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Review article

A comprehensive analysis of the machine learning pose estimation models used in human movement and posture analyses: A narrative review

Federico Roggio [a], Bruno Trovato [a], Martina Sortino [a], Giuseppe Musumeci [a,b,c,*]

[a] Department of Biomedical and Biotechnological Sciences, Section of Anatomy, Histology and Movement Science, School of Medicine, University of Catania, Catania, Italy
[b] Research Center on Motor Activities (CRAM), University of Catania, Catania, Italy
[c] Department of Biology, Sbarro Institute for Cancer Research and Molecular Medicine, College of Science and Technology, Temple University, Philadelphia, USA

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ABSTRACT

The accurate measurement and analysis of human movement are essential in fields ranging from rehabilitation and neuroscience to sports science and ergonomics. Traditional methods, though precise, are often constrained by cost, accessibility, and controlled environments. The advent of machine learning (ML) pose estimation models (PEMs) offers an alternative solution, enabling detailed motion analysis using low-cost imaging systems in various settings. The aim of this review is to evaluate ML PEMs and their impact on human movement sciences, focusing on recent advancements in machine learning and computer vision for accurate, non-invasive motion analysis using low-cost imaging systems. A narrative review was conducted by searching electronic databases, including PubMed and Google Scholar, using key terms such as "machine learning," "pose estimation models," and "human movement sciences." Thematic analysis identified key advancements, applications, and challenges in ML PEMs across clinical, sports, and ergonomic contexts. The review highlights the development, capabilities, and applications of models such as OpenPose, PoseNet, AlphaPose, DeepLabCut, HRNet, MediaPipe Pose, BlazePose, EfficientPose, and MoveNet, emphasizing their potential for non-invasive, cost-effective assessments. In clinical settings, these models enable objective gait and posture analysis, aiding in diagnosing musculoskeletal disorders and tracking rehabilitation progress. In sports, ML PEMs enhance performance analysis and injury prevention by providing real-time feedback and detailed biomechanical data. In ergonomics, they offer proactive solutions for workplace injury prevention through real-time posture and movement analysis. While promising, the implementation of ML PEMs faces challenges in accuracy, data quality, and integration into existing practices. Establishing standardized protocols and frameworks is crucial for ensuring reliable, interdisciplinary applications. This review can be useful for coaches, healthcare professionals, and researchers in evaluating and implementing ML PEMs, ultimately advancing the field of human movement sciences.

* Corresponding author. Department of Biomedical and Biotechnological Sciences, Section of Anatomy, Histology and Movement Science, School of Medicine, University of Catania, Catania, Italy.
E-mail address: g.musumeci@unict.it (G. Musumeci).

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1. Introduction

The accurate measurement and analysis of human movement underlines advancements across diverse scientific and medical disciplines. From motor rehabilitation and neuroscience to sports science and engineering, researchers face the challenge of precise motion quantification, even within laboratory settings [1]. Traditionally, this requires specialized equipment and controlled environments, limiting research scope and real-world applicability [2]. The advent of pose estimation algorithms offers a transformative solution, potentially liberating movement scientists from these constraints [3]. These algorithms enable in-depth motion analysis using low-cost imaging systems, facilitating the non-invasive data collection in different environments like clinics, homes, or outdoor settings. This approach has the power to significantly impact research by enabling larger, more diverse datasets, reducing biases, and ultimately providing a more accurate representation of the complex characteristics of human movement.

The existing methods to analyze human motion are undergoing a deep transformation driven by advancements in machine learning (ML) and computer vision methods. Specifically, the development of sophisticated pose estimation models (PEMs) changed the approaches commonly used for the anatomical landmarks extraction from images and videos. To date, Kinovea has been one of the most used software for the motion analysis from a RGB video which showed a good validity and reliability over time [4]. However, the introduction of ML models, reached many different fields ranging from healthcare and sports science to workplace ergonomics and entertainment [5,6]. The basic approach behind these models is the application of Convolutional Neural Networks (CNNs), a powerful

