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Machine and deep learning for sport-specific movement recognition: a systematic review of model development and performance

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ABSTRACT

Objective assessment of an athlete's performance is of importance in elite sports to facilitate detailed analysis. The implementation of automated detection and recognition of sport-specific movements overcomes the limitations associated with manual performance analysis methods. The object of this study was to systematically review the literature on machine and deep learning for sport-specific movement recognition using inertial measurement unit (IMU) and, or computer vision data inputs. A search of multiple databases was undertaken. Included studies must have investigated a sport-specific movement and analysed via machine or deep learning methods for model development. A total of 52 studies met the inclusion and exclusion criteria. Data pre-processing, processing, model development and evaluation methods varied across the studies. Model development for movement recognition were predominantly undertaken using supervised classification approaches. A kernel form of the Support Vector Machine algorithm was used in 53% of IMU and 50% of vision-based studies. Twelve studies used a deep learning method as a form of Convolutional Neural Network algorithm and one study also adopted a Long Short Term Memory architecture in their model. The adaptation of experimental set-up, data pre-processing, and model development methods are best considered in relation to the characteristics of the targeted sports movement(s).

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KEYWORDS
Sport movement classification; inertial sensors; computer vision; machine learning; performance analysis

1. Introduction

Performance analysis in sport science has experienced considerable recent changes, due largely to access to improved technology and increased applications from computer science. Manual notational analysis or coding in sports, even when performed by trained analysts, has limitations. Such methods are typically time intensive, subjective in nature, and prone to human error and bias. Automating sport movement recognition and its application towards coding has the potential to enhance both the efficiency and accuracy of sport performance analysis. The potential automation of recognising human movements, commonly referred to as human activity recognition (HAR), can be achieved through machine or deep learning model approaches. Common data inputs are obtained from inertial measurement units (IMUs) or vision. Detection refers to the identification of a targeted instance, i.e., tennis strokes within a continuous data input signal (Bulling, Blanke, & Schiele, 2014). Recognition or classification of movements involves further interpretations and labelled predictions of the identified instance (Bulling et al., 2014; Bux, Angelov, & Habib, 2017), i.e., differentiating tennis strokes as a forehand or backhand. In machine and deep learning, a model represents the statistical operations involved in the development of an automated prediction task (LeCun, Yoshua, & Geoffrey, 2015; Shalev-Shwartz & Ben-David, 2014).

Human activities detected by inertial sensing devices and computer vision are represented as wave signal features corresponding to specific actions, which can be logged and extracted. Human movement activities are considered hierarchically structured and can be broken down to basic movements. Therefore, the context of signal use, intra-class variability, and inter-class similarity between activities require consideration during experimental set-up and model development. Wearable IMUs contain a combination of accelerometer, gyroscope, and magnetometer sensors measuring along one to three axes. These sensors quantify acceleration, angular velocity, and the direction and orientation of travel respectively (Gastin, McLean, Breed, & Spittle, 2014). These sensors can capture repeated movement patterns during sport training and competitions (Camomilla, Bergamini, Fantozzi, & Vannozzi, 2018; Chambers, Gabbett, Cole, & Beard, 2015; J. F. Wagner, 2018). Advantages include being wireless, lightweight and self-contained in operation. Inertial measurement units have been utilised in quantifying physical output and tackling impacts in Australian Rules football (Gastin et al., 2014; Gastin, McLean, Spittle, & Breed, 2013) and rugby (Gabbett, Jenkins, & Abernethy, 2012, 2011; Howe, Aughey, Hopkins, Stewart, & Cavanagh, 2017; Hulin, Gabbett, Johnston, & Jenkins, 2017). Other applications include swimming analysis (Mooney, Corley, Godfrey, Quinlan, & Ólaighin, 2015), golf swing kinematics (Lai, Hetchl, Wei, Ball, & McLaughlin, 2011), over-ground running speeds (Wixted, Billing, & James, 2010), full motions in alpine skiing (Yu et al., 2016); and the detection and evaluation of cricket bowling (McNamara, Gabbett, Blanch, & Kelly, 2017; McNamara, Gabbett, Chapman, Naughton, & Farhart, 2015; Wixted, Portus, Spratford, & James, 2011).

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Computer vision has applications for performance analysis including player tracking, semantic analysis, and movement analysis (Stein et al., 2018; Thomas, Gade, Moeslund, Carr, & Hilton, 2017). Automated movement recognition approaches require several pre-processing steps including athlete detection and tracking, temporal cropping and targeted action recognition, which are dependent upon the sport and footage type (Barris & Button, 2008; Saba & Altameem, 2013; Thomas et al., 2017). Several challenges including occlusion, viewpoint variations, and environmental conditions may impact results, depending on the camera set-up (Poppe, 2010; Zhang et al., 2017). Developing models to automate sports-vision coding may improve resource efficiency and reduce feedback times. For example, coaches and athletes involved in time-intensive notational tasks, including post-swim race analysis, may benefit from rapid objective feedback before the next race in the event program (Liao, Liao, & Liu, 2003; Victor, He, Morgan, & Miniutti, 2017). For detecting and recognising movements, body worn sensor signals do not suffer from the same environmental constraints and stationary set-up of video cameras. Furthermore, multiple sensors located on different body segments have been argued to provide more specific signal representations of targeted movements (J. B. Yang, Nguyen, San, Li, & Shonali, 2015). But it is not clear if this is solely conclusive, and the use of body worn sensors in some sport competitions may be impractical or not possible.

Machine learning algorithms learn from data input for automated model building and perform tasks without being explicitly programmed. The algorithm goal is to output a response function $h\sigma(\bar{x})$ that will predict a ground truth variable y from an input vector of variables $\bar{x}$. Models are run for classification techniques to predict a target class (Kotsiantis, Zaharakis, & Pintelas, 2007), or regression to predict discrete or continuous values. Models are aimed at finding an optimal set of parameters σ to describe the response function, and then make predictions on unseen unlabelled data input. Within these, model training approaches can generally run as supervised learning, unsupervised learning or semi-supervised learning (Mohammed, Khan, & Bashier, 2016; Sze, Chen, Yang, & Emer, 2017).

Processing raw data is limited for conventional machine learning algorithms, as they are unable to effectively be trained on abstract and high-dimensional data that is inconsistent, contains missing values or noisy artefacts (Bux et al., 2017; Kautz, 2017). Consequently, several pre-processing stages are required to create a suitable data form for input into the classifier algorithm (Figo, Diniz, Ferreira, & Cardoso, 2010). Filtering (Figo et al., 2010; Wundersitz, Gastin, Robertson, Davey, & Netto, 2015), window capture durations (Mitchell, Monaghan, & O'Connor, 2013; Preece, Goulermas, Kenney, & Howard, 2009; Wundersitz et al., 2015), and signal frequency cut-offs (Wundersitz, Gastin, Richter, Robertson, & Netto, 2015; Wundersitz et al., 2015) are common techniques applied prior to data prior to dynamic human movement recognition. Well-established filters for processing motion signal data include the Kalman filter (Kautz, 2017; Titterton & Weston, 2009; D. Wagner, Kalischewski, Velten, & Kummert, 2017) and a Fourier transform filter (Preece et al., 2009) such as a fast Fourier transform (Kapela, Świetlicka, Rybarczyk, Kolanowski, & O'Connor, 2015; Preece et al., 2009). Near real-time processing benefits from reducing memory requirements, computational demands, and essential bandwidth during whole model implementation. Signal feature extraction and selection favours faster processing by reducing the signals to the critical features that can discriminate the targeted activities (Bulling et al., 2014). Feature extraction involves identifying the key features that help maximise classifier success, and removing features that have minimal impact in the model (Mannini & Sabatini, 2010). Thus, feature selection involves constructing data representations in subspaces with reduced dimensions. These identified variables are represented in a compact feature variable (Mannini & Sabatini, 2010). Common methods include principal component analysis (PCA) (Gløersen, Myklebust, Hallén, & Federolf, 2018; Young & Reinkensmeyer, 2014), vector coding techniques (Hafer & Boyer, 2017) and empirical cumulative distribution functions (ECDF) (Plötz, Hammerla, & Olivier, 2011). An ECDF approach has been shown to be advantageous over PCA as it derives representations of raw input independent of the absolute data ranges, whereas PCA is known to have reduced performance when the input data is not properly normalised (Plötz et al., 2011). For further detailed information on the acquisition, filtering and analysis of IMU data for sports application and vision-based human activity recognition, see (Kautz, 2017) and (Bux et al., 2017), respectively.

Deep learning is a division of machine learning, characterised by deeper neural network model architectures and are inspired by the biological neural networks of the human brain (Bengio, 2013; LeCun et al., 2015; Sze et al., 2017). The deeper hierarchical models create a profound architecture of multiple hidden layers based on representative learning with several processing and abstraction layers (Bux et al., 2017; J. B. Yang et al., 2015). These computational models allow data input features to be automatically extracted from raw data and transformed to handle unstructured data, including vision (LeCun et al., 2015; Ravi, Wong, Lo, & Yang, 2016). This direct input avoids several processing steps required in machine learning during training and testing, therefore reducing overall computational times. A current key element within deep learning is backpropagation (Hecht-Nielsen, 1989; LeCun, Bottou, Orr, & Müller, 1998). Backpropagation is a fast and computationally efficient algorithm, using gradient descent, that allows training deep neural networks to be tractable (Sze et al., 2017). Human activity recognition has mainly been performed using conventional machine learning classifiers. Recently, deep learning techniques have enhanced the bench mark and applications for IMUs (Kautz et al., 2017; Ravi et al., 2016; Ronao & Cho, 2016; J. B. Yang et al., 2015; Zebin, Scully, & Ozanyan, 2016; Zeng et al., 2014) and vision (Ji, Yang, Yu, & Xu, 2013; Karpathy et al., 2014a; Krizhevsky, Sutskever, & Hinton, 2012; Nibali, He, Morgan, & Greenwood, 2017) in human movement recognition producing more superior model performance accuracy.

The objective of this study was to systematically review the literature investigating sport-specific automated movement detection and recognition. The review focusses on the various technologies, analysis techniques and performance outcome measures utilised. There are several reviews within this field

that are sensor-based including wearable IMUs for lower limb biomechanics and exercises (Fong & Chan, 2010; M. O'Reilly, Caulfield, Ward, Johnston, & Doherty, 2018), swimming analysis (Magalhaes, Vannozzi, Gatta, & Fantozzi, 2015; Mooney et al., 2015), quantifying sporting movements (Chambers et al., 2015) and physical activity monitoring (C. C. Yang & Hsu, 2010). A recent systematic review has provided an evaluation on the in-field use of inertial-based sensors for various performance evaluation applications (Camomilla et al., 2018). Vision-based methods for human activity recognition (Aggarwal & Xia, 2014; Bux et al., 2017; Ke et al., 2013; Zhang et al., 2017), semantic human activity recognition (Ziaeefard & Bergevin, 2015) and motion analysis in sport (Barris & Button, 2008) have also been reviewed. However, to date, there is no systematic review across sport-specific movement detection and recognition via machine or deep learning. Specifically, incorporating IMUs and vision-based data input, focussing on in-field applications as opposed to laboratory-based protocols and detailing the analysis and machine learning methods used.

Considering the growth in research and potential field applications, such a review is required to understand the research area. This review aims to characterise the evolving techniques and inform researchers of possible improvements in sports analysis applications. Specifically: 1) What is the current scope for IMUs and computer vision in sport movement detection and recognition? 2) Which methodologies, inclusive of signal processing and model learning techniques, have been used to achieve sport movement recognition? 3) Which evaluation methods have been used in assessing the performance of these developed models?

2. Methods

2.1 Search strategy

The preferred PRISMA recommendations (Moher, Liberati, Tetzlaff, Altman, & Group, 2009) for systematic reviews were used. A literature search was undertaken by the first author on the following databases; IEEE Xplore, PubMed, ScienceDirect, Scopus, Academic Search Premier, and Computer and Applied Science Complete. The searched terms were categorised in order to define the specific participants, methodology and evaluated outcome measure in-line with the review aims. Searches used a combination of key words with AND/OR phrases which are detailed in Table 1. Searches were filtered for studies from January 2000 to May 2018 as no relevant studies were identified prior to this. Further studies were manually identified from the bibliographies of database-searched studies identified from the abstract screen phase, known as snowballing. Table 2 provides the inclusion and exclusion criteria of this review.

Table 1. Key word search term strings per database.

Database key word searches
IEEE Xplore: ((((inertial sensor OR accelerometer OR gyroscope OR IMU OR microsensor)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill) ((((sport OR athlete* OR player*)) AND (video OR vision)) AND movement classification)
PubMed: ((((inertial sensor OR accelerometer OR gyroscope OR IMU OR microsensor)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill) (((((((Vision OR video OR camera OR footage OR computer vision)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill))) AND human) NOT clinical)) NOT review
ScienceDirect: ((sport OR athlete* OR player*)) and ((inertial sensor OR accelerometer) ((sport OR athlete* OR player*)) and TITLE-ABSTR-KEY((vision OR video OR camera) AND (detection OR classification)).
Scopus: ((((inertial sensor OR accelerometer OR gyroscope OR IMU OR microsensor)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill) ((((sport OR athlete* OR player*)) AND (video OR vision)) AND movement classification)
Academic Search Premier: ((((inertial sensor OR accelerometer OR gyroscope OR IMU OR microsensor)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill) ((((sport OR athlete* OR player*)) AND (video OR vision)) AND movement classification)
Computer and Applied Science Complete: ((((inertial sensor OR accelerometer OR gyroscope OR IMU OR microsensor)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill) ((((Vision OR video OR camera OR footage OR computer vision)) AND (sport OR athlete* OR match OR game OR training)) AND (detection OR recognition OR classification)) AND (movement OR skill)

* Entails truncation, i.e., finding all terms that begin with the string of text written before it.

