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COMPUTER VISION TECHNOLOGIES FOR HUMAN POSE ESTIMATION IN EXERCISE: ACCURACY AND PRACTICALITY

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Abstract. *Information technologies are increasingly being integrated into all aspects of human life. Over the past few years, the use of machine learning models for human pose detection has significantly increased. As the realms of technology and physical activity converge, understanding the potential of these innovations becomes imperative for refining exercise monitoring systems. The aim of the research - evaluate the accuracy and viability of employing modern computer vision technologies in the identification of human pose during physical exercises. The study employed a combination of machine learning methods, video analysis, a review of scientific literature, and methods from mathematical statistics. The precision evaluation of contemporary machine learning models was conducted on a prepared dataset, comprising annotated images featuring students executing a body balance test with the camera positioned directly towards the subjects. The obtained data showed that both MediaPipe and OpenPose models proficiently recognize key anatomical landmarks during the conducted test. The MediaPipe model demonstrates a lower percentage of deviation from manual annotation compared to OpenPose for most key points: the mean deviation exceeds the threshold for 11 out of 15 key points and 7 out of 18 key points, as defined by the OpenPose and MediaPipe models, respectively. The most significant deviations are noticeable in the detection of points corresponding to the foot and wrist. The derived conclusions underscore the models can address only a portion of the tasks set. Essentially, this raises scepticism regarding the practical application of contemporary machine learning methods for human pose estimation without additional refinement.*

Keywords: *accuracy, balance test, computer vision, pose estimation, student.*

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Introduction

In an era marked by unprecedented advancements in technology, the intersection of computer vision and human physical activity has emerged as a focal point of research. As we witness a surge in the integration of smart technologies into various aspects of our lives, the synergy between modern computer vision technologies and the evaluation of human pose during exercise stands out as a consequential domain (Andriluka, Pishchulin, Gehler & Schiele, 2014; Beddiar, Nini, Sabokrou & Hadid, 2020). The Covid-19 pandemic, along with the shift of a portion of specialists to remote work formats, has only contributed to the development of this industry (Channa, Popescu, Skibinska & Burget, 2021).

The effective execution of physical exercises and control plays a pivotal role in sport and public health. While understanding and optimizing human movements during physical activity hold a central position in sports training and fitness sessions (Weinberg & Gould, 2019; Latyshev et al., 2021; Dindorf, Bartaguiz, Gassmann & Fröhlich, 2022). Modern computer vision technologies offer avenues for augmenting this comprehension, endowing the capability to dynamically scrutinize and interpret the subtleties inherent in human pose (Chung, Ong & Leow, 2022). A plethora of diverse open-source models is at disposal for addressing general human pose estimation objectives. However, a question arises regarding the accuracy, practicality, and reliability of contemporary machine learning models when employed without prior preparation.

The aim of the research – evaluate the accuracy and practicality of employing modern models of computer vision in the identification of human pose during physical exercises.

The study employed a combination of machine learning methods, video analysis, a review of scientific literature, and methods from mathematical statistics.

Literature review

Remarkable advancements have transpired in the field of information technology, concurrently permeating the domains of sports, physical exercises, and health (Cook, Burton, Hoogenboom & Voight, 2014; Carlson et al., 2020; Badiola-Bengoa & Mendez-Zorrilla, 2021). The progression of artificial intelligence, encompassing deep learning and computer vision, has forged pathways towards innovative applications. Utilizing advanced image processing methods, Computer Vision enables the extraction of valuable information from visual data, offering new possibilities to enhance performance, monitor health, and optimize training programs (Thomas, Gade, Moeslund, Carr & Hilton, 2017;

Zhu, 2021; Khanal et al., 2022). Working with statistical data in sports also remains an important aspect (Sainani et al., 2020; Latyshev et al., 2020).

Presently, Computer Vision technologies find applications across diverse spectra, encompassing the tracking of movements, both collective and individual, in team sports (Cioppa et al., 2020); the contemporaneous monitoring of athletes' performance (Citraro et al., 2020); body position tracking to prevent injury (Blythman et al., 2022); and the analysis of motion patterns during rehabilitative physical exercises as well as fitness activities (Rahmadani, Dewantara & Sari, 2022). Particular attention is merited for the domain encompassing the the human pose estimation during physical exercises (Andriluka, Pishchulin, Gehler & Schiele, 2014).

