Research on the Applications of Artificial Intelligence in Golf

Yixiong Hao[1a]

Saint Kentigern College, Auckland, New Zealand, 2010
y.hao@student.saintkentigern.com

Abstract
The emerging technologies from the field of artificial intelligence (AI) have been deployed in many industries such as various online services, construction, car, and cybersecurity. Such technologies are advantageous because they can process and react to their environment or inputs in a way similar to human intelligence, giving them the capability to complete tasks that otherwise only humans can complete. Most traditionally defined sports including golf have incorporated the use of computer technologies over the past decades. However, the applications of AI technologies in golf and sports, in general, have been very limited. This paper explores the current applications, research, future research directions, and possibilities of AI specifically in golf by examining and summarizing recent studies on this topic. It was found that existing applications of AI technologies are extremely limited, are neither widely used nor endorsed and offer no definite advantage. Currently, research into applying AI technologies in golf is in its early stages, are largely independent of each other, and only focuses on a small task or a very specific aspect, for instance, swing discrepancy detection. The resulting models from these studies often only produced numerical results which demonstrate their sufficiency in their specific task, however, cannot be interpreted in useful ways. Their proficiencies in completing their designated tasks, however, demonstrate potential for a strong AI specialized in golf that essentially plays the role of or even surpasses coaches. Nevertheless, extensive research and the development of large sets of labelled.

Keywords: *Golf, Artificial Intelligence, Machine Learning, Convolutional Neural Network*

1 INTRODUCTION

With golf's rising popularity, there has been an increased focus on the use of computer-based technology and data in the game of golf in recent years. More and more instructors have adopted technology such as swing analysis software, online coaching software, launch monitors (Trackman, GC Quad, etcetera), video databases, and data analysis software (Circles, etcetera) to aid their coaching and help players improve. Artificial intelligence is an emerging field of study. Its resulting technology is being deployed in many industries for its precision, ability to store and process information, quantitative and qualitative data. Experts in the field theorize a 'singularity' where the ability of a broad AI surpasses that of humans. This is already the case in the game go and chess where AI-based software AlphaGo and AlphaZero respectively surpassed the top human players of the games. In most industries, the adoption of artificial intelligence is the next step after the adoption of computer technologies as they serve as the basis on which AI technologies can operate. With the rapid development of computer vision, action and speech recognition models, microsensors, specialized cameras, golf databases, and machine learning models incorporating deep, convolutional, and recurrent neural networks, the deployment of artificial intelligence technologies in the game of golf is becoming increasingly feasible. However, the use of artificial intelligence is very limited in traditionally defined sports such as golf and is arguably underleveraged as a valuable resource. Artificial intelligence technologies and machine learning can potentially significantly impact the game of golf as they did with Go and Chess by uncovering new knowledge and enhancing our understanding of the game. This paper analyses and summarizes recent studies to provide insight on the current applications of artificial intelligence in golf, current research on the application of artificial intelligence in golf, how artificial intelligence technologies can benefit the game of golf and suggest future research directions.

© The Author(s) 2023
B. Fox et al. (Eds.): IC-ICAIE 2022, AHCS 9, pp. 1588-1595, 2023.
https://doi.org/10.2991/978-94-6463-040-4_240

2 LITERATURE REVIEW

2.1 *Golf and artificial intelligence*

In golf, players complete 18 holes by hitting their ball into each hole with a maximum of 14 clubs. The goal is to complete 18 holes with the fewest number of strokes possible. To achieve this, golfers need to be able to control the distance and direction of their shots consistently. The 3 main aspects of golf are full swings, short games, and putting, all of which involve complex body movements (full swing, pitching, chipping, and putting stroke) that require skill and coordination to execute proficiently. As such, golfers spend large amounts of time perfecting their swing for maximum speed and consistency. There are 10 major points in the golf swing that are generally used by instructors for evaluation as demonstrated by Figure 1. It is also desirable for golfers to have control over the shape of shots as golfers often need to hit certain shot shapes on the golf course. The 9 shot shapes: are demonstrated in Figure 2.