Table 2. Study inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
• Original peer reviewed published manuscripts • Aimed at a sport-specific movement or skill, • Used IMUs and/or computer vision input datasets for model development • Investigated as an in-field application of the technology to the sporting movement • Defined clear data processing and model development methods inclusive of machine or deep learning algorithms for semi-automated or automated movement recognition • Published as full-length studies written in English	• Solely investigated gait analysis for clinical purposes • Solely investigated every day or non-sport-specific locomotion i.e., walking downstairs • Solely investigated player field positional tracking methods using data such as X, Y coordinates or displacement without any form of sport-specific skill detection and classification associated to it • Used ball trajectory and audio cue data as the major determinant for event detection • Data collection conducted within a laboratory setting under controlled protocol • Data processing pipelines or recognition model development methodology not clearly defined • Review studies

2.2 Data extraction

The first author extracted and collated the relevant information from the full manuscripts identified for final review. A total of 18 parameters were extracted from the 52 research studies, including the title, author, year of publication, sport, participant details, sport movement target(s), device specifications, device sample frequency, pre-processing methods, processing methods, feature selected, feature extraction, machine learning model used, model evaluation, model performance accuracy, validation method, samples collected, and

computational information. A customised Microsoft Excel™ spreadsheet was developed to categorise the relevant extracted information from each study. Participant characteristics of number of participants, gender, and competition level, then if applicable a further descriptor specific to a sport, for example, "medium-paced cricket bowler". Athlete and participant experience level was categorised as written in the corresponding study to avoid misrepresentations. The age of participants was not considered an important characteristic required for model development. The individual ability in which the movement is performed accounts for the discriminative signal features associated with the movements. For the purposes of this review, a sport-specific movement was defined from a team or individual sport, and training activities associated with a particular sport. For example, weight-lifting as strength training, recognised under the Global Association of International Sports Federations. The targeted sports and specific movements were defined for either detection or recognition. Model development techniques used included pre-processing methods to transform data to a more suitable form for analysis, processing stages to segment data for identified target activities, feature extraction and selections techniques, and the learning algorithm(s). Model evaluation measures extracted were the model performance assessment techniques used, ground-truth validation comparison, number of data samples collected, and the model performance outcomes results reported. If studies ran multiple experiments using several algorithms, only the superior algorithm and relevant results were reported as the best method. This was done so in the interest of concise reporting to highlight favourable method approaches (Sprager & Juric, 2015). Any further relevant results or information identified from the studies was included as a special remark (Sprager & Juric, 2015). Hardware and specification information extracted included the IMU or video equipment used, number of units, attachment of sensors (IMUs), sample frequency, and sensor data types used in analysis (IMUs). Studies identified and full data extracted were reviewed by a second author.

3. Results

An outline of the search results and study exclusions has been provided in Figure 1. Of the initial database search which identified 4885 results, a final 52 studies met criteria for inclusion in this review. Of these, 29 used IMUs and 22 were vision-based. One study (Ó Conaire et al., 2010) used both sensors and vision for model development separately then together via data fusion. Table 3 – 8 provide a description of the characteristics of the reviewed studies, detailed in the following sections.

3.1 Experimental design

A variety of sports and their associated sport-specific movements were investigated, implementing various experimental designs as presented in Tables 5 and 7. Across the studies, sports reported were tennis (n = 10), cricket (n = 3), weightlifting or strength training (n = 6), swimming (n = 4), skateboarding (n = 2), ski jumping (n = 2), snowboarding (n = 1), golf

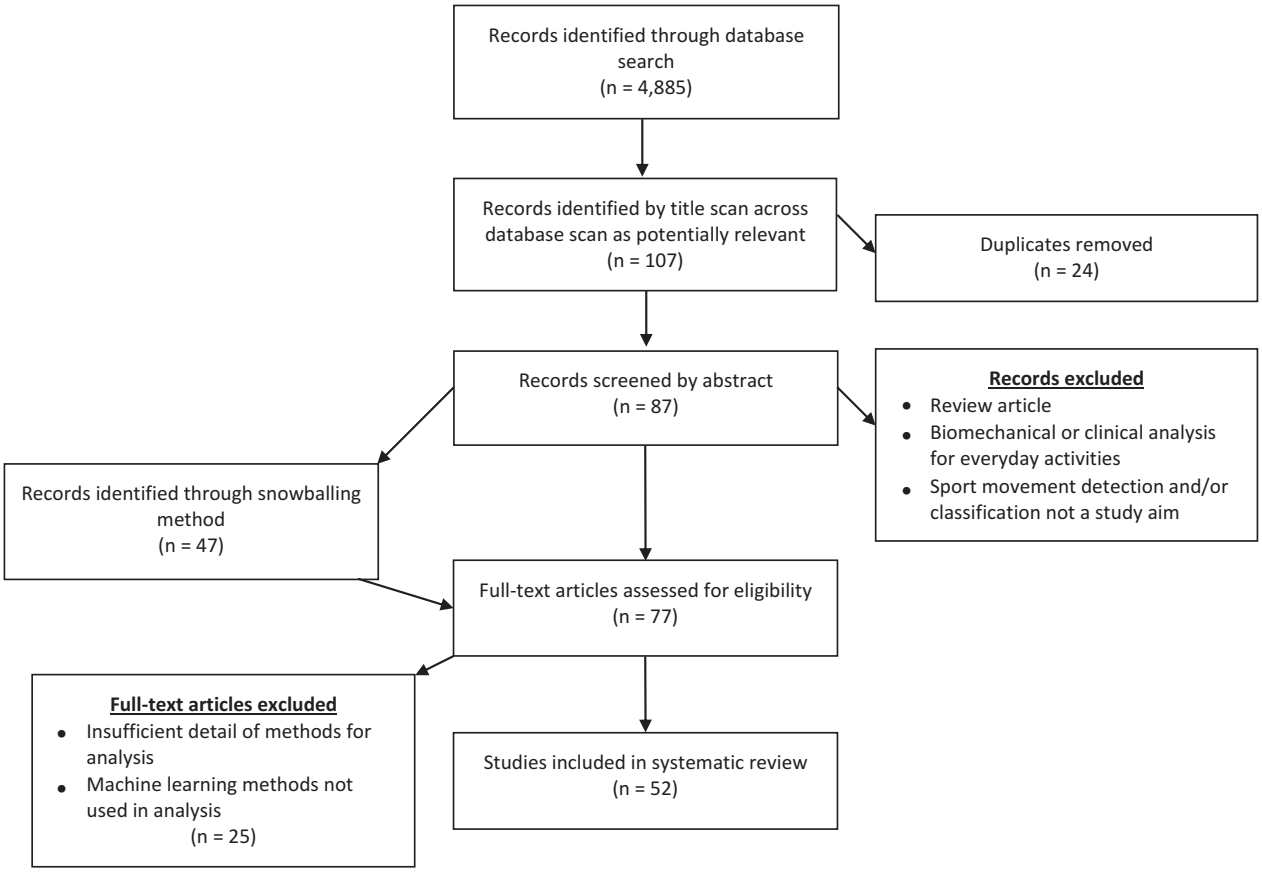

Figure 1. PRISMA flow diagram for study search, screen and selection process.

Table 3. Inertial measurement unit specifications.

				Accelerometer			Gyroscope			Magnetometer		
Reference	Sensor model	Sensor No.	Sensor placement	Axes	Range	Sample rate	Axes	Range	Sample rate	Axes	Range (1 Ga = 100 μT)	Sample rate
(Adelsberger & Tröster, 2013)	Ethos	3	Left ankle, wrist, lower back	3	± 6 g	NR	3	± 2000 °/s	NR	3	4 Ga	NR
(Anand et al., 2017)	Samsun Gear 2 smart watch	1	Wrist of hitting hand	3	± 8 g	100 Hz	3	± 2000 °/s	100 Hz			
(Brock & Ohgi, 2017)	Logical Product SS-WS1215/SS-WS1216, Fukuoka, Japan	9	Pelvis, right and left thighs, right and left shanks, right and left upper arms, both ski blades above the boot	3	± 5 g (body) ± 16 g (ski)	500 Hz	3	± 1500 °/s	500 Hz	3	± 1.2 Gauss full-scale	500 Hz
(Brock et al., 2017)	Logical Product SS-WS1215/SS-WS1216, Fukuoka, Japan	9	Pelvis, right and left thighs, right and left shanks, right and left ski anterior to ski binding, right and left upper arm	3	± 5 g (body) ± 16 g (ski)	500 Hz	3	± 1500 °/s	500 Hz	3	± 1.2 Gauss full-scale	500 Hz
(Buckley et al., 2017)	Shimmer3 (Realtime Technologies Ltb. Dublin, Ireland)	3	Right and left shanks 2cm above lateral malleolus, 5th lumbar spinous process	3	± 8 g	256 Hz	3	± 1000 °/s	256 Hz	3	± 4 Gauss full-scale	256 Hz
(Buthe et al., 2016)	EXLs33 IMU	3	Tennis racquet, on each shoe	3	± 16 g	200 Hz	3	± 500 °/s	200 Hz	3	NR	200 Hz
(Connaghan et al., 2011)	Custom Tyndall developed TennisSense WIMU system	1	Forearm of racquet arm	3	NR	NR	3	NR	NR	3	NR	NR
(Groh et al., 2015)	miPod sensor system	1	Underside of skateboard on the right side of front axis.	3	± 16g	200 Hz	3	± 2000 °/s	200 Hz	3	± 1200 μT	200 Hz
(Groh et al., 2016)	miPod sensor system	1	Top of snowboard behind the front binding	3	± 16 g	200 Hz	3	± 2000 °/s	200 Hz	3	± 1200 μT	200 Hz
(Groh et al., 2017)	miPod sensor system	1	Underside of skateboard on the right side of front axis.	3	± 16 g	200 Hz	3	± 2000 °/s	200 Hz	3	± 1200 μT	200 Hz
(Jiao et al., 2018)	NR	2	Golf club (location not specified)	3	NR	NR	3	NR	NR			
(Jensen et al., 2015)	Shimmer™ 2R sensor nodes (Realtime	1	Golf club head	3	± 1.5 g	256 Hz	3	± 500 °/s	256 Hz	NR	NR	NR
(Jensen et al., 2016)	Shimmer™ 2R sensor nodes (Realtime Technologies Ltb. Dublin, Ireland)	1	Back of head under a swim cap	3	± 1.5 g	10.24 Hz to 204.8 Hz	3	± 500 °/s	10.24 Hz to 204.8 Hz	NR	NR	NR
(Jensen et al., 2013)	Shimmer™ (Realtime Technologies Ltb. Dublin, Ireland)	1	Back of head above swim cap	3	± 1.5 g	200 Hz	3	± 500 °/s	200 Hz	NR	NR	NR
(Kautz et al., 2017)	Bosch BMA280	1	Wrist of dominant hand	3	± 16 g	39 Hz	NR	NR	NR	NR	NR	NR
(Kelly et al., 2012)	SPI Pro	1	Between the shoulder blades	3	NR	39 Hz	NR	NR	NR	NR	NR	NR
(Kobsar et al., 2014)	G-Link wireless accelerometer node (Microstrain Inc., VT)	1	Lower back on the L3 vertebra region	3	± 10 g	617 Hz	NR	NR	NR	NR	NR	NR
(Kos & Kramberger, 2017)	Custom sensor	1	Wrist of racquet arm	3	± 16 g	NR	3	± 2000 °/s	NR	NR	NR	NR
(Ó Conaire et al., 2010)	Custom sensor	6	Left and right wrists, left and right ankles, chest, lower back	3	± 12 g	120 Hz	NR	NR	NR	NR	NR	NR
(O'Reilly et al., 2015)	Shimmer™ sensor (Realtime Technologies Ltb. Dublin, Ireland)	1	5th lumbar vertebra	3	± 16 g	51.2 Hz	3	± 500 °/s	51.2 Hz	3	± 1 Ga	51.2 Hz

(*Continued*)

Table 3. (Continued).