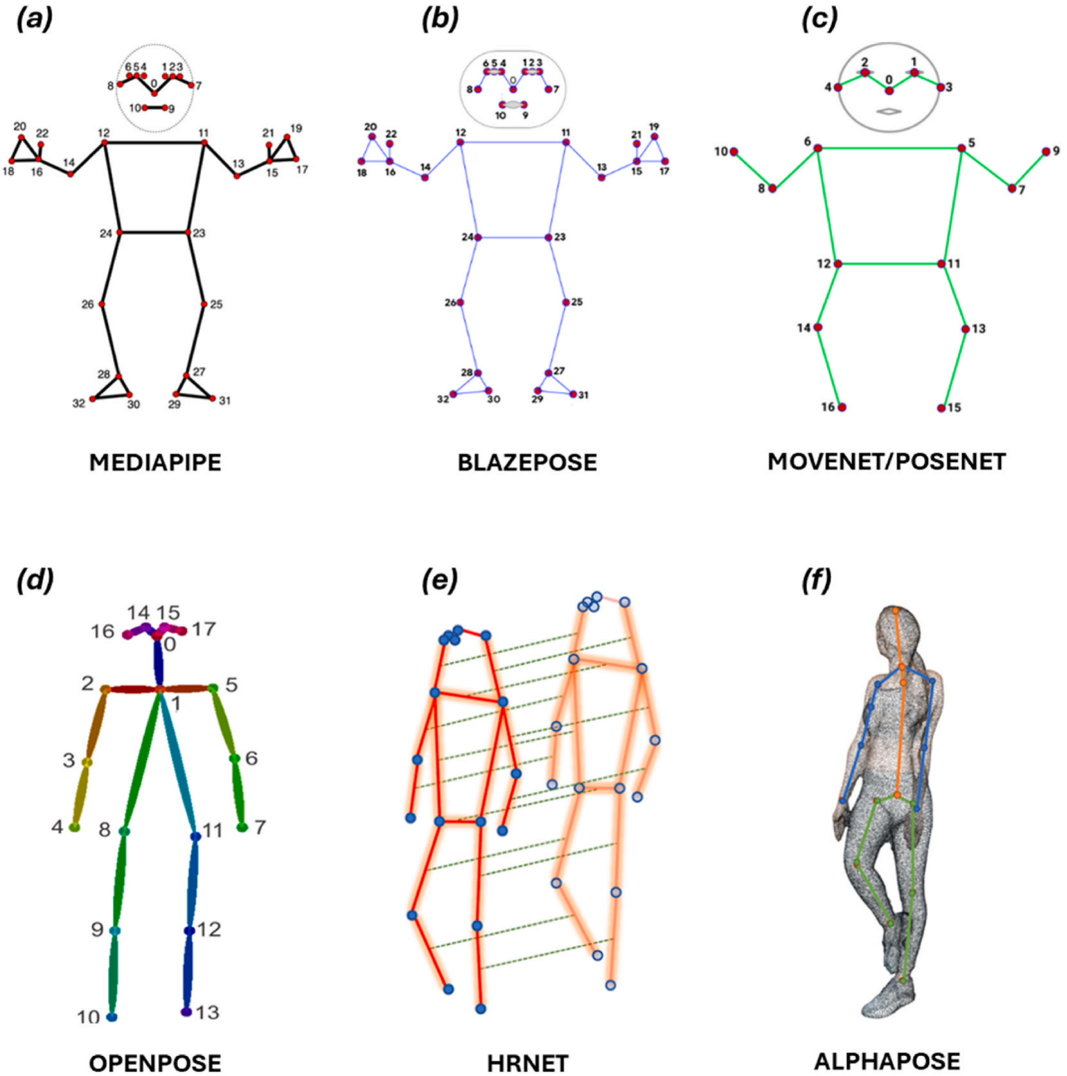

Fig. 1. Illustration of the skeletal landmarks detection conducted by the different ML pose estimation. a) MediaPipe detects a structure of 33 landmarks on the human body. b) BlazePose detects 33 landmarks on the human body. c) MoveNet detects 17 landmarks, focusing on the main body joints. d) OpenPose detects 18 landmarks for full-body pose estimation. e) HRNet detects 17 landmarks, emphasizing high-resolution representations for more accurate keypoint localization. f) AlphaPose detects 17 landmarks, prioritizing precision in pose estimation.

image analysis tools that excel at tasks like image recognition [7]. CNNs use convolutional layers to break images into feature maps, detecting patterns such as edges and textures. Pooling layers then reduce dimensionality, emphasizing the most important features. Fully connected layers at the end use these extracted features to classify the image [8]. To keep a high accuracy of detection, CNNs are trained using a process called backpropagation. During training, the network continuously adjusts its internal parameters based on the errors observed in the predictions. This iterative adjustment helps the network improve its ability to accurately examine and classify images [9]. Using this method, PEMs can automatically locate key anatomical landmarks on the body during the prediction phase (Fig. 1). Once obtained, they can be used for calculating joint angles, and quantify movement trajectories entirely through standard video recordings.

Traditionally, the study of human motion and posture often relied on manual assessments [10], specialized motion capture laboratories, or the use of wearable sensors [11]. These methods can be accurate but may face constraints relating to cost, accessibility, intrusiveness, and limitations in scalability [2]. ML PEMs, offer distinct advantages and tradeoffs compared to other motion analysis methods. Unlike marker-based systems like Vicon optoelectronic systems, they eliminate the need for physical markers and specialized lab settings, significantly enhancing accessibility and usability [2]. Compared to RGB-D sensors like Microsoft Kinect V2 [12], PEMs using standard cameras are less restricted by the environment. While the comparison with smartphones and Inertial Measurement Units (IMUs) may appear unnecessary, PEMs operating on video data potentially provide richer information, including full skeletal tracking. In the clinical field, ML PEMs hold potential for objective gait analysis [13] to diagnose musculoskeletal disorders [5] and track rehabilitation progress [14]. Their ability to facilitate non-invasive posture assessments empowers interventions for reducing pain and improving functional movement patterns. Sports scientists are using this technology for the analysis of athletic gestures, identifying subtle deviations for injury prevention and so enhancing the performance [15]. Additionally, ML PEMs are being applied in ergonomics, allowing the identification of dangerous movement patterns, guiding the design of preventive approaches for workplace-related musculoskeletal disorders [16]. While the main key features of these human PEMs, e.g., 2D vs 3D or single-view vs. multi-view, have been thoroughly discussed recently [17], to date, a comprehensive analysis of the well-known models and the various applications in the human movement sciences field has been not discussed yet.

This review will focus on comparing ML PEMs to traditional motion analysis methods, such as marker-based systems, RGB-D sensors, and wearable devices, highlighting their advantages and limitations. Additionally, it will explore the applications of ML PEMs in real-world settings, including clinics, homes, and outdoor environments, where they have the potential to enhance the analysis of gait, posture, athletic performance, and workplace ergonomics. The goal is to provide valuable insights for coaches, healthcare professionals, and researchers in evaluating and implementing ML PEMs to advance human movement sciences.

The scope of this narrative review is to offer a comprehensive evaluation of ML PEMs and their impact on human movement sciences. Specifically, it will address recent advancements in ML and computer vision techniques that enable accurate, non-invasive motion analysis using low-cost imaging systems.

1.1. *The most frequently used key pose estimation models*

Due to the speed with which the ML field is evolving, many models for pose estimation are being presented and discussed in the scientific scenario but some of these, are private or not accessible to all. Here we discuss those models that are highly prevalent in the ML scenario applied to motion analysis to highlight specific features and guide researchers toward the optimal model choice for their needs, as summarized in Table 1.

OpenPose, developed with C++ language by Carnegie Mellon University, had its initial major release around 2017, revolutionizing real-time human pose estimation [18], Fig. 1d. This computer vision library enables the detection of body keypoints in images and videos, even in scenarios involving multiple people [27]. The applications of OpenPose are extensive, including movement analysis in sports, fitness, and gesture recognition for human-computer interaction [28]. PoseNet, released by Google AI around 2017, excels in real-time human pose estimation in web environments [19] Fig. 1c. It has been designed to run directly within web browsers to estimate the poses of individuals in images and videos. Its primary applications include interactive experiences, fitness tracking, motion-based games, and telemedicine [29]. AlphaPose, released in 2017 by the SenseTime team, aimed to enhance the field of multi-person pose estimation like OpenPose, Fig. 1f. It introduced a novel Region Proposal Network based approach to first locate individuals within an image and subsequently refine their pose estimations [20]. AlphaPose finds its primary applications in scenarios requiring accurate tracking of multiple people, such as analyzing group dynamics in video footage, sports analytics, and surveillance

Table 1
general overview of the characteristics of each model.