With the integration of machine learning, the field of posture assessment has undergone significant transformation. Over the past years, this domain has experienced rapid development, and currently, there exist a considerable number of different models for human pose estimation (Chung, Ong & Leow, 2022). Despite the remarkable accuracy attained by contemporary methodologies, immediate practical applicability remains encumbered (Pardos, Tziomaka, Menychtas & Maglogiannis, 2022).

The majority of research is aimed at monitoring and correcting specific movements using human pose estimation. Additionally, there are studies focused on overseeing the execution of comprehensive exercises (Wang, Qiu, Peng, Fu & Zhu, 2019). It is pertinent to highlight the existence of alternative methodologies within information technologies for the assessment of human pose during exercises (Hutagalung, Akhmad & Irfan, 2023). The ability to maintain body balance plays a crucial role both in everyday life and in athletes' fitness levels (Bohannon et al., 1984; Bogle Thorbahn, Newton, 1996; Kaupuzs, Larins & Rizakova, 2016). The automation of balance control is a relevant task at present.

Methodology

The participants. Fourteen students, aged between 18 and 20, enrolled in the Faculty of Health, Physical Education, and Sports, were recruited for this research. Voluntary informed consent was obtained from all participants prior to their inclusion in the study. The experimental procedures adhered rigorously to universally acknowledged ethical norms and guidelines. The permission for conducting research with students is indicated in protocol 9 from the department meeting held on the 31st of August, 2023. All participants exhibited prior engagement in sporting activities. The designated task for the participants encompassed the execution of the Standing Stork Test, occasionally referenced as the Balance Stork Test (Kranti Panta, 2015; Lengkana et al., 2020; Hutagalung, Akhmad & Irfan, 2023). Detailed instructions and a video presentation were provided in advance, allowing participants to practice beforehand. Each participant was afforded a single attempt to achieve their maximal individual performance.

The procedural algorithm involved participants autonomously selecting a lower extremity (either right or left) for the test and assuming a biomechanically advantageous standing position. With hands placed on their hips, participants fixed the foot of one leg around the knee of the other, subsequently elevating onto the toes of the supporting leg, thereby disengaging the heel from the supporting surface. The primary objective was to sustain equilibrium in this position for maximal temporal duration. The temporal parameter, indicative of the duration until a balance perturbation occurred, was meticulously measured.

The video analysis. The execution of the exercise was recorded using Pixel 7 smartphones, leveraging the rear camera of the devices (50 MP Octa PD Quad Bayer wide camera). The camera of smartphone was chosen to approximate the video quality to a publicly accessible standard. The smartphone was securely affixed to tripods positioned anteriorly to the participants. During video registration, the smartphone camera was positioned at a height of approximately 1.5 meters above the sports hall surface. The distance from the camera to the student was around 5 meters.

All video segments were converted into images with a frame rate of 25 frames per second (fps). The resultant dataset comprised a total of 7036 images. For the specific purpose of annotating key body points and subsequent model accuracy evaluation, a random subset of 40 images was sampled from each video (560 images total).

The machine learnings methods (Computer Vision). In the domain of image processing, precision computation, and statistical analysis, the Python programming language served as the computational framework. The identification of anatomical landmarks was carried out through three methods: manual annotation and two machine learning approaches. It is pertinent to clarify that the pose estimation within an image is conducted in an ostensibly static state (captured at a discrete moment in time). Although it is understood that the student is performing a physical exercise and this is a dynamic action.

The dataset was meticulously annotated using the Computer Vision Annotation Tool (CVAT). This manual annotation process ensured precise labeling of key body joints and parts, forming the ground truth for model evaluation. The sequence of execution was as follows: initial point annotations were executed by one expert, with a subsequent verification process conducted by a second expert. Disputes or ambiguities were adjudicated through the informed judgment of a third expert.

The utilization of machine learning models, specifically MediaPipe and OpenPose, was undertaken to automate the inference of pose estimation. It is worth noting that, today, a sufficient number of models for Pose Estimation exist. These particular models were chosen due to their availability.

MediaPipe, a popular machine learning library, provides a robust solution for pose estimation (Kim, Choi, Ha & Choi, 2023; Mahmood, 2023). Its key strengths lie in its real-time performance and versatility. OpenPose is another widely used pose estimation model known for its accuracy and ability to handle complex body poses. OpenPose's open-source nature allows for flexibility and customization (Cao, Simon, Wei & Sheikh, 2017; Li, Chang, Cheng & Huang, 2021).