Reference	Sensor model	Sensor No.	Sensor placement	Accelerometer			Gyroscope			Magnetometer		
				Axes	Range	Sample rate	Axes	Range	Sample rate	Axes	Range (1 Ga = 100 μT)	Sample rate
(O'Reilly et al., 2017a)	Shimmer™ sensor (Realtime Technologies Ltb. Dublin, Ireland)	5	5th lumbar vertebra, mid-point on right and left thighs, right and left shanks 2cm above lateral malleolus	3	± 2 g	51.2 Hz	3	± 500 °/s	51.2 Hz	3	± 1.9 Ga	51.2 Hz
(O'Reilly et al., 2017b)	Shimmer™ sensor (Realtime Technologies Ltb. Dublin, Ireland)	5	Spinous process of the fifth lumbar vertebra, mid-point of both femurs, right and left shanks 2 cm above the lateral malleolus	3	± 2 g	51.2 Hz	3	± 500 °/s	51.2 Hz	3	± 1.9 Ga	51.2 Hz
(Pernek et al., 2015)	Custom sensor	5	Chest, left and right wrists, left and right upper arms	3	NR	30 Hz	NR	NR	NR	NR	NR	NR
(Qaisar et al., 2013)	Custom sensor	3	Bowling arm: upper arm, elbow joint, wrist	3	NR	150 Hz	3	NR	150 Hz	NR	NR	NR
(Rassem et al., 2017)	NR	1	NR	3	NR	50 Hz						
(Rindal et al., 2018)	IsenseU Move+	2	Chest, Lower arm	3	NR	20 Hz	3	NR	20 Hz			
(Salman et al., 2017)	Custom sensor	3	Bowling arm: upper arm, forearm, wrist	3	NR	150 Hz	3	NR	150 Hz	NR	NR	NR
(Schuldhaus et al., 2015)	Custom sensor	2	Cavity of each shoe	3	± 16g	1000 Hz	NR	NR	NR	NR	NR	NR
(Srivastava et al., 2015)	Samsung Gear S smart watch	1	Wrist of racquet arm	3	± 8 g	25 Hz	3	± 2000 °/s	25 Hz	NR	NR	NR
(Whiteside et al., 2017)	IMeasureU IMU (Auckland, New Zealand)	1	Wrist of racquet arm	3	± 16 g	500 Hz	3	± 2000 °/s	500 Hz	3	± 1200 μT	500 Hz

g G-forces, *Ga* gauss, *Hz* Hertz, *IMU* inertial measurement unit, *μT* micro Tesla
NR not reported: study either did not directly report the specification or the device did not include the sensor type

Table 4. Vision-based camera specifications.

Reference	Camera model	Modality	Camera No.	Data collection setting
(Bertasius et al., 2017)	GoPro Hero 3 Black Edition	RGB	1	100 fps 1280 x 960 pixels
(Couceiro et al., 2013)	Casio Exilim – High Speed EX-FH25. Focal length lens of 26 mm	RGB	1	Resolution 480 × 360 pixels 210 Hz
(Díaz-Pereira et al., 2014)	Sony Handycam DCR-SR78	RGB	1	
(Hachaj et al., 2015)	Kinetic 2 SDK system	3 Dimensional	1	30 Hz
(Horton et al., 2014)	NR	NR	NR	NR
(Ibrahim et al., 2016)	NR	NR	NR	NR
(Kapela et al., 2015)	NR	NR	NR	NR
(Karpathy et al., 2014a)	NR	NR	NR	NR
(Kasiri-Bidhendi et al., 2015)	Swisse-range SR4000 time-of-flight (MESA Imaging AG, Switzerland)	Depth Camera at 5 m overhead height	1	25 fps 176 x 144 pixels
(Kasiri et al., 2017)	Swisse-range SR4000 time-of-flight (MESA Imaging AG, Switzerland)	Depth Camera at 5 m overhead height	1	25 fps 176 x 144 pixels
(Li et al., 2018)	iPhone5s, 6, 6plus, 6s, 7	RGB	1	30 fps
(Liao et al., 2003)	NR	RGB	NR	NR
(Lu et al., 2009)	NR	RGB	NR	NR
(Montoliu et al., 2015)	NR	NR	16 synchronized and stationary with a 'bird's eye view' positioned along a soccer pitch	25 fps
(Nibali et al., 2017)	NR	RGB	One fixed	NR
(Ó Conaire et al., 2010)	IP camera	RGB	One overhead and eight around court baseline positioned	NR
(Ramanathan et al., 2015)	NR	NR	NR	NR
(Reily et al., 2017)	Kinetic 2	Depth Camera	1	NR
(Shah et al., 2007)	NR	RGB	NR	NR
(Tora et al., 2017)	NR	NR	NR	NR
(Victor et al., 2017)	NR	RGB	NR	Swimming: 50 fps Tennis: 30 fps
(Yao & Fei-Fei, 2010)	NR	RGB	NR	NR
(Zhu et al., 2006)	Live Broadcast vision	RGB	NR	Video compressed in MPEG-2 standard with a frame resolution 352 × 288 pixels

fps frames per second, *Hz* hertz, *MPEG* Moving Picture Experts Group, *RGB* red green blue
NR not reported: study either did not directly report the specification or the device did not include the sensor type

Table 5. Inertial measurement unit study description and model characteristics.

				Data pre-processing					
Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Filter	Processing	Detection	Feature extraction	Feature selection	Recognition algorithm
(Adelsberger & Tröster, 2013)	Weight-lifting: thruster (squat press)	16: four females and 12 males, beginner to expert		Low-pass filter	1 s window	Heuristically found threshold value to derive start and end indices of each thruster episode	Accelerometer magnitude modelled on sum of six Gaussian functions with four parameters each: scale *ai* , amplitude offset *βi* , standard deviation *σi* , and mean value *μi*	1.5 s window around detected signal peaks. Nelder Mead simplex direct search MATLAB	SVM
(Anand et al., 2017)	Tennis: forehand topspin, forehand slice, backhand topspin, backhand slice, serve Badminton: serve, clear, drop, smash Squash: forehand, backhand, serve	31 tennis players, 34 badminton players, 5 squash players	Total training set: ~ 8500. Total testing set: ~ 7100			Detection shot: 3 cues to identify shot regions across the three sports: 1) threshold, 2) jerk based detection, 3) shot shape-based detection. Once shot swing detected a fixed number or sample before and after impact point assigned as shot region	Seven shot windows developed for each stage of a shot. Three feature set types generated from all shot windows resulting in ~ 2000 features including: 1) statistical features, 2) pairwise correlation coefficients between elements of the window set, 3) shape-based features	Pearson correlation coefficient minimum redundancy maximum relevance (MRMR) technique	LR, bi-directional LSTM
(Brock & Ohgi, 2017)	Ski Jumping: error jump, non-error jump	Four: male, junior athletes					Set 1: discrete feature values based on one-dimensional data points built from the raw and processed data of every sensor Set 2: different time-series features based on the estimated positions and orientations of every sensor		SVM, DTW
(Brock et al., 2017)	Ski jumping: nine motion style errors in flight and landing (5 errors during aerial phase/4 error during landing phase)	Three: ski jump athletes	85 measured jump motions		1) removal of internal noise 2) sensor alignment to bone direction of mounted segment using standardised calibraticalibration measurement 3) neutralisation 4) segmentation of motion streams into jump phases 5) all sensor streams down-sampled by factor of 2 along temporal domain		CNN model – transformed every pre-processed data segment into a multi-channel motion image of size [R, C, D] with D = 3		CNN, SVM
(Buckley et al., 2017)	Running: classification of running form as a non-fatigued or fatigued state	21: 11 females, 10 males, recreationally active	584 extracted stride repetitions labelled as 292 non-fatigued and 292 fatigued	Low-pass Butterworth filter with a frequency cut-off of 5 Hz od order n = 5	Additional signals computed: Euler, pitch, roll, yaw and Quaternion W, X, Y, Z using algorithms on board the Shimmer IMUs. Stride segmentation by an adaptive algorithm		16 time-domain and frequency-domain features computed to describe the 16 IMU signals over each stride repetition.	Wilcoxon Rank Sum Test, the top 20 signal features extracted	RF, SVM, kNN, NB

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing: Filter	Data pre-processing: Processing	Detection	Feature extraction	Feature selection	Recognition algorithm
(Buthe et al., 2016)	Tennis: forehand topspin, forehand slice, backhand topspin, backhand slice, smash, shot steps, side steps	Four: male athletes, three intermediate and 1 advanced	Shots n = 200 Steps n = 640		Shots: discretize data using kMeans algorithm Steps: deadreckoning technique				Shots: LCS Steps: SVM
(Connaghan et al., 2011)	Tennis: serve, forehand, backhand	Eight: two novices, three intermediate, three advanced athletes	2543			Compute length 3D acceleration vector with a W s window around largest absolute magnitude			NB
(Groh et al., 2015)	Skateboarding: ollie, nollie, kickflip, heelflip, pop shove-it, 360-flip	Seven: male, advanced skateboarders as three regular and four goofy stance directions	210		Rider stance correction: x-axes and z-axes for all goofy rider stance data inverted	Accelerometer signal segmented into window lengths 1 s with 0.5 s overlap. Energy of window calculated as sum of squares of all axes. Threshold-based detection defined	Total 54 features calculated: mean, variance, skewness, kurtosis, dominant frequency, bandwidth, x-y-correlation, x-z-correlation, y-z-correlation	Embedded Classification Software Toolbox using the best-first forward selection method	NB, PART, SVM (radial bases kernel), kNN
(Groh et al., 2016)	Snowboarding: two trick categories (Grinds and Airs) with three trick classes each category	*Part A* Four: male snowboarders, as two regular and two goofy stance directions. *Part B* Seven: male snowboarders, as four regular and three goofy stance directions	275 tricks total (119 Grinds and 156 Airs)		Calibration of accelerometer and gyroscope data using static measurements and rotations about all axes. Rider stance correction: x-axes and z-axes of all goofy rider stance data inverted	Peak detected in accelerometer signal landing after trick. L^1-norm Sa, t computed for all times t. Window-based threshold of length 50 samples (0.25s), overlap 49 samples. Threshold determined by LOOCV	Trick category: defined threshold approaches from magnetometer signals Trick class: nine gyroscope signal features of total rotation, rotation for first half of trick, and rotation from s half of trick for each axis		Trick category: NB Trick class: NB, kNN, SVM, C4.5
(Groh et al., 2017)	Skateboarding: 11 trick types, trick fail, resting period	11: skateboard athletes	905 trick events		Calibration. Signal y-axes and z-axes inverted	Accelerometer peaks and gyroscope landing impact signals	Accelerometer: x–z-axes correlation after a landing impact Gyroscope: correlation of the x–y-, x–z- and y–z-axes, and specified rotation features	Trick event interval defined as 1 s before and 0.5 s after landing impact	NB, RF, LSVM, SVM (radial-basis kernel), kNN

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing: Filter	Data pre-processing: Processing	Detection	Feature extraction	Feature selection	Recognition algorithm
(Jensen et al., 2015)	Golf: putt phases, putt event, no-putt event	15: inexperienced golfers	272		Sensor data calibration using the 9DOF Calibration Software (version 2.3). Sensor data transformation using a Direction Cosine Matrix	HMM with sliding windows (500 samples, 1.95 s) with a 50% overlap	31 kinematic parameters from 6D IMU data: (1) phase length and ratios of phase lengths (2) angles and ratios of angles (3) velocity at impact (4) summed acceleration around impact (5) velocity and acceleration profiles in fore-swing		AB
(Jensen et al., 2016)	Swimming: rest period, turn, butterfly, backstroke, breaststroke, freestyle	11: high level junior swimmers			Sliding windows between 1 s to 3.5 s with 0.5 s increments. Feature normalization		48D feature vectors per window, computed on each axis: signal energy, min, max, mean, STD, kurtosis, skewness, variance	Best First Search wrapper algorithm	AB, LR, PART, SVM
(Jensen et al., 2013)	Swimming: butterfly, backstroke, breaststroke, freestyle, turns	12: five females and 7 males, high-level swimmers				Spatial energy and head position	48 features total (8 features x 6 axes): mean, STD, variance, energy, kurtosis, skewness, min, max		DT
(Jiao et al., 2018)	Golf: nine swing types	Four: amateur to professional ranked golfers	213 raw samples, 917 samples after augmentation		Dataset augmented to balance swing counts in each class				Vanilla CNN

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing: Filter	Data pre-processing: Processing	Data pre-processing: Detection	Feature extraction	Feature selection	Recognition algorithm
(Kautz et al., 2017) Machine learning approach	Volleyball: nine shot skill types, one null class	30: 11 females and 19 males, novice to professional	4284	High-pass Butterworth filter with an 8 Hz cut-off frequency	*L*1-norm of the high-passed signal was computed. Signal was smoothed using a low-pass Butterworth filter with a 3 Hz cut-off frequency	Threshold based approach with calculated indicators. C4.5 with LOOCV	39 features: median, mean, STD, skewness, kurtosis, dominant frequency, amplitude of spectrum at dominant frequency, max, min, position of the max, position of the minimum, energy. Pearson correlation coefficients for the correlations between x-axis and y-axis, between x-axis and z-axis, and between y-axis and z-axis	Filter based on the Adjusted Rand Index	SVM, (radial basis kernel function), kNN, Gaussian NB, CART, RF, VOTE
(Kautz et al., 2017) Deep learning approach	Volleyball: nine shot skill types, one null class	30: 11 females and 19 males, novice to professional	4284		Resampling of raw data				Deep CNN defined as two conv layers with ReLUs and max-pooling, followed by two FC layers with soft-max
(Kelly et al., 2012)	Rugby Union: tackle and non-tackle impacts	Nine: professional athletes		Low-pass filter on magnitude signals		Local maxima with an amplitude cut-off of 0.25 Hz	Static window features: max, min, mean, variance, kurtosis, skewness Impact region features: calculated from a window with dynamically calculated start and end points. Impact region signal features: temporal changes in each accelerometer raw data signals		SVM, HCRF, Learning Grid approach with model fusion by AB