Model	Year	Developer	Landmarks	Coordinates	2D/3D	Single/Multi	Pre-trained	Mobile
OpenPose [18]	2017	Carnegie Mellon Univ.	135	x, y	2D	Multi	COCO, MPII	Limited
PoseNet [19]	2017	Google AI	17	x, y	2D	Single	COCO, internal	Yes
AlphaPose [20]	2017	SenseTime	17	x, y	2D	Multi	COCO, MPII	Limited
DeepLabCut [21]	2018	Mackenzie Mathis Lab	User-defined	x, y	2D	Both	Internal	Limited
HRNet [22]	2019	Microsoft	17	x, y	2D	Both	COCO, MPII, others	Limited
MediaPipe Pose [23]	2019	Google AI	33	x, y, z	3D	Both	Internal	Yes
BlazePose [24]	2020	Google AI	33+	x, y, z	3D	Single	Internal	Yes
EfficientPose [25]	2020	Megvii	17	x, y	2D	Both	COCO, MPII	Yes
MoveNet [26]	2021	Google AI	17	x, y	2D	Both	COCO, internal	Yes

systems [30]. DeepLabCut was introduced in 2018 by the Mackenzie Mathis Lab, initially focusing on markerless animal pose estimation. Although its primary application centered on analyzing animal behavior and movement using standard cameras and videos [21], DeepLabCut has proven highly adaptable for human motion analysis. Eliminating the need for physical markers, DeepLabCut is used extensively in sports science to evaluate athletic performance, such as running kinematics [31] and open environments sport analyses [32]. It is also employed in clinical settings to assess and monitor movement disorders of neurologic patients, aiding in the development of rehabilitation protocols [33]. HRNet developed by Microsoft in 2019, introduced a novel architecture for human pose estimation that maintains high-resolution representations throughout the estimation process [22], Fig. 1e. The name stems from the full name "High-Resolution Network" as its strength lies in achieving highly accurate human pose estimation, especially in challenging scenarios. Today, HRNet is a key component in systems demanding superior precision, such as applications involving detailed motion analysis or augmented reality experiences where accuracy is mandatory [34].

MediaPipe Pose was made available around 2019 as part of the larger MediaPipe framework of Google AI, a collection of tools for building ML pipelines [23], Fig. 1a. This pose estimation solution focuses on real-time, high-fidelity body tracking. It is a framework designed to enable data inference from sensory inputs such as video streams or photos, making it perfect for quickly prototyping perception pipelines. Due to its versatility, MediaPipe Pose is accessible for use within web environments, mobile applications, and across various platforms. Shortly thereafter, Google AI announced BlazePose in early 2020 as a fast and accurate pose estimation solution specifically tailored for mobile and embedded devices [24], Fig. 1b. Its main applications involve real-time body tracking for fitness tracking and gesture control interfaces. BlazePose is primary designed to deliver reliable results even on lower-power devices, making it widely adopted in mobile applications where speed and efficiency are crucial [35]. EfficientPose, published by Megvii in 2020, aimed to balance accuracy and computational efficiency in human pose estimation [25]. Its primary applications involve scenarios demanding both precision and speed, such as real-time pose tracking or use on less powerful devices. Due to its scalable architecture, it allows for flexible trade-offs between performance and accuracy, resulting in a valid foundation for the next-generation markerless movement analysis [25]. MoveNet, representing one of the latest models introduced by Google AI in 2021, pushed the boundaries of real-time pose estimation with its exceptional speed and accuracy [26]. This model was released in two variations to address specific needs: the 'Lightning' version for latency-critical applications and the 'Thunder' version for applications requiring high accuracy. Due to its versatility, MoveNet is currently being employed in interactive fitness experiences and gesture recognition systems [36].

The development of PEMs is highly collaborative, with innovations building on each other. For instance, OpenPose has influenced subsequent models like tf-pose-estimation in TensorFlow. Despite its popularity, it has limitations in precision and high computational cost, making it less suitable for applications requiring high accuracy, such as elite sports and medical assessments. Different models serve specific needs: BlazePose is optimized for mobile use in resource-limited settings, while HRNet offers high accuracy and is influenced by PoseNet. MoveNet builds on PoseNet and BlazePose, aiming for lightweight, real-time performance. This collaborative development is currently pushing the progress in the field of human pose estimation through ML.

2. Methods

This narrative review synthesizes relevant literature on ML PEMs and their applications in human movement sciences. The literature search was conducted using electronic databases, including PubMed and Google Scholar. Key terms used in the search included "machine learning," "pose estimation models," "motion analysis," "human movement sciences," "sports performance," "gait analysis," and "ergonomics."

Articles were selected based on their relevance to advancements in ML and computer vision techniques, as well as the development of ML PEMs for applications in clinical, sports, and ergonomic contexts. The inclusion criteria focused on peer-reviewed studies, conference papers, and reviews published between 2010 and 2024. Additionally, we reviewed the references of key articles to retrieve valuable publications from earlier years. Given the narrative nature of this review, a formal quality assessment of the studies was not conducted. Instead, emphasis was placed on identifying major trends, key advancements, and the comparative benefits and limitations of ML PEMs across various fields. The selected literature was organized thematically to highlight the significant advancements, applications, and challenges in implementing ML PEMs in human movement sciences.

3. Results

We gathered and synthesized the key information from the studies that utilized PEMs, including the application domains, model types, and main findings, and summarized them in Table 2. Each application domain was then discussed individually, providing a deeper analysis of how different models have been applied, their effectiveness, and the insights gained from their use in various contexts.

3.1. Machine learning pose estimation in posture analysis

Posture can be regarded as the calling card of each human being drawing elements from the human psyche, daily life, work and sports. While it plays a crucial role in our overall health and well-being, poor posture has been linked to numerous musculoskeletal issues, including back pain, headaches, and increased risk of injuries [65]. Traditionally, posture analysis has relied on subjective visual assessments by clinicians or the use of specialized tool like goniometers or plumb lines. Postural assessment is an important part of medical examinations, enabling health professionals to build tailored therapeutic programs [66]. While physical examination is a

Table 2
Main findings of the studies included in the narrative review for each domain of human movement analysis.