P1. Setup position

P2. Shaft parallel to ground during backswing

P3. Left arm parallel to ground during backswing

P4. Top position (transition from backswing to downswing)

P5. Left arm parallel to ground during downswing

P6. Shaft parallel to ground during downswing

P7. Impact position

P8. Shaft parallel to ground during follow through

P9. Right arm parallel to ground during follow through

P10. Finish position

Figure 1: 10 Swing positions front on and down the line perspective, Tiger Woods (TaylorMade Golf, 2020)

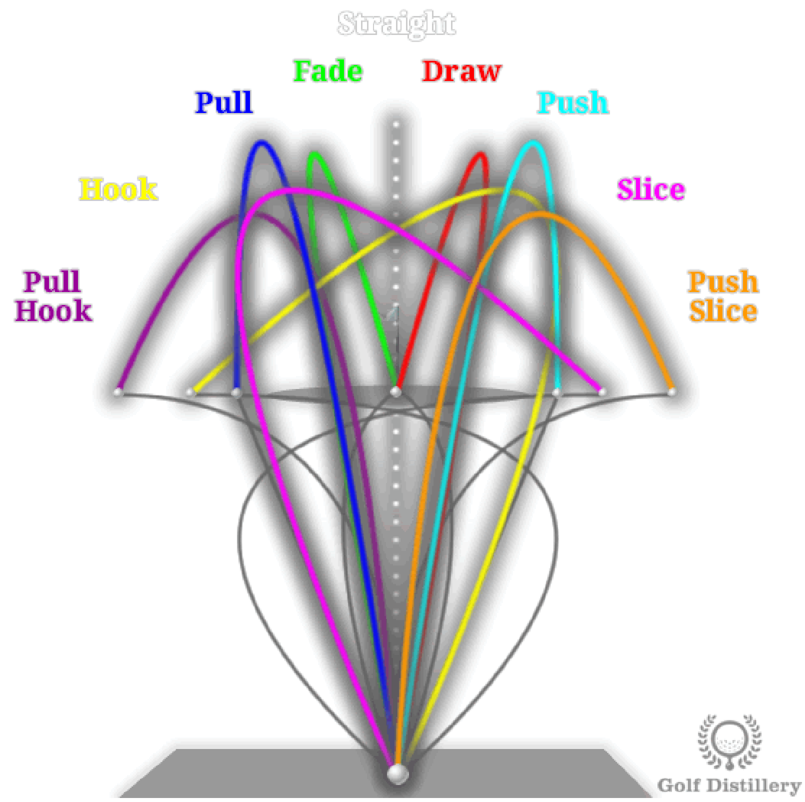

Figure 2: 9 shot shapes

Artificial intelligence refers to machines (computers) and algorithms which demonstrate human 'intelligence', which can include the ability to reason, problem-solve, recognize speech, objects, patterns, and make decisions. There are many different definitions of artificial intelligence. However, in essence, this field of study attempts to combine computers' superior accuracy, precision, ability to store & process information, and perform repetitive tasks with humans' intelligence to perform tasks currently done by humans.

Machine learning is a sub-field of artificial intelligence that aims to achieve human like intelligence by learning from the surrounding environment [1]. One of the goals of machine learning is pattern recognition. Regression and classification are two main aspects of machine learning. Regression predicts the value of one variable depending on another variable (s) while classification groups data based on certain characteristics. Within classification, supervised learning trains the algorithm with labeled datasets with the aim of classing unfamiliar data into one of the identified categories. Unsupervised learning on the other hand feeds the algorithm raw data with the aim of discovering certain patterns.

Decision trees are a type of supervised learning that splits data continuously according to its parameters to class the data into one of the identified categories. The earliest splits are considered the most important in deciding the category of the data. Random forest algorithms train a set of decision trees and take the average of all of their output to produce more accurate output. In addition, instead of looking for the most important parameter at each node, it looks for the most important parameter in a random subset of parameters for a wide diversity.