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing: Filter	Data pre-processing: Processing	Data pre-processing: Detection	Feature extraction	Feature selection	Recognition algorithm
(Kobsar et al., 2014)	Running: motion patterns to predict training background and experience level	14, soccer athletes. 16, first time marathon runners. 12, experienced marathon runners	Per participant: 15 s	accelerometer data equating to ~ 20 – 25 footfalls		RMS of accelerations in the vertical, medio-lateral, anteroposterior, and resultant direction calculated. The economy of accelerations determined as the RMS in each axis divided by the gait speed. Outliers adjusted using a Winsorizing technique. All variables standardized to a mean of 0 and a STD of 1		DWT procedure of 5-level wavelet	decomposition using Daubechies 5-mother wavelet
PCA	LDA (binary classification)								
(Kos & Kramberger, 2017)	Tennis: forehand, backhand, serve	Seven: junior to senior athletes	446			Defined threshold based on two-point derivative of acceleration curves			Unsupervised discriminative analysis
(Ó Conaire et al., 2010)	Tennis: serve, backhand, forehand	Five: elite nationally ranked	300		Normalization of stroke data by rescaling for variance to equal 1	1 s window over accelerometer peaks detected from a threshold approach	Normalized signal x, y, z vectors		SVM (radial basis function kernel), kNN
(O'Reilly et al., 2015)	Squat: correct or incorrect technique and specific technique deviations	22: 4 females and 18 males, with prior experience and regular squat training in regime	682	Low-pass Butterworth filter with a frequency cut-off of 20 Hz			30 features: min and max range accelerometer and gyroscope x, y, z signals, pitch, roll, yaw		Back-propagation NN
(O'Reilly et al., 2017a)	Lunge: discriminate between different levels of lunge performance and identify aberrant techniques	80: 23 females, 57 males, with prior experience and regular lunge training in regime	3440	Low-pass Butterworth filter with frequency cut-off of 20 Hz of order n = 8	3D orientation of IMU computed from all axes using a gradient descent algorithm. Acceleration and gyroscope magnitude calculated. Each exercise repetition resampled to length of 250 samples.		240 features per IMU calculated and extracted including: signal peak, valley, range, mean, standard deviation, skewness, kurtosis, signal energy, level crossing rate, variance, 25^{th} and 75^{th} percentile, median, variance of both the approximate and detailed wavelet coefficients using the Daubechies 5 mother wavelet to level 6		RF

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing: Filter	Data pre-processing: Processing	Data pre-processing: Detection	Feature extraction	Feature selection	Recognition algorithm
(O'Reilly et al., 2017b)	Deadlifting: technique deviations	135: 41 females and 94 males, with prior lifting experience	2245	Low-pass Butterworth filter with a frequency cut-off of 20 Hz	Rotation quaternions were converted to pitch, roll and yaw signals. Magnitude of acceleration and rotational velocity computed. Time-normalization by exercise repetitions resampled to a length of 250 samples		17 time and frequency domain features each signal: mean, RMS, STD, kurtosis, median, skewness, range, variance, max, min, energy, 25th percentile, 75th percentile, fractal dimension, level crossing-rate, variance of approximate and detailed wavelet coefficients		RF
(Pernek et al., 2015)	Weightlifting: six dumbbell lifting exercises	11: three females and 8 males	~ 2904		Temporal alignment. Uniform resampling of sample rate to 25 Hz		Min, max, range, arithmetic mean, STD, RMS, correlation	Sliding window approach	SVM (Gaussian radial basis function kernel)
(Qaisar et al., 2013)	Cricket: correct and incorrect medium paced bowls	One: medium paced cricket bowler	40		Calibration by filter using signal processing techniques and interpolated to smooth out the filtered data		Mean, mode, STD, peak to peak value, min, max, first deviation, second deviation	K-means clustering	K-means clustering, Markov Model, HMM.
(Rassem et al., 2017)	Cross-country skiing: gears variations	NR	416,737		Data segmented into training, validation, testing set applied with a window size 1 sec with 50% overlap				Recurrent LSTM, CNN, MLP
(Rindal et al., 2018)	Cross-country skiing: eight technique sub-classes	10: 9 male, 1 female, trained amateurs to professional world-cup skiers	8616	Chest accelerometer data filtered with Gaussian low-pass filter 0.0875 s (1.75 samples) standard deviation in the time domain			Samples were decimated or interpolated into 30 samples per cycle and then appended into one feature vector of 94 samples		NN with three hidden layers of 50, 10, 20 neurons in each layer respectively

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Table 5. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset sample No.	Data pre-processing			Feature extraction	Feature selection	Recognition algorithm
				Filter	Processing	Detection			
(Salman et al., 2017)	Cricket: detect legal or illegal bowls	14: male cricketers, medium and fast paced bowlers	150	Calibration and filter	Outliers removed using IQR method. Missing values in each attribute replaced with corresponding mean values of attribute, conditional of 10% limit of missing values per attribute before discarded	Data divided into tagged windows corresponding to phases of bowling action. Ball release point was the maxima to denote start process of windowing and tagging	Seven features per axis of accelerometer and gyroscope signals: mean, median, STD, skewness, kurtosis, min, max	Correlation-based feature selection with Greedy search method resulting in the top 21 features	SVM (redial basis function kernel), kNN, NB, RF, NN (three-layer feed-forward)
(Schuldhaus et al., 2015)	Soccer: shot, pass, event leg, support leg, other soccer events	23: male athletes	64 passes, 12 shots	High-pass Butterworth filter		Accelerometer peak detection using a Signal Magnitude Vector. Segmented windows of 1 s around peaks	Four features from each accelerometer axis: mean, variance, skewness, kurtosis		SVM (linear kernel), CART, NB
(Srivastava et al., 2015)	Tennis: forehand, backhand, serve, sub-shot types (flat, topspin, slice)	14: five professional and nine novices	~ 1000 shots from professional athletes, ~ 1800 shots from novice athletes			Pan Tomkin's algorithm to isolate shot signal from noise. Accelerometer x-axis differentiated and squared. Moving window integration with window size 3* the sampling rate. Identified potential shot impact region using thresholding			Two Level hierarchical classifier: (1) DTW, (2) QDTW
(Whiteside et al., 2017)	Tennis: serve, forehand (rally, slice, volley), backhand (rally, slice, volley), smash, false shot	19: 8 females and 11 males, junior national development athletes	Per athlete: mean 1504 ± 971		Saturated signals reconstructed using a linear interpolation method. Signals smoothed with 50-point (0.1 sec) moving average.	Threshold algorithm with a window size 0.5 s either side of the detected shot. Shot instances temporally aligned with exported coded vision file.	40 features (5 features across 8 waveforms): min, med, integral, discrete value at time of impact		SVM (linear, quadratic, cubic, Gaussian kernels), CT (10, 25, 50 splits), kNN (k of 1, 3, 5), NN, RF, DA (linear and quadratic)

3D three dimensions, *AB* Adaptive Boosting, *C4.5* decision tree analysis type, *CART* classification and regression tree, *CNN* convolutional neural network, *CT* classification tree, *DA* discriminative analysis, *DOF* degrees of freedom, *DT* decision tree, *DWT* dynamic time warp, *FC* fully-connected, *HCRF* hidden conditional random field, *HMM* Hidden Markov Model, *HZ* hertz, *IMU* inertial measurement unit, *IQR* interquartile range, *kNN* k-Nearest Neighbour, *LCS* Longest Common Subsequence algorithm, *LDA* linear discriminative analysis, *LOOCV* leave-one-out-cross-validation, *LR* logistic regression, *LSTM* long short term memory, *LSVM* linear support vector machine, *MLPs* multi-layer perceptrons, *NB* Naïve Bayesian, *NN* neural network, *NR* not reported, *PART* partial decision tree, *QDTW* Quaternions based Dynamic Time Warping, *ReLUs* rectifier linear unit, *RF* random forests, *RMS* root mean square, *STD* standard deviation, *SVM* Support Vector Machine, *VOTE* vote classifier.

Table 6. Inertial measurement unit study model performance evaluation characteristics.

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Anand et al., 2017)	Detection: precision, recall, F1-score Classification: CA		Detection of squash: • Precision 0.95 • Recall 0.96 • F1- score 0.96 CA: • Tennis: CNN 93.8% • Badminton: BLSTM 78.9% • Squash: BLSTM 94.6%	In-house developed tool to align recorded vision and sensor data to tag shot types in which tagged data serves as ground truth for analysis	
(Adelsberger & Tröster, 2013)	Detection accuracy, CA	75%/25% train-test dataset split	Detection accuracy: • 100% (when athletes did not move between reps) Classification: • CA 94.117% (between expert and beginner level) Classification: • CA 93.395% (individual thruster instances)	Video footage with performances labelled by a certified coaching expert	Dataset split details: Tennis: training set ~ 4500 shots by 15 players testing set ~ 5000 shots by 16 players Badminton: training set ~ 3500 shots by 20 players testing set ~ 2000 shots by 14 players Squash: training set ~ 500 shots by 3 players testing set ~ 100 shots by 2 players
(Brock & Ohgi, 2017)	Precision, recall, CA, error rate		SVM: CA 52% – 82%	Video control data	For each classifier algorithm, 72 experiments were conducted varying in factor sampling rate (4 variations), windows size (6 variations) and feature selection strategy (3 variations). Error rate defined as the difference between classification accuracy and 1.0
(Brock et al., 2017)	CA, cross-entropy loss	8-fold cross validation	CNN 1 layer: CA 93 ± 0.08%	Jump style annotated by qualified judge under the judging guidelines of the International Skiing Federation	
(Buckley et al., 2017)	CA, sensitivity, specificity, F1-score,	LOO-CV 10-K-fold cross validation	Global Classifier: • LIMU lumbar spine CA 75% • IMU right shank CA 70% • IMU left shank CA 67% Personalised classifier: • IMU lumbar spine CA 89% • IMU right shank CA 99% • IMU left shank CA 100%	Manual labelling	Personalised classifiers appear more computationally efficient than global classifiers as they require less training data and memory storage.
(Buthe et al., 2016)	Detection accuracy, confusion matrix, recall, precision, user-specific dataset comparison for train and test	LOO-CV	Step detection accuracy: • Overall 76% • Side steps 96% • Shot steps 63% LOOCV: • Precision 0.49 ± 0.04% • Recall 0.49 ± 0.22% User-specific: • Precision 98% • Recall 87%		Gyroscope signals showed to be more suitable than accelerometer signals to separate shot movements and identify fast foot movements

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Table 6. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Connaghan et al., 2011)	Detection accuracy, CA	10-fold cross validation	Detection accuracy: • Candidate strokes 85% • Non-candidate strokes 85% Classification accuracy: • 3 sensor fusion overall accuracy 90% • Accelerometer 7 player model 97% • Gyroscope 7 player model 76% • Magnetometer 7 player model 76%		Accelerometer signals were the most effective at classifying different skill levels
(Groh et al., 2015)	Detection: sensitivity, specificity Classification: CA, computational effort	LOSO-CV	Detection: • Sensitivity 94.2% • Specificity 99.9% Classification: • CA 97.8% (NB and SVM) Computation effort (lowest): • NB (operations 360, time 6.2 s) • PART (operations 41, time 10.6 s)	Video footage and expert analysis of trick quality	Computational effort defined as the time and required operations for one model run without grid search
(Groh et al., 2016)	Precision, recall, CA	LOSO-CV	Event detection: • Recall 0.99 • Precision 0.368 Trick category classification: • Grind recall 0.966 • Grind precision 0.885 • Airs recall 0.974 • Airs precision 0.910 Trick class CA: • Grind 90.3% (SVM) • Airs 93.3% (kNN)	Video footage	
(Groh et al., 2017)	Detection: precision, recall Classification: CA, confusion matrix	Classification: LOSO-CV	Detection: • Precision 0.669 • Recall 0.964 Classification: • Correct trick execution CA 89.1% (SVM) • All tricks modelled 79.8% CA (RF)	Video footage with manual annotation	