Field	Author (year)	ML PEM used	Key findings
Posture analysis	Samkari E. et al. (2023) [37]	–	Convolutional and Recurrent Neural Networks are the most used for Human Pose Estimation, but challenges like occlusion and crowded scenes hinder performance.
	Moreira R. et al. (2022) [38]	PoseNet	The NLMeasurer proved to be a valid tool for assessing postural measurements from a frontal view. Surface markers on anatomical landmarks can enhance accuracy and reliability.
	Roggio F. et al. (2024) [39]	MediaPipe	Significant sex differences were detected in shoulder and hip adduction angles, with no variations in horizontal inclinations.
Gait analysis	Hii C.T.S. et al. (2023) [13]	MediaPipe	MediaPipe Pose shows good to excellent agreement with the Vicon system, with moderate agreement in a few parameters. It offers reliable results for monitoring gait changes and evaluating interventions.
	Khera P. et al. (2020) [40]	–	This review found that support vector machines were the most effective classifiers, while reinforcement learning, and neural networks excelled in controlling rehabilitation devices and capturing participant variability.
	Toshev A. et al. (2014) [41]	Own Algorithm	The human pose estimation method using deep neural networks (DNNs) achieved high accuracy results with a cascade of DNN regressors.
	Stenum J. et al. (2021) [42]	OpenPose	This study compared OpenPose with 3D motion capture for gait analysis, showing small errors in temporal parameters and step lengths. The workflow is accessible, accurate, and suitable for broader gait analysis applications.
	Kim W. et al. (2021) [43]	Own Algorithm	The proposed method successfully detected gait abnormalities using Kinect data, with k-NN and SVM classifiers showing potential for accurate classification without the need for complex setups or wearable sensors.
	Li Y. et al. (2020) [44]	Own Algorithm	A smartphone-based lower body rehabilitation system was developed, achieving a 70.8 AP score on COCO val2017 with only 4.7M parameters. The system allows patients to perform exercises at home, with encrypted data processed locally and reports shared with doctors.
	Lin C.B. et al. (2020) [45]	OpenPose	The fall detection system using OpenPose is based on tracking human joint movements, reducing the impact of environmental factors and improving training time.
	Moro M. et al. (2022) [46]	Pose ResNet	The study compared a new RGB video-based markerless system with a marker-based motion capture system for 3D gait analysis. Similar spatio-temporal parameters were observed, with slight underestimation in ankle and knee flexion.
	Menychtas D. et al. (2023) [47]	OpenPose and MediaPipe	The study proposes an artificial intelligence-powered annotation tool that allows users to correct errors, especially those of small joint movements, by combining accuracy with the efficiency of automatic systems.
Sport analysis	Afrouzian R. et al. (2016) [48]	Own Algorithm	The proposed algorithm accurately estimates 3D human poses from multiple uncalibrated cameras using previous frame viewpoints, achieving high accuracy on a soccer player dataset.
	Badiola-Bengoa A. et al. (2021) [49]	–	The estimation of human poses in sport is based on generic systems such as OpenPose but requires more public data to improve performance in all contexts.
	Pagnon D. et al. (2022) [50]	OpenPose	Pose2Sim demonstrated high accuracy for lower-limb kinematics, with errors averaging 3.0°–4.1° across walking, running, and cycling tasks, and a coefficient of multiple correlation above 0.9 in most cases.
	Citraro L. et al. (2020) [51]	OpenPose	The proposed framework accurately estimates camera parameters in real time from sports field images using deep learning, outperforming current methods on soccer, basketball, and volleyball datasets.
	Ota M. et al. (2020) [52]	OpenPose	OpenPose showed high reliability and validity for joint angle estimation, though biases were present in certain joints. It offers a low-cost, user-friendly alternative, but requires bias correction for clinical use.
	Luvizon D.C. et al. (2022) [53]	ResNet-U	The proposed 3D human pose estimation method in camera coordinates reduced prediction error by 32 % and achieved 80 mm error for monocular and 51 mm for multi-view estimations on key datasets.
Injury Prevention	Zhou G. et al. (2022) [54]	OpenPose	The proposed method accurately classified lifting risk and predicted perceived exertion using body movements, posture, and facial expressions.
	Van Eetvelde H. et al. (2021) [55]	–	Machine learning methods show potential in predicting sports injuries, with performance ranging from poor to strong, but improvements in model interpretation and methodological quality are needed.
	Tack C. et al. (2019) [56]	–	Machine learning can enhance musculoskeletal medicine by automating diagnostics, data analysis, and clinical decision support, often matching or surpassing human accuracy.
Remote Physical Activity Tracking	Raza A. et al. (2023) [57]	MoveNet	The proposed LogRF method for feature selection improved human pose estimation. This enhances exercise correction, injury prevention, and remote physiotherapy monitoring.
	Yang L. et al. (2021) [58]	OpenPose	The software uses OpenPose to analyze exercise posture and provides corrective feedback for squats and push-ups, improving form and preventing injury.
	Cai Z. et al. (2022) [59]	MoveNet	The study proposes PoseBuddy, a mobile app that uses computer vision and the MoveNet model to provide personalized workouts with real-time audio feedback on exercise form.

(*continued on next page*)

Table 2 (*continued*)

Field	Author (year)	ML PEM used	Key findings
	Rosique F. et al. (2021) [60]	OpenPose	ExerCam, a low-cost augmented reality telerehabilitation tool, uses a webcam for pose detection, offering remote patient management, ROM calculation, and gamified therapy, with positive results.
Ergonomics	Mehrizi R. et al. (2018) [61]	Own Algorithm	The proposed predicts 3D pose during lifting tasks, achieving an average error of 14.72 mm, comparable to marker-based methods, and outperforms state-of-the-art techniques on the HumanEva-I dataset.
	Chen C. et al. (2020) [62]	Own Algorithm	The study achieved 92.8 % accuracy in recognizing assembly actions using YOLOv3 and 82.1 % accuracy in estimating repetitive assembly operating times through joint coordinate extraction.
	Kim W. et al. (2021) [63]	OpenPose	OpenPose outperformed Kinect in measuring joint angles and conducting ergonomic assessments, especially in non-ideal conditions with body occlusions or non-frontal views, showing potential for real workspace applications.
	Ying W. et al. (2021) [64]	OpenPose	The proposed method using 2D video and machine learning classifiers effectively automates scaffolding workface assessment, proving to be a feasible and practical solution for activity classification.

cost-free method that does not require the use of expensive equipment, it may be biased by the ability and accuracy of the clinician [67]. Further, exposing the patient to x-rays imaging when not required, increases the negative impact of radiation exposure [68].