For each selected image earmarked for analysis, specific body key points were identified: 20 points were manually annotated, 33 points were determined utilizing the MediaPipe model, and 19 points were discerned using the OpenPose model. Notably, 14 key points exhibited congruence across all three methodologies (Left Eye, Right Eye, Left Shoulder, Right Shoulder, Left Elbow, Right Elbow, Left Wrist, Right Wrist, Left Hip, Right Hip, Left Knee, Right Knee, Left Ankle, Right Ankle). Anatomical points that were manually marked were placed in the area of the joint, at points where rotation (turn) of the anatomical part of the body occurs (Robertson, Caldwell, Hamill, Kamen & Whittlesey, 2013). Identifying the precise axis of rotation presents a formidable challenge, compounded by multifarious factors such as clothing, camera perspective, among others. However, to enhance the precision of this marking, the process was carried out by three experts.

The mathematic and statistic methods. Model accuracy was determined by assessing the deviation between points generated by the model and manually set points. The differences were quantified as the Euclidean distance in a two-dimensional space between the coordinate sets of the respective points. Following this, both the mean and standard deviation were computed for all values associated with each key point. For enhanced perceptibility of the data, all differences were proportionally converted into a percentage of the participant's height (the difference was divided by the participant's height on the manually annotated image; height was measured as the distance from the apex of the head to the heel on the manually annotated image).

Research results

The illustration portrays a frame capturing the execution of the Stork Standing Test by a student. The student adheres to the initial posture, with hands placed on the hips, and one foot securely positioned atop the other near the knee. Three frames of the student in the same position are presented in the illustration (from left to right): the first frame is annotated with manually marked anatomical points; the second frame includes points determined using the MediaPipe model; the third frame incorporates points obtained through the OpenPose model (Fig. 1).

Figure 1 ***A Visual Evaluation of Pose Estimation Models in Stork Standing Test: Annotated Manually, MediaPipe Model and OpenPose Model***

A comparative analysis of anatomical landmarks, manual annotation, and the outcomes of MediaPipe and OpenPose models furnishes information regarding the accuracy and consistency in assessing the student's posture during the execution of the exercise. The identification of key points through diverse methods highlights the nuanced advantages and limitations intrinsic to each approach, thereby enriching the discourse on the reliability and applicability of these computational models within this specific domain. A visual comparative analysis reveals a more precise outcome from the MediaPipe model compared to the OpenPose model.

The next step, was the analysis involved scrutinizing the performance of the MediaPipe algorithm with a dynamic subject (Fig. 2). A specific two-second interval, encapsulating the initiation of the test marked by a rise onto the toes, underwent examination. Key points from subsequent frames were overlaid onto the initial frame to illustrate the movement of all key points (excluding those associated with the head).

Key points annotated within a two-second temporal window from the commencement of the test exhibit a discernible trajectory. Evidently, a predominant upward displacement of key points is discernible, signifying the elevation of the entire body, notably accentuated at the shoulder, hip, elbow, wrist, and knee positions. Post-elevation, a directional shift towards the upper thoracic region is observable, indicative of an adaptive mechanism aimed at preserving bodily coordination. Conversely, the key points corresponding to the ankle, heel, and proximal phalanx of the hallux lack a clearly defined trajectory, aggregating into a diffuse cluster. Within this cluster, the detection of a discernible movement trajectory becomes inherently intricate.

Figure 2 ***Dynamics of Stork Pose Initiation: Annotated Key Points Analysis***

Table 1 ***Analyzing Differences: Model-Predicted and Manually Annotated Key Points***

Key points of body	The percentage difference of model-predicted key points from manually annotated key points, X±SD	
	MediaPipe, %	OpenPose, %
Left Eye	1.68 ± 1.13	3.02 ± .48
Right Eye	1.67 ± 1.03	2.64 ± .69
Left Shoulder	1.61 ± .94	4.64 ± 1.21
Right Shoulder	2.12 ± 1.13	3.13 ± 1.84
Left Elbow	3.35 ± 1.57	8.12 ± 4.08
Right Elbow	2.10 ± 1.27	5.07 ± 3.17
Left Wrist	5.62 ± 3.69	8.60 ± 3.63
Right Wrist	4.12 ± 2.97	7.85 ± 2.56
Left Hip	2.54 ± .98	3.91 ± 1.84
Right Hip	2.99 ± 1.29	5.85 ± 2.56
Left Knee	2.68 ± 1.90	4.90 ± 1.28
Right Knee	1.95 ± 1.06	2.76 ± 1.72
Left Ankle	4.92 ± 2.98	9.60 ± 4.08
Right Ankle	2.53 ± 1.46	3.97 ± 1.60

For the assessment of accuracy and subsequent analytical endeavors pertaining to the models, the displacement between model-predicted points and manually annotated points was quantified. The resulting data is expressed as a percentage relative to the stature of the participant (Table 1).