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Table 6. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Jensen et al., 2015)	Detection accuracy, false positive rate		Overall detection rate 68.2%. False positive rate 2.4%	Video footage	Detection rate: $DR = \frac{N_d}{N_p}$ False positive rate: $FPR = \frac{N_m}{N_m + N_p}$ N_d number of detected putts N_p number of performed putts N_m number of misdetected putts
(Jensen et al., 2016)	CA	LOSO-CV	Maximum CA 86.5% (SVM) Average CA 82.4% (SVM)	Video footage manually labelled	72 methodological experiments were conducted. A sampling rate of 10.25 Hz and increased window sizes produced higher classification accuracy.
(Jensen et al., 2013)	CA	LOSO-CV	Turn CA 99.8%. Swim stroke CA 95%		
(Jiao et al., 2018)	CA, precision, recall	10-fold cross validation	CA 95% Precision 0.95 average Recall 0.95 average F1-score 0.95 average		
(Kautz et al., 2017) Machine learning approach	Confusion matrix, sample accuracy, balanced accuracy, computational time	Detection: LOSO-CV Classification: leave-three-subjects-out cross validation	Sample accuracy 67.2% (VOTE) Balanced accuracy 60.3% (VOTE) Training computational time: • 18.1 ms (NB with feature selection) Class prediction computational time: • 0.53 µs (CART)	Video footage manually labelled	Sample accuracy: $\lambda_s = \frac{\sum_{c=1}^{M} r_c}{\sum_{c=1}^{M} N_c}$ Balanced accuracy: $\lambda_b = \frac{1}{M} \sum_{c=1}^{M} \frac{r_c}{N_c}$ N_c number of samples from class c r_c number of sample from class c classified correctly M number of classes
(Kautz et al., 2017) Deep learning approach	Sample accuracy, balanced accuracy	Leave-two-out cross-validation	Sample accuracy 83.2% Balanced accuracy 79.5%	Video footage manually labelled	
(Kelly et al., 2012)	Recall, precision, TP, TN, FP, FN		Learning Grid approach: • Recall 0.933 • Precision 0.958	Video footage manually labelled by the medical staff of the elite rugby union team involved	
(Kobsar et al., 2014)	CA	LOO-CV	Training background CA 96.2% Experience level CA 96.4%		
(Kos & Kramberger, 2017)	CA		Serve CA 98.8%, forehand CA93.5%, backhand CA 98.6%	Video footage	Gyroscope signals were found to be more discriminative between stroke types
(Ó Conaire et al., 2010)	Detection accuracy, CA	LOO-CV	Detection accuracy: 100% Classification: • Right arm data CA 89.41% (kNN) • Full-body data CA 93.44% (kNN)		Data fusion of accelerometer and vision data improved CA: • Vision back viewpoint with full body accelerometer 100% CA (kNN) Data fusion overcame viewpoint sensitivity • Vision trained on side viewpoint and tested on back viewpoint fused with full body accelerometer data 96.71% CA (kNN)

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Table 6. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(O'Reilly et al., 2015)	CA, sensitivity, specificity	LOSO-CV	Binary classification: • Sensitivity 64.41% • Specificity 88.01% • CA 80.45% Multi-label classification; • Sensitivity 59.65% • Specificity 94.84% • CA 56.55%	Chartered Physiotherapist evaluation based on the National Strength and Conditioning Association guidelines	
(O'Reilly et al., 2017a)	CA, sensitivity, specificity, out-of-bag error	LOSO-CV	Classify acceptable and aberrant technique Five lower limb IMU set-up: • CA 90% • Sensitivity 80% • Specificity 92% Classify specific technique deviations Five lower limb IMU set-up: • CA 70% • Sensitivity 70% • Specificity 97%	Chartered physiotherapist and strength and conditioning trained practitioner. Correct technique described by the National Strength and Conditioning Association (NSCA) guidelines.	
(O'Reilly et al., 2017b)	CA, sensitivity, specificity	LOSO-CV	Natural technique deviations binary CA: • Global classifier 73% (RF) • Personalized classifier 84% (RF) Natural technique deviations multi-class CA: • Global classifier 54% (RF) • Personalized classifier 78% (RF)	Video footage labelled by a Chartered Physiotherapist	Personalized classifiers outperformed the global classifiers and were more computationally efficient. kNN, SVM, NB tested during analysis against RF, but did not improve results and some caused increased computational times in some cases.
(Pernek et al., 2015)	CA, prediction error, confusion matrix	LOSO-CV, 10-fold cross-validation, 75%/25%train-test dataset split	Methodology experiments: • CA range 84.2 ± 11.3% to 93.6 ± 0.5% Intensity error: • range 1.2% to 6.6 ± 2.5%	Video footage with manual annotation	A 2 s window size with 50% overlap data processing yielded the best performance results.
(Qaisar et al., 2013)	CA		Overall CA: 90.2% (HMM) • Wrist sensor data 100% • Elbow sensor data 88.24% • Upper arm sensor data 82.35%	Video footage	

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Table 6. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Rassem et al., 2017)	Average testing classification error over the model run. MLP model used as performance benchmark for DL models		Standard LSTM: 1.6% class error value CNN: 2.4% class error value		Data was divided into training, validation and testing sets with a segmentation process applied of window size one second with a 50% overlap.
(Rindal et al., 2018)	CA, sensitivity, precision, confusion matrix	Validation dataset was used to evaluate which of the 20 trained neural networks to use for final model. Test set created from six different athlete data	CA 99.8% on training dataset CA 96.5% on validation dataset CA 93.9% on combined tests sets	Manual video labelling	Artificially expanded training dataset by taking every cycle in the original training data and created a new cycle by keeping the x-axis and z-axis, whereas the y-axis was flipped resulting in 8616 cycles from the original 4308 training cycles.
(Salman et al., 2017)	Detection accuracy, CA, recall, precision, F1-score	LOSO-CV	Detection of ball release point 100% accuracy. CA 81 ± 3.12% (SVM) Recall 0.80 (SVM) Precision 0.82 (SVM) F1-score 0.81 (SVM)	Video footage evaluated by an expert cricketer	
(Schuldhaus et al., 2015)	CA	LOSO-CV	Set protocol conditions CA (SVM): • Leg type 99.9% • Other events 96.7% • Pass or shot 88.6% Match conditions CA (SVM): • Shot 86.7% • Pass 81.7%	Video footage manually labelled	
(Srivastava et al., 2015)	Detection accuracy, CA		Shot detection accuracy: • Professional 99.58% • Novice 98.96% • Total 99.41% Shot CA: • Class professional player 99.6% • Class novice player 99.3% • Sub-shot types professional player 90.7% • Sub-shot types novice player 86.2%		
(Whiteside et al., 2017)	CA, confusion matrix, precision, recall	10-fold cross-validation	Mean CA (SVM – cubic kernel): • Condition one 97.43 ± 0.24% • Condition two 93.21 ± 0.45%	Video footage manually labelled by a performance analyst	SVM algorithms were constructed using linear, quadratic, cubic and Gaussian kernels, and a one-versus-one approach. kNN classifiers were built using a k of 1,3 and 5. CT were constructed using a maximum of 10, 25 and 50 splits. NN included a conventional single-layer model and multi-layer deep network

CA classification accuracy, *CART* classification and regression tree, *CT* classification tree, *FN* false negative, *FP* false positive, *Hz* hertz, *kNN* k-Nearest Neighbour, *LOO-CV* leave-one-out cross validation, *LOSO-CV* leave-one-subject-out cross validation, *MLP* multi-layer perceptrons, *NB* Naïve Bayesian, *PART* partial decision tree, *RF* random forests, *SVM* Support Vector Machine, *TN* true negative, *TP* true positive, *VOTE* vote classifier.

Table 7. Vision-based study description and model characteristics.

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset samples	Pre-processing	Processing	Feature extraction and selection	Recognition
(Bertasius et al., 2017)	Basketball: some-body shooting a ball, camera wearer possessing the ball, camera wearer shooting the ball	48: male US College players	10.3 hours of recorded vision			Gaussian mixture function	CNN, Multi-path convolutional LSTM
(Couceiro et al., 2013)	Golf Putting: athlete signature features	Six: male, expert level	180 trial shots (30 trials per athlete)		Darwinian particle swarm optimization method		LDA, QDA, NB with Gaussian distribution, NB with kernel smoothing density estimate, LS-SVM with RBF kernel
(Díaz-Pereira et al., 2014)	Gymnastics: 10 actions grouped into three categories of jumps, rotations, pre-acrobatics	Eight: junior gymnasts	560 video shots (5 – 7 actions per gymnast)	Motion Vector Flow Instance		PCA and LDA	kNN
(Hachaj et al., 2015)	Oyama Karate: 10 classes of actions grouped into 4 defence types, 3 kick types, 3 stands	Six: advanced Oyama karate martial artists	1236	Pre-classification: data pre-processed based on z-scores calculations for each feature value	Segmentation: GDL classifier approach training with an unsupervised R-GDL algorithm. A Baum-Welch algorithm to estimate HMM parameters	Angle-based features	Continuous Gaussian density forward-only HMM classifiers
(Horton et al., 2014)	Soccer: Pass quality	Dataset: English Premiership 2007/2008 season games	2932 passes across four matches			Features: basic geometric prediction variables, sequential predictor variables, physiological predictor variables, strategic predictor variables	Multinomial logistic regression, SVM, RUSBoost algorithm
(Ibrahim et al., 2016)	Volleyball: six team activity classes, seven individual athlete actions	Dataset: 15 YouTube volleyball videos	1525 annotated frames			CNN	CNN, LSTM
(Kapela et al., 2015)	Rugby, Basketball, Soccer, Cricket, Gaelic football, Hurling: 8 scene types	Dataset	50 hours	Video de-coding: storage of every 5th frame in the buffer		FFT	DT, Feed-forward MLP NN, Elman NN
(Karpathy et al., 2014a)	Sports-1M dataset	Dataset	1 million YouTube videos containing 487 classes with 1000 –3000 videos per class	Optimization: Downspur Stochastic Gradient Descent	Data augmentation: (1) crop centre region and resize to 200 × 200 pixels, randomly sampling 170 × 170 region, and randomly flipping images horizontally with 50% probability. (2) subtract constant value of 117 from raw pixel values		CNN (several approaches to fusing data across temporal domains)
(Kasiri-Bidhendi et al., 2015)	Boxing: 6 punch types of straight, hook, uppercut from both rear and lead hand	Eight: elite orthodox boxers	192 punches (32 for each type)		Detection of body parts: fuzzy inference method based on 2D chamfer distance and geodesic distances	Spatial-temporal features of each punch	RF, Linear SVM, Hierarchical SVM

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Table 7. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset samples	Pre-processing	Processing	Feature extraction and selection	Recognition
(Kasiri et al., 2017)	Boxing: 6 punch types of straight, hook, uppercut from both rear and lead hand	14: elite orthodox and southpaw boxers across different weight classes	605 punches		Detection of body parts: fuzzy inference method based on 2D chamfer distance, depth values and geodesic distances	Transition-invariant trajectory features of hand and arm descriptors extracted. Feature ranking for feature reduction experimented using PCA, RF, SVM-reclusive feature eliminator	Multi-class SVM, RF
(Liao et al., 2003)	Swimming: backstroke, breaststroke, butterfly, freestyle	Dataset	50 clips	Associated limb region detection: RGB images converted to HSV space. Associated skin colour detection: pixels labelled between 0.3 to 1.5 hue values.	Upper body sections isolated using heuristic, threshold approach	LR analysis	DT
(Li et al., 2018)	Golf: key swing gesture detection		Golf front angle swing vision from 553 players, Golf side angle swing vision from 790 players, Baseball swing vision from 3363 players			Multi-scale aggregate channel feature method	AD-DWTAdaBoost Linear SVM
(Lu et al., 2009)	Ice Hockey: skating movement directions of down, up, left, right	Male unspecified athletes	5609 images of 32 × 32 grayscale images	Tracking: HSV, HOG combined with SVM. Template updating: SPPCA	Multi-target tracking by incorporated SPPCA with an action recognizer using an AB algorithm		SMLR
(Montoliu et al., 2015)	Soccer: team activities of ball possessions, quick attack, set pieces	Private dataset: professional Spanish soccer team	Two matches of 90 min each	All camera images combined via algorithmic approach for a unique image covering field length		Bag-of-Words Optical Flow	kNN, SVM, MLP
(Nibali et al., 2017)	Diving: 5 dive properties or rotation type, pose type, number of somersaults, number of twists, handstand beginning inclusion	Dataset: high-level divers from the Australian Institute of Sport	Training set: 25 hours with 4716 non-overlapping dives. Test set: day's footage of 612 dives	Temporal action localisation: TALNN – built from volumetric Convolutional layers. Smoothing: Hann Window Function	Spatial Localisation: full regression, partial regression, segmentation, and Global constraints (RANSAC algorithm).		C3D volumetric convolutional network (3x3x3 kernels, ReLUs, dropouts)
(Ó Conaire et al., 2010)	Tennis: serve, forehand, backhand	Five: elite nationally ranked			Contour features: back-ground subtraction and image morphology	Player foreground region divided into 16 pie segments centred on player centroid and normalization	SVM with RBF kernel, kNN
(Ramanathan et al., 2015)	Basketball: 11 match activity classes and frame key player detection	Dataset: 257 NCAA games from YouTube	1143 training clips, 856 validation clips, 2256 testing clips	Each clip subsampled to six fps at four seconds in length		Each video-frame represented by a 1024-dimensional feature vector. Appearance features extracted using the Inception7 (Szegedy & Ibarz, 2015) network and spatially pooling th e response from the lower layer. Features corresponded to a 32 × 32 spatial histogram combined with a spatial pyramid	LSTM and BLSTM RNNs

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Table 7. (Continued).