To overcome these limitations, recent advancements in ML PEMs are providing new approaches for the posture analysis thanks to the automatic detection of anatomical landmarks from photos or videos [37]. By identifying key points such as the shoulders, hips, knees, and head, these models can calculate angles, distances, vertical and horizontal alignments that quantify various aspects of posture alterations. This technology eliminates the need for manual measurements and subjective interpretations, enabling a more standardized and data-driven approach to posture analysis [38]. By integrating ML PEMs, posture assessment becomes non-invasive and low-cost, significantly increasing its feasibility in various settings, such as schools and workplaces. To date, research into the application of ML models for posture analysis remains limited [38]. In a recent study, we applied a human PEM to assess biomechanical posture in a cohort of 200 healthy adults, aiming to enhance musculoskeletal disorder prevention through objective analysis [39]. Utilizing photographs from multiple angles, the study identified significant gender-specific differences in shoulder and hip adduction angles, with a Intraclass Correlation Coefficient peaking at 0.95. We also employed ML analysis methods such as principal component and cluster analyses, uncovering new patterns in postural analysis, like differences in shoulder–hip distance. Since this approach is providing valuable results compared with gold standard methods [69] but at the same time it may seem simplistic, it has the potential to generate large-scale datasets of human posture. Such datasets could facilitate the identification of subtle postural deviations, serving as early indicators of developing musculoskeletal disorders. This would enable the implementation of timely preventive interventions [5]. While the technology itself is accessible, its successful integration into clinical practice requires a collaborative approach between healthcare professionals, engineers, and computer scientists.

3.2. Machine learning pose estimation in gait analysis

Traditionally, gait analysis often relied on specialized motion capture laboratories equipped with expensive marker-based systems and trained clinicians [2]. However, advancements in ML have guided a new era of landmark detection models, revolutionizing the accessibility and potential applications in gait analysis [40]. ML PEMs are typically trained on large datasets and, through deep learning techniques, they learn to identify complex patterns and relationships within images, enabling the prediction of landmarks locations on previously unseen images or videos [41]. This ability eliminates the need for physical markers and time-consuming manual labeling which may bring into collection bias. The advantages of ML pose landmark detection models in gait analysis are various. They facilitate cost-effective and portable analysis setups, making them ideal for use outside traditional laboratory environments. The flexibility of ML models results in lightness in the field of analysis both from the point of view of organization, preparation, reproducibility and versatility [40]. These models are able to collect basic spatiotemporal parameters, i.e., stride length, cadence, gait speed, to complex kinematic patterns, i.e., joint angles, allowing for faster and reliable biomechanics analyses [42]. These data can be used for diagnosing gait abnormalities [43], quantifying the effectiveness of rehabilitation interventions [44], and potentially predicting fall risk through the identification of subtle movement deviations [45]. Researchers investigated the reliability of MediaPipe by comparing it with an optoelectronic system [13] and demonstrated good to excellent agreement across all spatio-temporal parameters, with an intraclass correlation coefficient >0.75. They further justified their use of MediaPipe, highlighting its top-down approach that allows for more precise landmark detection compared to other methods.

While ML PEMs show promising results, it is important to be aware of the limitations behind these methods. Currently, the accuracy of landmarks detection is influenced by factors such as training of the ML model, source quality, or video occlusions [70]. Although this approach is showing promising results as the ML results are comparable to marker-based methods [46], understanding the limitations and potential sources of error is crucial for responsible implementation [47].

3.3. Machine learning pose estimation in sports motion analysis

In the Sports field, the ability to precisely analyze movement patterns is crucial for enhancing the performance, optimizing the technique, and minimizing injury risk [71,72]. Traditional motion analysis methods in sports often fall into two categories: observation by coaches, with subsequent subjective assessment, and biomechanics analyses performed in specialized laboratories with highly sophisticated tools. ML PEMs, with their ability to automatically track anatomical landmarks from videos, are enabling two types of analysis: in-field analysis during training sessions and post-match analysis [48]. Unlike traditional motion capture labs, ML PEMs eliminate the need for specialized settings. Analysis takes place directly on the field, court, or gyms, providing insights into real-world sports performance [49]. They also offer a more affordable and accessible alternative to the expensive equipment and controlled environments of motion capture [50]. While motion capture labs often excel at precise 3D movement reconstruction, ML PEMs can prioritize the extraction of specific, sport-relevant kinematic data (joint angles, velocities, etc.), providing targeted analysis tailored to the needs of coaches and athletes. A research compared different ML models for the match analysis in basketball, volleyball ad soccer matches [51]. The results highlighted a valid accuracy in localizing and identifying 2D player movements as well as field lines, offering valuable insights for sports analysis. Further, another study employed OpenPose for the evaluation of the squat exercise, a common but potentially injury-prone movement [73]. Researchers compared OpenPose to a marker-based gold standard method and found high intraclass correlation coefficients (0.92–0.96), indicating good validity for this specific application [52]. However, more studies are needed to fully confirm the validity of these methods across a wider range of workout exercises.

Despite the undeniable advantages of ML PEMs in sports analysis, accuracy remains a challenge. Unlike traditional marker-based motion capture systems, ML PEMs can be affected by factors such as camera angles and lighting conditions. These variations can influence the model's interpretation of video data, introducing potential errors. Recent research [53], has proposed a consensus-based optimization algorithm to address this issue. This algorithm enables multi-view predictions from uncalibrated images using a single monocular training process. While this represents a sophisticated approach, coaches and sport scientists must still be aware of the potential for inaccuracies when using RGB cameras for sports analysis with ML PEMs.

