerful tool for early talent identification and personalized development programs (Mahmoud & Sørensen, 2024). For instance, we can imagine a physical education teacher working with a class of thirty students that display different degrees of coordination, strength, and agility. Traditional observational methods would require extensive time and subjective evaluations, that could lead to inconsistencies due to the evaluator fatigue or the difficulty in comparing students or athletes that performed at a great distance of time from each other. By integrating AI analysis, the teacher could obtain profiles of each student’s movement quality in an objective way, and this would allow to easily create clusters of students with similar abilities with higher precision. Consequently, it would be more feasible to apply targeted motor training interventions, and better tracking of individual improvements over time (Barbieri et al., 2024). In sports training, particularly in academies or developmental leagues, AI’s ability to distinguish levels of expertise could significantly refine both the scouting and the training programs (Aditya & Yunus, 2024; Saleh, 2024). For instance, basketball clubs often carry out tryouts involving many athletes. In such cases, coaches must make rapid assessments that will influence which players receive scholarships, developmental contracts, or entry into elite training programs. An AI system can be trained on specific movements relevant to a given sport in order to provide an additional, objective evaluation, individuating players which display biomechanical qualities and motor skills more similar to professionals (Gálvez et al., 2025; Ivankovi et al., 2010). Moreover, the AI evaluation could assist in identifying hidden deficiencies in professional players, allowing coaches to intervene early and reduce injury risk associated with poor movement patterns (Leckey et al., 2025).

Furthermore, in coaching education, the implementation of AI assistant may also enhance the educator observational skills. Currently, coaches and educators mainly rely on their own experience in evaluating what they see with their own eyes or the outputs from technologies (Celik et al., 2022). Integrating AI tools could provide coaches with objective examples of good versus poor movement control. For instance, they could practice analysing data outputs and video footage alongside AI-generated reports, improving their diagnostic abilities in a structured and accelerated manner. Over time, this could raise the overall standard of coaching and teaching. Furthermore, it is also important to consider the motivational aspects for athletes and students. The possibility of gamifying motor skill improvement through AI feedback could enhance engagement, particularly among younger populations who are already accustomed to digital interaction and immediate feedback systems. It would represent an optimal integration between technology and an active lifestyle, where, through gamification, AI is able to assess an individual's motor skills level, propose stimulating activities of increasing difficulty, and then evaluate engagement, track improvement, and provide motivating feedback (Suresh Babu & Dhakshina Moorthy, 2024). This approach can also be developed by taking into account the importance of inclusivity, thus training the AI on heterogeneous populations so that it is prepared to manage, always under the supervision of a trained educator, different levels of motor skills, including any special educational needs (Lin & Chang, 2024). However, it is important to emphasize that AI should be viewed as a complement, not a replacement, for human expertise. The 80% accuracy found in this study, while promising, also highlights that AI is not infallible. Coaches and educators must interpret AI outputs critically, considering the broader context of an individual's development, motivation, and overall well-being. Moreover, ethical considerations regarding data privacy, informed consent, and the psychological impact of algorithmic evaluations must be carefully managed to ensure that AI serves as a positive force in educational and sports settings.

Conclusions

In conclusion, the ability of AI to classify individuals based on their movements with high (although not perfect) accuracy suggests the possibility for a transformative opportunity for education and sport. It enhances objectivity, accelerates feedback, democratizes talent identification, and creates new possibilities for research and development. Used wisely and ethically, AI-based movement analysis could lead to more inclusive, effective, and empowering experiences for learners and athletes alike, helping to realize their full potential in a scientifically informed and supportive environment.

Author contributions

Emahnuel Troisi Lopez conceived the study and wrote the original manuscript; Mario De Luca processed and analysed the data; Arianna Polverino processed the data and created the figures; Enrica Gallo created the figures and contributed to data interpretation; Roberta Minino supervised the work and contributed to data interpretation; all authors reviewed the manuscript.

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