Reference	Sport: target movement(s)	Participants Number: gender, level	Dataset samples	Pre-processing	Processing	Feature extraction and selection	Recognition
(Reily et al., 2017)	Gymnastics: Pommel horse routine spinning	Unspecified male gymnasts	10,115 frames recorded as 16-bit PNG images, organized into 39 routines	DOI segmentation: (1) Parazen window (2) Identified signal peaks padded with neighbourhood 10% max depth		SAD3D: The gymnast in each frame is described by features: (1) width of their silhouette, (2) height of their silhouette, (3–4) depth values at the leftmost and rightmost ends of the silhouette, (5 – 8) shift in the left-most x, right-most x, upper y, and lower y coordinates compared to the previous frame.	SVM with radial basis function kernel. Smoothing techniques after classification
(Shah et al., 2007)	Tennis: forehand, backhand, other	Dataset: male and female unspecified athletes	150 games each clipped to 10 min segments	Optical flow calculated between consecutive frames	Image segmentation and weight calculation by global adaptive thresholding. Player appearance modelling by Expectation Maximization algorithm	Oriented histogram of skeletonized binary images of athletes	SVM with RBF kernel
(Tora et al., 2017)	Ice Hockey: dump in, dump out, pass, shot, loose puck recovery	Dataset: National Hockey League videos	2507 training events, 250 testing events			Features extracted by the fc7 layers of AlexNet (Krizhevsky et al., 2012). Max-pooling of features of individual players in frames to incorporate player interactions	LSTM
(Victor et al., 2017)	Swimming: backstroke, breaststroke, butterfly, freestyle Tennis: stroke detection	Datasets: Swimming: 40 athletes Tennis: 4 athletes	15k swimming strokes labelled in 650k fames. 1.3k tennis strokes labelled in 270 frames	Swimming: pre-processed using Hough transform as in (Sha, Lucey, Morgan, Pease, & Sridharan, 2013) to extract the lanes from colour information. Tennis: excluded unlabelled tennis strokes from input dataset. Input data frames down sampled to 192 × 128 pixels	Model parameters initialized. Adedelta optimizer. MSE loss function. All frame's pixels encoded in YUV colour-space and down sampled to 128 x 48		Regression: CNN with a base architecture based off the VGG-B CNN (Simonyan & Zisserman, 2014)
(Yao & Fei-Fei, 2010)	Human-object interaction sport activities: cricket defensive shot, cricket bowling, croquet shot, tennis forehand, tennis serve, volleyball smash	Dataset	350 images (50 images per 6 classes)	Gaussian over the number of edges and randomization of initialization connectivity to different starting points	Hill-climbing approach with a Tabu list	Parameter estimation with a max-margin learning method	Composition inference method
(Zhu et al., 2006)	Tennis: left and right swings	Professional tennis athletes	6035 frames of 1099 left swing strokes and 1071 right swing strokes		Player tracking: SVR particle filter and background subtraction.	Motion descriptor extraction: optical flow computed using Horn-Sckunck algorithm with half-wave rectification and Gaussian smoothing. Feature discrimination: slice-based optical flow histograms	SVM

2D two dimensional, *BLSTM* bidirectional LSTM, *CNN* convolutional neural network, *DOI* Depth of interest segmentation, *DT* decision tree, *ELU* Exponential Linear Units, *FFT* Fast Fourier Transform, *GDL* Gesture Description Language, *HMM* Hidden Markov Model, *HOG* Histogram of Oriented Gradients, *HSV* Hue-Saturation-Value-Colour-Histogram, *kNN* k-Nearest Neighbour, *LDA* linear discriminative analysis, *LR* logistic regression, *LS-SVM* least squares support vector machine, *MLP* multi-layer perceptron, *NB* Naïve Bayesian, *NN* neural network, *PCA* principal component analysis, *PNG* Portable Network Graphics, *QDA* quadratic discriminative analysis, *RBF* radial basis function, *RF* random forests, *RUSBoost* Random Under Sampling Boosting, *SAD3D* Silhouette Activity Descriptor in 3 Dimensions, *SPPCA* Switching Probabilistic Principal Component Analysis, *SVM* Support Vector Machine, *SVR* Support Vector Regression.

Table 8. Vision-based study model performance evaluation characteristics.

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Bertasius et al., 2017)	F1-score	24 videos for training dataset, 24 videos for testing dataset	Basketball event detection mean F1-score 0.625. Basketball athlete performance evaluation model F1-score 0.793.	Manual labelling and athlete performance assessment by a former professional basketball player	Compared model's performance to first-person activity recognition baselines and a video activity recognition baseline C3D
(Couceiro et al., 2013)	Confusion matrix, ROC		LS-SVM overall best performance		1) five classifiers evaluated for detecting signature patterns 2) best classifier method applied to extract individual golf putt signatures
(Díaz-Pereira et al., 2014)	True/false recognition rates for binary classification, sensitivity, specificity	10-fold cross validation	Specificity 85% overall Sensitivity 90% overall		
(Hachaj et al., 2015)	CA, confusion matrix	LOO-CV	Overall CA range across classes 93 ± 7% to 100% (four-state HMM)		Five HMM classifiers tested with number of hidden states ranging from 1 (GMM) to 5
(Horton et al., 2014)	CA, precision, recall, F1-score	80%/20% train-test dataset split. Tests set was stratified so per class frequency was consistent with the distribution in training examples	Three-class model 85.5% (SVM)	Labelled data of pass events. Rating of pass quality by observers (6-point Likert Scale) Cohen's Kappa for heuristic measure of agreement between ratings	Experiments conducted using two labelling schemes: (1) six-class labels assigned by observers. (2) three-class scheme (aggregation of six-classes) Test dataset was stratified so per-class frequency consistent with distribution in training dataset.
(Ibrahim et al., 2016)	CA, confusion matrix	2/3rd of total data as training set, 1/3rd as testing set	51.1% CA		Compared model performance to several baseline models
(Kapela et al., 2015)	Modified accuracy (focused around detection performance), precision, modified precision		Overall precision 0.96	Manual annotation	Modified accuracy $= \frac{(DE-DTE)}{NE}$ Precision $= \frac{DTE}{DE}$ Modified precision $= \frac{DTE}{NE}$
(Karpathy et al., 2014a)	Prediction classification accuracy %, per-class average precision, confusion matrix	Dataset split: 70% training set, 10% validation set, 20% test set	CNN model average CA 63.9% Slow fusion model CA 60.9%	Labelled data classes	
(Kasiri-Bidhendi et al., 2015)	CA, confusion matrix	LOO-CV Model trained on data from seven participants and tested on withheld data from one participant	Hierarchal SVM CA 92 – 96%	Start and end frames of each punch labelled by expert analysts	
(Kasiri et al., 2017)	CA, feature numbers, confusion matrix		Hierarchical SVM CA 97.3%	Start and end frames of each punch labelled by expert analysts	
(Liao et al., 2003)	Developed scoring system based on measure of proximity to the prominent feature of a specific style				
(Li et al., 2018)	CA, precision, recall, computational time	Cross-validation (not specified). Dataset split: 80% train/10% validation/10% test set	CA 97% Average recognition time of 2.38 ms		
(Lu et al., 2009)	CA, average computing speed, confusion matrix		SMLR and HOG approach CA 76.37% Computing speed: average total time classification image 0.206s (SMLR and HOG approach)	Manual image retrieval and division into the four classes	Compared developed model against benchmark action recognizers.

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Table 8. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Montoliu et al., 2015)	CA	5-fold cross-validation, LOO-CV	RF CA 92.89 ± 0.2%	Manual vision annotation by expert	
(Nibali et al., 2017)	CA, precision, recall, F1-score		Dive property CA from 86.89 – 100%	Labelled training data	Segmentation works best (spatial localisation). Dilated convolutions boosted CA.
(Ó Conaire et al., 2010)	CA	LOO-CV	Back viewpoint CA 98.67% (kNN) Side viewpoint CA 95% (kNN)		Data fusion of accelerometer and vision data improved CA: • Vision back viewpoint with full body accelerometer CA 100% (kNN) Data fusion overcame viewpoint sensitivity • Vision trained on side viewpoint and tested on back viewpoint fused with full body accelerometer data CA 96.71% (kNN)
(Ramanathan et al., 2015)	Mean average precision	Hyperparameters chosen by cross-validating on the validation dataset	Event classification 0.516 mean average precision Event detection 0.435 mean average precision Key player attention 0.618 mean average precision	Manually labelled videos through an Amazon Mechanical Turk task	Event classification from isolated video clips was compared against different control setting and baseline models
(Reily et al., 2017)	CA, computational time, error rates (RMSE, average absolute), approach tested on CAD60 dataset benchmark		ID depth interest CA 97.8% Spin detection CA 93.81% Smoothing processing improved spin CA to 94.83%. Spin consistency performance analysis in comparison to ground truth RMSE 12.9942 ms from ground truth timestamp.	Manually labelled dataset	Study model reduces late stage data amount processing to perform calculations on 37.8% of the original data.
(Shah et al., 2007)	CA, confusion matrix		Forehand CA 97.24% Backhand CA 96.42% No stroke CA 98.02%	Manually labelled segment frames	Model computational performance speed was 20 fps
(Tora et al., 2017)	CA, Confusion matrix		Overall 49.2% CA		Model compared to several baseline models
(Victor et al., 2017)	F1-score, average frame distance, average distance to smoothed	80%/20% train-test dataset split	Swimming F1-score 0.922 Tennis F1-score 0.977	Manually labelled dataset by expert analysts	Experimented with how temporal information incorporated into the model, data input style, and three smoothing functions. Developed model tested and validated on tennis stroke dataset
(Yao & Fei-Fei, 2010)	CA, compared developed model to previous published benchmarks and a baseline measure (bag-of-words with a linear SVM)	60%/40% train-test dataset split	Activity CA 83.3%	Labelled training dataset	

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Table 8. (Continued).

Reference	Evaluation	Cross validation or dataset split approach	Performance	Ground truth	Special remarks
(Zhu et al., 2006)	Precision, recall		Tennis stroke classification using video frames: • Left recall 84.08%, • Left precision 89.80% • Right recall 90.20%, • Right precision 84.66%. Tennis stroke classification using action clips: • Left recall 87.50%, • Left precision 90.74% • Right recall 89.80%, • Right precision 86.27%		

CA classification accuracy, *CNN* convolutional neural network, *DE* detected events, *DTE* detected true events, *GMM* Gaussian mixture model, *HMM* Hidden Markov Model, *kNN* k-Nearest Neighbour, *LOO-CV* leave-one-out cross validation, *LOSO-CV* leave-one-subject-out cross validation, *LS-SVM* least squares support vector machine, *NE* number of events, *RF* random forests, *ROC* receiver operation characteristic curve, *SVM* Support Vector Machine.

(n = 4), volleyball (n = 2), rugby (n = 2), ice hockey (n = 2), gymnastics (n = 2), karate (n = 1), basketball (n = 3), Gaelic football (n = 1), hurling (n = 1), boxing (n = 2), running (n = 2), diving (n = 1), squash (n = 1), badminton (n = 1), cross-country skiing (n = 2) and soccer (n = 4). The Sports 1-M dataset (Karpathy et al., 2014b) was also reported, which consists of 1,133,158 video URLs annotated automatically with 487 sport labels using the YouTube Topic API. A dominant approach was the classification of main characterising actions for each sport. For example, serve, forehand, backhand strokes in tennis (Connaghan et al., 2011; Kos & Kramberger, 2017; Ó Conaire et al., 2010; Shah, Chokalingam, Paluri, & Pradeep, 2007; Srivastava et al., 2015), and the four competition strokes in swimming (Jensen, Blank, Kugler, & Eskofier, 2016; Jensen, Prade, & Eskofier, 2013; Liao et al., 2003; Victor et al., 2017). Several studies further classified sub-categories of actions. For example, three further classes of the two main classified snowboarding trick types Grinds and Airs (Groh, Fleckenstein, & Eskofier, 2016), and further classifying the main tennis stroke types as either flat, topspin or slice (Srivastava et al., 2015). Semantic descriptors were reported for classification models that predicted athlete training background, experience and fatigue level. These included running (Buckley et al., 2017; Kobsar, Osis, Hettinga, & Ferber, 2014), rating of gymnastic routines (Reily, Zhang, & Hoff, 2017), soccer pass classification based on its quality (Horton, Gudmundsson, Chawla, & Estephan, 2014), cricket bowling legality (Qaisar et al., 2013; Salman, Qaisar, & Qamar, 2017), ski jump error analysis (Brock & Ohgi, 2017; Brock, Ohgi, & Lee, 2017) and strength training technique deviations (M. A. O'Reilly, Whelan, Ward, Delahunt, & Caulfield, 2017a; M. O'Reilly et al., 2015; M. O'Reilly, Whelan, Ward, Delahunt, & Caulfield, 2017). One approach (Yao & Fei-Fei, 2010), encoded the mutual context of human pose and sporting equipment using semantics, to facilitate the detection and classification of movements including a cricket bat and batsman coupled movements.