3.4. Machine learning pose estimation for injury prevention

Injuries, particularly those resulting from musculoskeletal overuse or improper movement patterns, represent a significant challenge in sports [74]. They have both short- and long-term consequences. In the short term, injuries can have strong psychological repercussions as it impairs return to play, increases the risk of re-injury and even leads to the development of mental disorders [75]. Further, untreated injuries can lead to incomplete recovery, abandonment of sports activity, and, in the long term, can cause degeneration of the joint such as osteoarthritis [76,77]. Preventing injuries is crucial for athlete well-being, performance optimization, healthcare cost reduction, and preventing long-term health issues. ML PEMs applied in sports analysis offers a powerful new tool in injury prevention, enabling a shift from reactive treatment to proactive risk assessment. Traditional injury prevention often focuses on analyzing risk factors after an injury occurs. In contrast, ML PEMs can identify subtle deviations, asymmetries, or compensatory mechanisms in movement patterns, indicating the predisposition of an athlete to injury [78]. For example, a recent study validated ML as a prevention tool by combining different techniques [54]. The authors used OpenPose to analyze the movement biomechanics, SelFlow to anticipate the movements and OpenFace to understand the facial expression. This mixed approach helped them discover specific behavioral patterns that predict changes in load lifting and perceived exertion during the task.

While common methods rely on specialized laboratories, using deep learning methods to process vast amounts of movement data can enhance our understanding of sports movements and reveal common patterns linked to injury risk [55]. This fast and non-invasive method would ideally involve collecting the baseline data of the athlete for successive comparisons. Coaches could use this informed analysis to tailor training programs, implement corrective exercises, modify techniques to reduce risk, and even guide physical therapists in providing optimal support for the athlete [56].

However, while this optimistic framework would be appealing to many sports organizations, it is essential to consider the current limitations. The predictive power of models depends on the quality and relevance of training datasets [79]. These methods are still under development in the sports field, where gold-standard techniques are often preferred. This preference is understandable since high-level athletes require the highest accuracy. However, a major limitation of ML models is their need for large volumes of data; without this, the framework described above cannot be fully realized. Additionally, coaches need proper guidance in interpreting the information provided by ML PEMs to fully unlock their potential.

3.5. Machine learning pose estimation in remote physical activity tracking

The COVID-19 pandemic accelerated a significant shift in the perception of remote tracking. While the concept of remote tracking is not new, and the use of wearables for monitoring physical activity has been widely explored [77], these trackers have a notable limitation: they primarily collect data such as heart rate or burned calories during a session rather than providing real-time feedback. Alongside the evolution of fitness tracking, the telehealth field from the physical therapy [80] to cardiac rehabilitation [81], also experienced a digital transformation spurred by the rise of digital approaches. Wearables undoubtedly collect valuable physiological data, but they lack the ability to assess biomechanical parameters. While useful for measuring spatiotemporal aspects of movement, their applicability in analyzing the movement itself is limited [82].

ML PEMs for posture, gait, and movement analysis offer a promising approach for analyzing biomechanics during remote fitness or rehabilitation sessions delivered through online platforms. The key application of these models lies in their ability to provide objective, automated analysis of exercise form and movement, eliminating the need for in-person supervision or specialized sensors.

During live video sessions, trainers can support the customer with real-time feedback on exercise form, repetition counts, range of motion, and other essential aspects of exercise execution [57]. This mitigates the risk of incorrect form and potential re-injury.

OpenPose has been successfully employed for this purpose, and researchers have demonstrated that the system can detect human body posture, obtain key point coordinates, analyze exercise posture, and provide relevant suggestions based on correct exercise form definitions [58]. Similarly, a smartphone app has been developed using MoveNet to support customers during their workouts [59]. Utilizing the camera of the phone for real-time video, the app feeds data into a high-accuracy PEM. This model then provides real-time audio feedback during exercise, supported by an additional ML algorithm.

Furthermore, PEMs can facilitate in-depth biomechanical analysis by extracting quantitative data like joint angles, range of motion, and movement velocity. This empowers trainers and therapists with a precise, data-driven understanding of the functional limitations, movement patterns, and potential asymmetries of their clients [60]. For example, a PoseNet-based system has been developed for in-home rehabilitation. This system included statistical analysis tools, empowering clinicians to analyze the recovery status of the patients. Researchers observed that it accurately measured elbow and knee joint angles during movements, calculating range of motion with a simple laptop webcam [29]. Additionally, clinicians could compare movement execution across multiple days to evaluate quality and determine recovery rate.

This approach has the potential to expand access to expert guidance, bridging geographical gaps and making professional trainers and therapists accessible to individuals who might not otherwise have access to a gym or in-person support. This makes it easier to track progress objectively and empowers trainers and therapists to provide more informed suggestions during training sessions.

3.6. *Machine learning pose estimation in ergonomics*

Work-related musculoskeletal disorders (MSDs) pose a major public health challenge, causing pain, disability, lost productivity, and significant economic burdens [83,84]. Ergonomics is crucial in preventing MSDs, traditionally utilizing observational tools like the Rapid Upper Limb Assessment (RULA) survey [85]. Tools like inertial measurement units and motion capture systems provide high accuracy but come with limitations such as cost, technical expertise requirements, and potential movement interference [86,87]. Although accurate, they may not fully meet the needs of ergonomists, who are called upon to assess the worker in their real working context, where movement is natural, tasks vary, and long-term impact must be considered.

In response to this need, ML PEMs emerge as a useful tool for ergonomic assessments, empowering proactive interventions to safeguard worker health and well-being. Compared to traditional ergonomic assessments, ML PEMs offer a more scalable and objective approach by automatically analyzing postures and movements from readily available video recordings of workers performing their tasks [61]. These models can identify awkward postures, sustained exertions, repetitive motions, and other biomechanical risk factors associated with MSDs, such as low back pain or carpal tunnel syndrome [62,88]. A key advantage of ML pose estimation for ergonomics is its potential for real-time or near real-time analysis.

A recent study employed OpenPose for the postural assessment across various common work tasks, i.e., trunk flexion and rotation, sitting, holding and lifting a box, leg crossed and desk tasks [63]. The authors validated the ML model against a marker-based gold standard and integrated the RULA tool for injury risk calculation. The results demonstrated that the proposed ML method showed good performance at all conditions with also a good agreement of RULA action level, suggesting that OpenPose could be a promising technology to measure joint angles for ergonomic postural assessments in the real workspace. Another study successfully employed OpenPose to classify scaffolding activities, further highlighting the versatility of this model [64]. These findings collectively suggest that OpenPose offers a robust and practical solution for ergonomic assessment within dynamic, real-world workspaces.