The table presents data for information pertaining to key anatomical landmarks concurrently identifiable in both models. However, an additional analysis was conducted with certain key points that align exclusively with a specific model. The MediaPipe model: Left Heel (6.05 ± 3.92 %), Right Heel (3.02 ± 1.81 %), Left Foot Index (6.96 ± 3.87 %), Right Foot Index (4.36 ± 2.93 %). The OpenPose model: Neck (5.08 ± 1.76 %).

Conclusions and Discussion

Presently, the pervasive integration of information technologies encompasses a broad spectrum of human endeavors. Moreover, their application is expanding in the domains of sports, physical exercises, and health, posing specific challenges to the professionals in these fields. The continuous advancement of artificial intelligence and machine learning further contributes to the transformation of approaches within these industries (Thomas, Gade, Moeslund, Carr & Hilton, 2017; Zhu, 2021).

In this study, we sought to assess the practical feasibility of utilizing open-access machine learning models for monitoring the execution of physical exercises. Some scholars contend that direct utilization of models is challenging, necessitating additional refinement (Carlson et al., 2020; Pardos, Tziomaka, Menychtas & Maglogiannis, 2022; Khanal et al., 2022). Our findings align with these perspectives, indicating the models' capacity to address only a subset of the stipulated tasks. The margin of error extends up to 10.0% of human height for certain points, a considerable deviation. In prior research (Rafi, Leibe, Gall & Kostrikov, 2016), a 3.13% (8/256) deviation is conventionally accepted as the threshold for acceptable accuracy.

Upon data, it becomes apparent that both MediaPipe and OpenPose models proficiently discern key anatomical landmarks during the administered test. However, disparities in accuracy exist, and it is crucial to consider them when interpreting the results. The MediaPipe model demonstrates a lower percentage deviation from manual annotation compared to OpenPose for the majority of key points. The advantages of the MediaPipe model are further substantiated in other studies (Chung, Ong & Leow, 2022; Kale, Kulkarni, Kumbhkarn, Khuspe & Kharde, 2023). The computed mean deviation surpasses the defined threshold for more than 70% of points (eleven key points) ascertained by the OpenPose model and over 30% of points (seven key points) by the MediaPipe model. Foremost deviations are discernible in the detection of points corresponding to the foot (ankle, heel, foot index) and wrist. Concurrently, the range of errors associated with key anatomical landmarks, such as eyes, shoulders, hips, and knees (1 to 3%, MediaPipe), is smaller compared to other key points.

Examination of data pertaining to right and left sides of the human body reveals some differences in the accuracy of model predictions. Our interpretation posits that this phenomenon is contingent upon the predominant selection of the right leg as the supporting limb by the majority of participants, an aspect unrelated to peculiarities in model functionality.

The Stork Test exercise consists of several phases. The initiation of an exercise execution is identifiable through specific anatomical landmarks. However, precise tracking of the participant's pose during execution and completion (balance loss) of the exercise proves to be a challenging task. Some key points in identification exhibit relatively high imprecision, forming a distinct point cloud (Fig. 2) that requires additional scrutiny (Hellsten, Karlsson, Shamsuzzaman & Pulkkis, 2021).

A salient consideration lies in acknowledging the imperative nature of interdisciplinary collaboration. In general, Pose Estimation models play a crucial role in automatically determining the body's spatial position. However, the accuracy and reliability of these models can be significantly enhanced through collaborative efforts of specialists. Their expertise and experience are essential for a deeper understanding of movements and postures, which can contribute to optimizing the performance of Pose Estimation models in various contexts, including sports and physical exercises. The collaborative efforts of professionals from computer science, data sciences, biomechanics, sport, physical exercises and health are pivotal in shaping accurate, efficient, and practical solutions for the benefit of individuals engaging in physical activities.

Prospective ways of our research converge toward the conceptualization and realization of an application for monitoring human body balance using a machine learning model, enabling individuals to autonomously track their progress. This will enable the practical use of this method, as well as assess the accuracy of this method and compare it with other similar methods.

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