Total participant numbers for IMU-based studies ranged from one (Qaisar et al., 2013) to 30 (Kautz et al., 2017). Reported data individual instance sample sizes for sensor studies ranged from 150 (Salman et al., 2017) to 416, 737 (Rassem, El-Beltagy, & Saleh, 2017). Vision-based studies that explicitly reported total participant details ranged from five (Ó Conaire et al., 2010) to 40 (Victor et al., 2017). Vision dataset sample sizes varied across studies, from 50 individual action clips (Liao et al., 2003) to 15, 000 (Victor et al., 2017). One study (Karpathy et al., 2014a) used the publicly available Sports-1M, as previously described. Vision-based studies also reported datasets in total time, 10.3 hours (Bertasius, Park, Yu, & Shi, 2017), 3 hours (Montoliu, Martín-Félez, Torres-Sospedra, & Martínez-Usó, 2015), 1, 500 minutes (Shah et al., 2007), and 50 hours (Kapela et al., 2015), and by frame numbers, 6, 035 frames (Zhu, Xu, Gao, & Huang, 2006) and 10, 115 frames (Reily et al., 2017).

3.2 Inertial measurement unit specifications

A range of commercially available and custom-built IMUs were used in the IMU-based studies (n = 30), as presented in Table 3. Of these, 23% reported using a custom-built sensor.

Of the IMU-based studies, the number of sensors mounted or attached to each participant or sporting equipment piece ranged from one to nine. The majority of studies (n = 22) provided adequate details of sensor specifications including sensor type, axes, measurement range, and sample rate used. At least one characteristic of sensor measurement range or sample rate used in data collection was missing from eight studies. All studies used triaxial sensors and collected accelerometer data. For analysis and model development, individual sensor data consisted of only accelerometer data (n = 8), both accelerometer and gyroscope data (n = 15), and accelerometer, gyroscope and magnetometer data (n = 7). The individual sensor measurement ranges reported for accelerometer were ± 1.5 g to ± 16 g, gyroscope ± 500 ◦/s to ± 2000 ◦/s, magnetometer ± 1200 μT or 1.2 to 4 Ga. Individual sensor sample rates ranged from 10 Hz to 1000 Hz for accelerometers, 10 Hz to 500 Hz for gyroscopes and 50 Hz to 500 Hz for magnetometers.

3.3 Vision capture specification

Several experimental set-ups and specifications were reported in the total 23 vision-based studies (Table 4). Modality was predominately red, green, blue (RGB) cameras. Depth cameras were utilised (Kasiri, Fookes, Sridharan, & Morgan, 2017; Kasiri-Bidhendi, Fookes, Morgan, Martin, & Sridharan, 2015; Reily et al., 2017), which add depth perception for 3-dimensional image mapping. Seven studies clearly reported the use of a single camera set-up (Couceiro, Dias, Mendes, & Araújo, 2013; Díaz-Pereira, Gómez-Conde, Escalona, & Olivieri, 2014; Hachaj, Ogiela, & Koptyra, 2015; Kasiri et al., 2017; Kasiri-Bidhendi et al., 2015; Nibali et al., 2017; Reily et al., 2017). One study reported 16 stationary positioned cameras at a "bird's eye view" (Montoliu et al., 2015), and Ó Conaire et al. (2010) reported the use of one overhead and 8 stationary cameras around a tennis court baseline, although data from two cameras were only used in final analysis due to occlusion issues. Sample frequency and, or pixel resolution were reported in seven of the studies (Couceiro et al., 2013; Hachaj et al., 2015; Kasiri et al., 2017; Kasiri-Bidhendi et al., 2015; Montoliu et al., 2015; Victor et al., 2017; Zhu et al., 2006), with sample frequencies ranging from 30 Hz to 210 Hz.

3.4 Inertial measurement unit recognition model development methods

Key stages of model development from data pre-processing to recognition techniques for IMU-based studies are presented in Table 5. Data pre-processing filters were reported as either a low-pass filter (n = 7) (Adelsberger & Tröster, 2013; Buckley et al., 2017; Kelly, Coughlan, Green, & Caulfield, 2012; M. A. O'Reilly et al., 2017a; M., 2015, 2017; Rindal, Seeberg, Tjønnås, Haugnes, & Sandbakk, 2018), high-pass filter (n = 2) (Kautz et al., 2017; Schuldhaus et al., 2015), or calibration with a filter (Salman et al., 2017). Processing methods were reported in 67% of the IMU-based studies (Adelsberger & Tröster, 2013; Anand, Sharma, Srivastava, Kaligounder, & Prakash, 2017; Brock et al., 2017; Buckley et al., 2017; Buthe, Blanke, Capkevics, & Tröster, 2016; Groh et al., 2016; Groh, Fleckenstein, Kautz, & Eskofier, 2017; Groh, Kautz, & Schuldhaus, 2015; Jensen et al., 2016, 2015; Jiao, Wu, Bie, Umek, & Kos, 2018; Kautz et al., 2017; Kobsar et al., 2014; M. A. O'Reilly et al., 2017a; M., 2017; Ó Conaire et al., 2010; Pernek, Kurillo, Stiglic, & Bajcsy, 2015; Qaisar et al., 2013; Salman et al., 2017; Schuldhaus et al., 2015). Methods included, calibration of data (Groh et al., 2016, 2017; Jensen et al., 2015; Qaisar et al., 2013), a one-second window centred around identified activity peaks in the signal (Adelsberger & Tröster, 2013; Schuldhaus et al., 2015), temporal alignment (Pernek et al., 2015), normalisation (Ó Conaire et al., 2010), outlier adjustment (Kobsar et al., 2014) or removal (Salman et al., 2017), and sliding windows ranging from one to 3.5 seconds across the data (Jensen et al., 2016). The three studies that investigated trick classification in skateboarding (Groh et al., 2017, 2015) and snowboarding (Groh et al., 2016) corrected data for different rider board stance styles, termed Regular or Goofy, by inverting signal axes.

Movement detection methods were specifically reported in 16 studies (Adelsberger & Tröster, 2013; Anand et al., 2017; Connaghan et al., 2011; Groh et al., 2016, 2017, 2015; Jensen et al., 2013, 2015; Kautz et al., 2017; Kelly et al., 2012; Kos & Kramberger, 2017; Ó Conaire et al., 2010; Rindal et al., 2018; Salman et al., 2017; Schuldhaus et al., 2015; Whiteside, Cant, Connolly, & Reid, 2017). Detection methods included thresholding (n = 5), windowing segmenting (n = 4), and a combination of threshold and windowing techniques (n = 5).

Signal feature extraction techniques were reported in 80% of the studies, with the number of feature parameters in a vector ranging from a vector of normalised X, Y, Z accelerometer signals (Ó Conaire et al., 2010) to 240 features (M. A. O'Reilly et al., 2017a). Further feature selection to reduce the dimensionality of the feature vector was used in 11 studies. Both feature extraction and selection methods varied considerably across the literature (Table 5).

Algorithms trialled for movement recognition were diverse across the literature (Table 5). Supervised classification using a kernel form of Support Vector Machine (SVM) was most prevalent (n = 16) (Adelsberger & Tröster, 2013; Brock & Ohgi, 2017; Brock et al., 2017; Buckley et al., 2017; Buthe et al., 2016; Groh et al., 2016, 2017, 2015; Jensen et al., 2016; Kautz et al., 2017; Kelly et al., 2012; Ó Conaire et al., 2010; Pernek et al., 2015; Salman et al., 2017; Schuldhaus et al., 2015; Whiteside et al., 2017). The next highest tested were Naïve Bayesian (NB) (n = 8) (Buckley et al., 2017; Connaghan et al., 2011; Groh et al., 2016, 2017, 2015; Kautz et al., 2017; Salman et al., 2017; Schuldhaus et al., 2015) and k-Nearest Neighbour (kNN) (n = 8) (Buckley et al., 2017; Groh et al., 2016; 2017, 2015; Kautz et al., 2017; Ó Conaire et al., 2010; Salman et al., 2017; Whiteside et al., 2017), followed by Random Forests (RF) (n = 7) (Buckley et al., 2017; Groh et al., 2017; Kautz et al., 2017; M. A. O'Reilly et al., 2017a; M., 2017; Salman et al., 2017; Whiteside et al., 2017). Supervised learning algorithms were the most common (n = 29). One study used an unsupervised discriminative analysis approach for detection and classification of tennis strokes (Kos & Kramberger, 2017). Five IMU-based study investigated a deep learning approach including using Convolutional Neural Networks (CNN) (Anand et al., 2017; Brock et al., 2017; Jiao et al., 2018; Kautz et al., 2017;

Rassem et al., 2017) and Long Short Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997) architectures (Rassem et al., 2017; Sharma, Srivastava, Anand, Prakash, & Kaligounder, 2017). In order to assess the effectiveness of the various classifiers from each study, model performance measures quantify and visualise the predictive performance as reported in the following section.

3.5 Inertial measurement unit recognition model evaluation

Reported performance evaluations of developed models across the IMU-based studies are shown in Table 6. Classification accuracy, as a percentage score for the number of correct predictions by total number of predictions made, was the main model evaluation measure (n = 24). Classification accuracies across studies ranged between 52% (Brock & Ohgi, 2017) to 100% (Buckley et al., 2017). Generally, the reported highest accuracy for a specific movement was ≥ 90% (n = 17) (Adelsberger & Tröster, 2013; Anand et al., 2017; Buckley et al., 2017; Connaghan et al., 2011; Groh et al., 2015; Jensen et al., 2013; Jiao et al., 2018; Kobsar et al., 2014; Kos & Kramberger, 2017; M. A. O'Reilly et al., 2017a; Ó Conaire et al., 2010; Pernek et al., 2015; Qaisar et al., 2013; Rindal et al., 2018; Schuldhaus et al., 2015; Srivastava et al., 2015; Whiteside et al., 2017) and ≥ 80% to 90% (n = 7) (Brock & Ohgi, 2017; Brock et al., 2017; Groh et al., 2017; Jensen et al., 2016; M. O'Reilly et al., 2015, 2017; Salman et al., 2017). As an estimate of the generalised performance of a trained model on $n - x$ samples, a form of leave-one-out cross validation (LOO-CV) was used in 47% of studies (Buthe et al., 2016; Groh et al., 2016, 2017, 2015; Jensen et al., 2016, 2013; Kobsar et al., 2014; M. O'Reilly et al., 2015, 2017; Ó Conaire et al., 2010; Pernek et al., 2015; Salman et al., 2017; Schuldhaus et al., 2015). Precision, specificity and sensitivity (also referred to as recall) evaluations were derived for detection (n = 6) and classification models (n = 10). Visualisation of prediction results in the form of a confusion matrix featured in six studies (Buthe et al., 2016; Groh et al., 2017; Kautz et al., 2017; Pernek et al., 2015; Rindal et al., 2018; Whiteside et al., 2017).

3.6 Vision recognition model development methods

Numerous processing and recognition methods featured across the vision-based studies to transform and isolated relevant input data (Table 7). Pre-processing stages were reported in 14 of studies, and another varied 13 studies also provided details of processing techniques. Signal feature extraction and feature selection methods used were reported in 78% of studies.

Both machine (n = 16) and deep learning (n = 7) algorithms were used to recognise movements from vision data. Of these, a kernel form of the SVM algorithm was most common in the studies (n = 10) (Couceiro et al., 2013; Horton et al., 2014; Kasiri-Bidhendi et al., 2015; Kasiri et al., 2017; Li et al., 2018; Montoliu et al., 2015; M. A. O'Reilly, Whelan, Ward, Delahunt, & Caulfield, 2017b; Ó Conaire et al., 2010; Reily et al., 2017; Shah et al., 2007; Zhu et al., 2006). Other algorithms included kNN (n = 3) (Díaz-Pereira et al., 2014; Montoliu et al., 2015; Ó Conaire et al., 2010), decision tree (DT) (n = 2) (Kapela et al., 2015; Liao et al., 2003), RF (n = 2) (Kasiri et al., 2017; Kasiri-Bidhendi et al., 2015), and Multilayer Perceptron (MLP) (n = 2) (Kapela et al., 2015; Montoliu et al., 2015). Deep learning was investigated in seven studies (Bertasius et al., 2017; Ibrahim, Muralidharan, Deng, Vahdat, & Mori, 2016; Karpathy et al., 2014a; Nibali et al., 2017; Ramanathan et al., 2015; Tora, Chen, & Little, 2017; Victor et al., 2017) of which used CNNs or LSTM RNNs as the core model structure.

3.7 Vision recognition model evaluation

Performance evaluation methods and results for vision-based studies are reported in Table 8. As with IMU-based studies, classification accuracy was the common method for model evaluations, featured in 61%. Classification accuracies were reported between 60.9% (Karpathy et al., 2014a) and 100% (Hachaj et al., 2015; Nibali et al., 2017). In grouping the reported highest accuracies for a specific movement that were ≥ 90% (n = 9) (Hachaj et al., 2015; Kasiri-Bidhendi et al., 2015; Kasiri et al., 2017; Li et al., 2018; Montoliu et al., 2015; Nibali et al., 2017; Ó Conaire et al., 2010; Reily et al., 2017; Shah et al., 2007), and ≥ 80% to 90% (n = 2) (Horton et al., 2014; Yao & Fei-Fei, 2010). A confusion matrix as a visualisation of model prediction results was used in nine studies (Couceiro et al., 2013; Hachaj et al., 2015; Ibrahim et al., 2016; Karpathy et al., 2014a; Kasiri et al., 2017; Kasiri-Bidhendi et al., 2015; Lu, Okuma, & Little, 2009; Shah et al., 2007; Tora et al., 2017). Two studies assessed and reported their model computational average speed (Lu et al., 2009) and time (Reily et al., 2017).