This approach has the potential to impact workplace safety by identifying common risk patterns, enabling targeted interventions and broader workplace design improvements. ML PEMs simplifies data collection, facilitating longitudinal tracking of worker postures and movements. This rich dataset could train ML models for preventing specific work-related injuries. By monitoring the effectiveness of ergonomic interventions over time, this approach can promote a safer, more productive workforce while potentially reducing healthcare costs. However, it is essential to acknowledge the importance of domain expertise and responsible implementation. Ergonomists and occupational health specialists play a crucial role in interpreting the data generated by PEMs, designing interventions, and ensuring that they truly address the root causes of MSD risk.

4. Discussion

The application of ML PEMs in human movement sciences brings both opportunities and challenges, particularly concerning model reliability and the selection of the most appropriate model for specific needs. Choosing the right model involves balancing accuracy, generalizability, and computational demands, making reliability a key consideration for researchers and practitioners. It is essential to evaluate the performance of these models using standardized datasets and metrics to ensure consistent results across diverse applications. Additionally, understanding the specific requirements of the application domain, such as real-time analysis or precision in detecting fine movements, can help guide the selection of the most suitable model.

4.1. *The question of reliability, how to choose the best model*

Selecting the optimal model means balancing the unique requirements of the application against the trade-offs inherent in each model design. Consider desired accuracy, speed, computational limitations, portability needs, and whether 2D or 3D analysis is essential. A fundamental issue exists between the precision of a model in locating keypoints and its computational speed. Models excelling in accuracy often demand significant processing power, hindering real-time scenarios. Conversely, speed-optimized models may compromise some accuracy [89]. Analyzing complex athletic movements to refine technique may necessitate prioritizing a slower, highly accurate model, while building a responsive mobile fitness app might lean towards a less precise but real-time capable option (Table 3, Fig. 2). As many specific features need to be addressed when discussing the best-performing ML model, a recent article thoroughly discussed the main aspects of many of the renowned models [17]. A complex model might be ideal in theory but is useless if it works poorly on a phone. Conversely, a lighter model could be ineffective if used on a powerful system. Understanding the target environment (mobile, web, or workstation) is essential. This awareness allows tailoring the model choice and investigating optimizations specific to those platforms [17].

Concerning the accuracy, several studies investigated the validity of these ML PEMs by comparing them with the marker-based gold standard, but the results were not promising [90,91], most likely to be related to the absence of correct synchronization between the systems. On the contrary, another study attempted to evaluate the accuracy of OpenPose, AlphaPose and DeepLabCut performing walking, running and counter-movement jumps tasks [92]. The performance of OpenPose and AlphaPose across the tasks was comparable with a systematic difference of $\sim$ 1–5 mm and random errors of $\sim$ 1–3 mm, while larger systematic and random errors were observed for DeepLabCut. However, the authors stated that the difference between the ML PEMs and the gold standard could have occurred due to a mislabeling of ground truth data in the training datasets, concluding that these methods do not yet match the performance of marker-based motion capture at all joint centers [92].

Also, the validity of the MediaPipe joint inference tracking technique has been rigorously investigated. Lafayette et al. [93] conducted a quantitative and statistical assessment of MediaPipe's angular estimation capabilities, comparing it the gold-standard Qualisys motion capture system. The authors demonstrated that MediaPipe offers excellent absolute error relative to clinical error and strong data correlation with Qualisys with mean Pearson's correlation coefficients of 0.80 ± 0.1 for lower limb movements and 0.91 ± 0.08 for upper limb movements. Additionally, its validity is supported by its 100 % accuracy in classifying exercise postures (25) and detecting human movements in non-standard videos with over 90 % accuracy (26). Similarly, BlazePose and MoveNet have been compared with gold standard methods. BlazePose provided in the 70.9 % of trials a mean absolute errors below 30 mm, and for measuring joint angles (elbows, hips, and knees) 43 % were below 5° in the push-up movement [94]. MoveNet obtained a root mean squared error of $3.24 \pm 1.19°$ and mean absolute error of $2.66 \pm 1.00°$ from tenfold cross validation when assessing the knee joint angle during waking tasks [36]. On the contrary, to date, not valid articles are present that clearly stated the accuracy of PoseNet, HRNet and EfficientPose to marker-based gold standard. Although it is not mandatory for developing a ML PEM, for the researchers working within the biomechanics field, being unsure about the real reliability of new approaches can generate little confidence and disinterest in implementing these approaches in current practice.

4.2. *Future perspectives on the application of machine learning in human movement sciences*

The future of ML in the human movement sciences field holds immense potential, particularly for biomechanics, sports, and healthcare. The integration of ML in various contexts is not merely a distant future. The rapid evolution of this sector exposes us to different solutions, whose limits and potential are important to consider so as not to introduce an approach into the sector that is distant from the real needs of those who work in this field every day.

Augmented Reality (AR) represents a field where computer vision and ML could enhance the understanding of human movements. Integrating ML with AR through smart lenses and wearable devices has the potential to revolutionize biomechanics and posture analysis. These AR devices can provide real-time feedback on posture and movement by overlaying digital information directly onto the field of vision of the user. AR can be considered in two ways: as an aiding tool for the coach or therapist, and as a guiding tool for the athlete or patient. For example, coaches could wear smart glasses during training sessions, allowing them to see real-time data on athletes' joint angles, stride length, or posture corrections without needing to stop and review footage, thereby enhancing training in real-time [95]. This approach also shows great promise in the rehabilitation field. In clinical settings, AR combined with ML could support clinicians during patient rehabilitation by providing information on exercises or guiding patients with instant feedback and corrections. The ability to monitor progress and adjust exercises in real-time would personalize treatment plans and potentially speed up recovery times [96].

Sports decision-making represents a field where ML could revolutionize the decisions of sports teams, from player performance and injury prevention to game strategy. For performance analysis, ML can process vast amounts of data from games, training sessions, and

Table 3
Applicability of each model in the human movement sciences field.