4 Discussion

The aim of this systematic review was to evaluate the use of machine and deep learning for sport-specific movement recognition from IMUs and, or computer vision data inputs. Overall, the search yielded 52 studies, categorised as 29 which used IMUs, 22 vision-based and one study using both IMUs and vision. Automation or semi-automated sport movement recognition models working in near-real time is of particular interest to avoid the error, cost and time associated with manual methods. Evident in the literature, models are trending towards the potential to provide optimised objective assessments of athletic movement for technical and tactical evaluations. The majority of studies achieved favourable movement recognition results for the main characterising actions of a sport, with several studies exploring further applications such as an automated skill quality evaluation or judgement scoring, for example automated ski jump error evaluation (Brock et al., 2017).

Experimental set-up of IMU placement and numbers assigned per participant varied between sporting actions. The sensor attachment locations set by researchers appeared dependent upon the specific sporting conditions and movements, presumably to gain optimal signal data. Proper fixation and alignment of the sensor axes with limb anatomical axes is important in reducing signal error (Fong & Chan, 2010). The attachment site hence requires a biomechanical basis for accuracy of the movement being targeted to obtain reliable

data. Single or multiple sensor use per person also impacts model development trade-off between accuracy, analysis complexity, and computational speed or demands. In tennis studies, specificity whilst using a single sensor was demonstrated by mounting the IMU on the wrist or forearm of the racquet arm (Connaghan et al., 2011; Kos & Kramberger, 2017; Srivastava et al., 2015; Whiteside et al., 2017). A single sensor may also be mounted in a low-profile manner on sporting equipment (Groh et al., 2016, 2017, 2015; Jensen et al., 2015). Unobtrusive use of a single IMU to capture generalised movements across the whole body was demonstrated, with an IMU mounted on the posterior head in swimming (Jensen et al., 2016, 2013), lower back during running (Kobsar et al., 2014), and between the shoulder blades in rugby union (Kelly et al., 2012).

The majority of vision-based studies opted for a single camera set-up of RGB modality. Data output from a single camera as opposed to multiple minimises the volume of data to process, therefore reducing computational effort. However, detailed features may go uncaptured, particularly in team sport competition which consists of multiple individuals participating in the capture space at one time. In contrast, a multiple camera set-up reduces limitations including occlusion and viewpoint variations. However, this may also increase the complexity of the processing and model computational stages. Therefore, a trade-off between computational demands and movement recording accuracy often needs to be made. As stated earlier, the placement of cameras needs to suit the biomechanical nature of the targeted movement and the environment situated in. Common camera capture systems used in sports science research such as Vicon Nexus (Oxford, UK) and OptiTrack (Oregon, USA) were not present in this review. As this review targeted studies investigating during on-field or in-situation sporting contexts, efficiency in data collection is key for routine applications in training and competition. A simple portable RGB camera is easy to set-up in a dynamic and changing environment, such as different soccer pitches, rather than a multiple capture system such as Vicon that requires calibrated precision and are substantially more expensive.

Data acquisition and type from an IMU during analysis appears to influence model trade-off between accuracy and computational effort of performance. The use of accelerometer, gyroscope or magnetometer data may depend upon the movement properties analysed. Within tennis studies, gyroscope signals were the most efficient at discriminating between stroke types (Buthe et al., 2016; Kos & Kramberger, 2017) and detecting an athlete's fast feet court actions (Buthe et al., 2016). In contrast, accelerometer signals produced higher classification accuracies in classifying tennis stroke skills levels (Connaghan et al., 2011). The authors expected lower gyroscope classification accuracies as temporal orientation measures between skill levels of tennis strokes will differ (Connaghan et al., 2011). Conversely, data fusion from all three individual sensors resulted in a more superior model for classifying advanced, intermediate and novices tennis player strokes (Connaghan et al., 2011). Fusion of accelerometer and vision data also resulted in a higher classification accuracy for tennis stroke recognition (Ó Conaire et al., 2010).

Supervised learning approaches were dominant across IMU and vision-based studies. This is a method which involves a labelled ground truth training dataset typically manually annotated by sport analysts. Labelled data instances were recorded as up to 15, 000 for vision-based (Victor et al., 2017) and 416, 737 for sensor-based (Rassem et al., 2017) studies. Generation of a training data set for supervised learning can be a tedious and labour-intensive task. It is further complicated if multiple sensors or cameras are incorporated for several targeted movements. A semi-supervised or unsupervised learning approach may be advantageous as data labelling is minimal or not required, potentially reducing human errors in annotation. An unsupervised approach could suit specific problems to explain key data features, via clustering (Mohammed et al., 2016; Sze et al., 2017). Results computed by an unsupervised model (Kos, Ženko, Vlaj, & Kramberger, 2016) for tennis serve, forehand and backhand stroke classification compared favourbaly well against a proposed supervised approach (Connaghan et al., 2011).

Recognition of sport-specific movements was primarily achieved using conventional machine learning approaches, however nine studies implemented deep learning algorithms. It is expected that future model developments will progressively feature deep learning approaches due to development of better hardware, and the advantages of more efficient model learning on large data inputs (Sze et al., 2017). Convolutional Neural networks (CNN) (LeCun, Bottou, Bengio, & Haffner, 1998) were the core structure of five of the seven deep learning study models. Briefly, convolution applies several filters, known as kernels, to automatically extract features from raw data inputs. This process works under four key ideas to achieve optimised results: local connection, shared weights, pooling and applying several layers (LeCun et al., 2015; J. B. Yang et al., 2015). Machine learning classifiers modelled with generic hand-crafted features, were compared against a CNN for classifying nine beach volleyball actions using IMUs (Kautz et al., 2017). Unsatisfactory results were obtained from the machine learning model, and the CNN markedly achieved higher classification accuracies (Kautz et al., 2017). The CNN model produced the shortest overall computation times, requiring less computational effort on the same hardware (Kautz et al., 2017). Vision-based CNN models have also shown favourable results when compared to a machine learning study baseline (Karpathy et al., 2014a; Nibali et al., 2017; Victor et al., 2017). Specifically, consistency between a swim stroke detection model for continuous videos in swimming which was then applied to tennis strokes with no domain-specific settings introduced (Victor et al., 2017). The authors of this training approach (Victor et al., 2017) anticipate that this could be applied to train separate models for other sports movement detection as the CNN model demonstrated the ability to learn to process continuous videos into a 1-D signal with the signal peaks corresponding to arbitrary events. General human activity recognition using CNN have shown to be a superior approach over conventional machine learning algorithms using both IMUs (Ravi et al., 2016; J. B. Yang et al., 2015; Zebin et al., 2016; Zeng et al., 2014; Zheng, Liu, Chen, Ge, & Zhao, 2014) and computer vision (Ji et al., 2013; Krizhevsky et al., 2012; LeCun et al., 2015). As machine learning

algorithms extract heuristic features requiring domain knowledge, this creates shallower features which can make it harder to infer high-level and context aware activities (J. B. Yang et al., 2015). Given the previously described advantages of deep learning algorithms which apply to CNN, and the recent results of deep learning, future model developments may benefit from exploring these methods in comparison to current bench mark models.

Model performance outcome metrics quantify and visualise the error rate between the predicted outcome and true measure. Comparatively, a kernel form of an SVM was the most common classifier implemented and produced the strongest machine learning approach model prediction accuracies across both IMU (Adelsberger & Tröster, 2013; Brock & Ohgi, 2017; Buthe et al., 2016; Groh et al., 2016, 2017, 2015; Jensen et al., 2016; Pernek et al., 2015; Salman et al., 2017; Schuldhaus et al., 2015; Whiteside et al., 2017) and vision-based study designs (Horton et al., 2014; Kasiri et al., 2017; Kasiri-Bidhendi et al., 2015; Li et al., 2018; Reily et al., 2017; Shah et al., 2007; Zhu et al., 2006). Classification accuracy was the most common reported measure followed by confusion matrices, as ways to clearly present prediction results and derive further measures of performance. Further measures included sensitivity (also called recall), specificity and precision, whereby results closer to 1.0 indicate superior model performance, compared to 0.0 or poor model performance. The F1-score (also called a F-measure or F-score) conveys the balances between the precision and sensitivity of a model. An in-depth analysis performance metrics specific to human activity recognition is located elsewhere (Minnen, Westeyn, Starner, Ward, & Lukowicz, 2006; Ward, Lukowicz, & Gellersen, 2011). Use of specific evaluation methods depends upon the data type. Conventional performance measures of error rate are generally unsuitable for models developed from skewed training data (Provost & Fawcett, 2001). Using conventional performance measures in this context will only take the default decision threshold on a model trained, if there is an uneven class distribution this may lead to imprecision (Provost & Fawcett, 2001; Seiffert, Khoshgoftaar, Van Hulse, & Napolitano, 2008). Alternative evaluators including Receiver Operating Characteristics (ROC) curves and its single numeric measure, Area Under ROC Curve (AUC), report model performances across all decision thresholds (Seiffert et al., 2008). Making evaluations between study methodology have inherent complications due to each formulating their own experimental parameter settings, feature vectors and training algorithms for movement recognition. The No-Free-Lunch theorems are important deductions in the formation of models for supervised machine learning (David H. Wolpert, 1996), and search and optimisation algorithms (D H Wolpert & Macready, 1997). The theorems broadly reference that there is no "one model" that will perform optimally across all recognition problems. Therefore, experiments with multiple model development methods for a particular problem is recommended. The use of prior knowledge about the task should be implemented to adapt the model input and model parameters in order to improve overall model success (Shalev-Shwartz & Ben-David, 2014).

Acquisition of athlete specific information, including statistics on number, type and intensity of actions, may be of use in the monitoring of athlete load. Other potential applications include personalised movement technique analysis (M. O'Reilly et al., 2017), automated performance evaluation scoring (Reily et al., 2017) and team ball sports pass quality rating (Horton et al., 2014). However, one challenge lies in delivering consistent, individualised models across team field sports that are dynamic in nature. For example, classification of soccer shots and passes showed a decline in model performance accuracy from a closed environment to a dynamic match setting (Schuldhaus et al., 2015). A method to overcome accuracy limitations in dynamic team field sports associated with solely using IMUs or vision may be to implement data fusion (Ó Conaire et al., 2010). Furthermore, vision and deep learning approaches have demonstrated the ability to track and classify team sport collective court activities and individual player specific movements in volleyball (Ibrahim et al., 2016), basketball (Ramanathan et al., 2015) and ice hockey (Tora et al., 2017). Accounting for methods from experimental set-up to model evaluation, previous reported models should be considered and adapted based on the current problem. Furthermore, the balance between model computational efficiency, results accuracy and complexity trade-offs calculations are an important factor.

In the present study, meta-analysis was considered however variability across developed model parameter reporting and evaluation methods did not allow for this to be undertaken. As this field expands and further methodological approaches are investigated, it would be practical to review analysis approaches both within and between sports. This review was delimited to machine and deep learning approaches to sport movement detection and recognition. However, statistical or parametric approaches not considered here such as discriminative functional analysis may also show efficacy for sport-specific movement recognition. However, as the field of machine learning is a rapidly developing area shown to produce superior results, a review encompassing all possible other methods may have complicated the reporting. Since sport-specific movements and their environments alter the data acquisition and analysis, the sports and movements reported in the present study provide an overview of the current field implementations.

5 Conclusions

This systematic review reported on the literature using machine and deep learning methods to automate sport-specific movement recognition. In addressing the research questions, both IMUs and computer vision have demonstrated capacity in improving the information gained from sport movement and skill recognition for performance analysis. A range of methods for model development were used across the reviewed studies producing varying results. Conventional machine learning algorithms such as Support Vector Machines and Neural Networks were most commonly implemented. Yet in those studies which applied deep learning algorithms such as Convolutional Neural Networks, these methods outperformed the machine learning algorithms in comparison.

Typically, the models were evaluated using a leave-one-out cross validation method and reported model performances as a classification accuracy score. Intuitively, the adaptation of experimental set-up, data processing, and recognition methods used are best considered in relation to the characteristics of the sport and targeted movement(s). Consulting current models within or similar to the targeted sport and movement is of benefit to address bench mark model performances and identify areas for improvement. The application within the sporting domain of machine learning and automated sport analysis coding for consistent uniform usage appears currently a challenging prospect, considering the dynamic nature, equipment restrictions and varying environments arising in different sports.

Future work may look to adopt, adapt and expand on current models associated with a specific sports movement to work towards flexible models for mainstream analysis implementation. Investigation of deep learning methods in comparison to conventional machine learning algorithms would be of particular interest to evaluate if the trend of superior performances is beneficial for sport-specific movement recognition. Analysis as to whether IMUs and vision alone or together yield enhanced results in relation to a specific sport and its implementation efficiency would also be of value. In consideration of the reported study information, this review can assist future researchers in broadening investigative approaches for sports performance analysis as a potential to enhancing upon current methods.

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