Model	Gait Analysis (Fig. 2a)	Posture Analysis (Fig. 2b)	Injury Prevention (Fig. 2c)	Motion Analysis (Fig. 2d)	Remote Fitness Tracking (Fig. 2e)	Ergonomics (Fig. 2f)
OpenPose [18]	High	High	Medium	High	Medium	High
PoseNet [19]	Medium	Medium	Low	Medium	High	Moderate
AlphaPose [20]	Medium	Medium	Medium	High	Low	Moderate
DeepLabCut [21]	Medium	Medium	Medium	Medium	Low	High
HRNet [22]	High	High	Medium	Medium	Low	High
MediaPipe Pose [23]	High	Medium	Medium	Medium	High	Moderate
BlazePose [24]	Medium	Medium	Medium	High	High	Moderate
EfficientPose [25]	Medium	Medium	Medium	Medium	Medium	Moderate
MoveNet [26]	Medium	Medium	Medium	Medium	High	Moderate

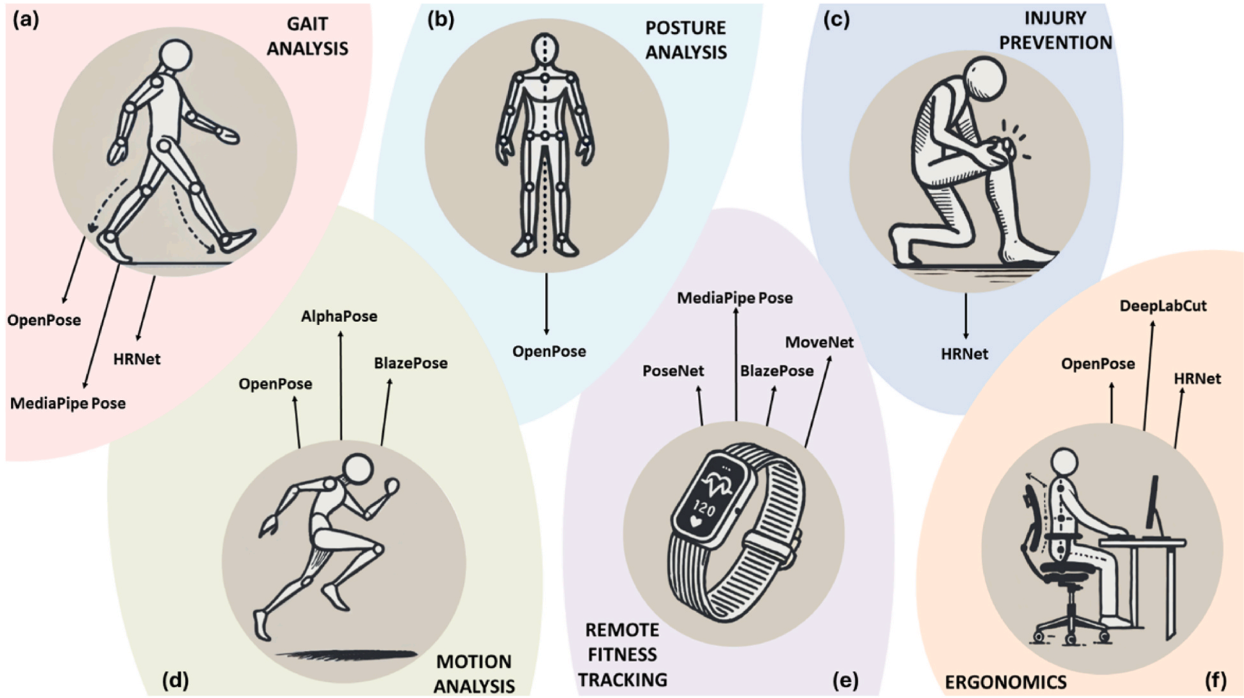

Fig. 2. Main application fields of the considered machine learning pose estimation models in the fields of gait analysis (a), posture analysis (b), injury prevention (c), motion analysis (d), remote fitness tracking (e), ergonomics (f).

wearable sensors. These models can identify patterns and correlations that might not be meaningful to human analysts. For example, ML algorithms can track player movements, assess their efficiency, and provide insights into optimal positioning and movement patterns. By processing real-time data on player performance and opponent strategies, data scientists can suggest optimal tactics and substitutions. For instance, in soccer, an ML model could analyze the formation of the opposing team and suggest counter-strategies that exploit their weaknesses. This real-time decision support can be a game-changer, providing teams with a competitive edge. However, ethical considerations must also be addressed. Beyond the use of private data and obtaining athlete consent, it is important to consider the boundaries of what is allowed to protect human interests. There is a risk of excessive use of these methods, driven by the inherent human desire to find the best advantage. Therefore, governments should establish valid rules and guidelines to ensure that ethics requirements will be met. To date, the European Commission is creating an AI Office to oversee general-purpose models, advised by independent experts, to develop ways to evaluate the capabilities of these models and monitor related risks [97]. With these measures in place, the integration of ML in sports can be both innovative and ethical, ensuring fair competition and the well-being of athletes.

5. Conclusions

The integration of ML PEMs into the analysis of human movement marked a significant advancement in fields such as clinical practice, sports science, and ergonomics. These models provide an accessible, cost-effective, and non-invasive approach to detailed motion analysis, avoiding the limitations of traditional methods that require specialized equipment and controlled environments. This comprehensive review highlighted the capabilities and applications of prominent ML PEMs, showing their potential to revolutionize gait analysis, posture assessment, sports motion analysis, and injury prevention. This approach fosters an objective and automated assessment of human movement, enhancing the accuracy of biomechanical analyses. In clinical settings, they can facilitate the diagnosis and monitoring of musculoskeletal disorders, offering valuable insights for rehabilitation. In sports, these models can provide real-time feedback and detailed performance data, aiding in technique optimization and injury prevention. Finally, in ergonomics, they can identify risky movement patterns, guiding interventions to prevent workplace-related musculoskeletal disorders. However, before their complete integration, ethical considerations, particularly regarding data privacy and their responsible use in sports and healthcare, must be addressed to ensure fair and beneficial applications.

CRediT authorship contribution statement

Federico Roggio: Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Bruno Trovato:** Writing – original draft, Visualization, Investigation, Conceptualization. **Martina Sortino:** Writing – original draft, Visualization, Conceptualization. **Giuseppe Musumeci:** Writing – review & editing, Writing – original draft, Validation, Supervision,

Resources, Project administration, Funding acquisition.

Data and code availability

No data was used for the research described in the article.

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