Another important subset of machine learning is neural networks. They are a method of supervised learning that mimics how the human brains work [2]. A neural network consists of node layers, an initial layer, a hidden layer(s), and an output layer. Nodes of each layer are connected to the next with an associated weight and threshold, similar to how biological neurons are connected. Each node can be thought of as its own regression or classification model, if its output is above a certain threshold value (found though training), its data is passed onto the next layer. Deep neural networks describe neural networks with a large number of hidden layers. Convolutional neural networks are aNNs that specialise in image classification and object detection.

CNNs reduce input images into a form that is easier to process without losing critical features needed for accurate predictions [3]. Learnable (through training data) importance is assigned to different parts/aspects of the image to simplify and feed into the neural network layers to reduce the amount of computation.

2.2. *Advantages of Artificial Intelligence over Existing Technology and Practices*

Artificial intelligence can be divided into 2 parts, strong and weak AI. Strong AIs are machines that 'think' and be able to do all the things humans are capable of, it is not only specialised to do one task. Weak AIs are machines that act as if they are intelligent and are usually only able to do a particular task. Thinking like features such as neural networks, decision trees, regression, and classification models are added to make them useful tools. To this day, strong AIs remain mostly theoretical, however, weak AIs are being widely implemented as tools in many industries.

Current technology used in golf, such as launch monitors and slow-motion cameras, only output what they collect without further processing. They cannot be used to their full potential without a coach to think and analyse their output. A 'strong' (only specialised in golf, but governs every aspect) golf AI has the potential to provide comprehensive coaching to players without a human coach. AI technologies can operate 24/7 at a very low cost to the players compared to traditional coaches if they learn how to navigate an API and operate the hardware. Furthermore, traditional coaches usually rely on their experience to give suggestions to players. However, the experience of any individual or group of coaches is limited. Artificial intelligent systems can learn and gain experience exponentially fasters than any human coach given a big enough database which can be gathered as the AI is being used. For instance, an AI system can gain data and 'experience' quickly if the same system is deployed globally; given enough computing power, it can 'learn' from data from every user and improve itself during use.

2.3 *Current use of Artificial Intelligence in Golf*

The current use of artificial intelligence technologies in golf is very limited, the following describes some of the notable current applications of AI in golf.

Callaway golf claims to have used AI technologies with their supercomputer to design the clubface and a 'speed frame' in their 2021 Epic line up and 2022 Rogue line up of drivers [4]. Their technology is named Jailbreak A.I. and its objective is to optimize the design of the clubface to produce maximum ball speed for more distance. This AI-designed structure is claimed to 'improve stability in the horizontal and torsional direction', 'allow the forged face cup to flex more', and 'produce exceptional ball speeds across the face.' Although there seems to be no significant ball speed improvement compared to other modern drivers, these 2-line ups have received positive reviews from professional players such as Rick Shiels.

Trackman also has an AI named Tracy that works with their launch monitor. Based on the data from players hitting shots, Tracy suggests which data (speed, attack angle, clubface, club path, etc) the player will benefit the most from improving or has the most potential to be improved [5]. Although it is not disclosed how Tracy does this, it is likely that Tracy compares players' data with the data of professional players and the billions of shots trackman monitors have collected in the past. Tracy also provides quantitative metrics to evaluate players' performance and suggests whether players will benefit from improving the consistency or shifting a particular data. Tracy needs to be accompanied by traditional coaching as it can only identify what to improve on, but now how to improve.

3 CURRENT RESEARCH ON ARTIFICIAL INTELLIGENCE IN RELATION TO GOLF

3.1 *Research on Artificial Intelligence in Swing Analysis*

There was relatively extensive research on the use of AI in swing analysis in golf likely due to the development of computer vision technologies and the importance of the swing in golf. Since convolutional neural networks are shown to be proficient at action recognition, video representation, spatial-temporal action detection and localization [6], they have been a popular approach to golf swing analysis. Kim et al. (2020) attempted to find key frames (P1 through to 10) of the swing using a combination of AI and data analysis techniques [7]. An existing ML model named PoseNet with a CNN architecture is run on a tensor processing unit to detect joint positions and hence swing positions in each frame from a down-the-line perspective.. Key frames are then found when key joints intersect each other, however, an evaluation was not provided. Their study also found distinguishable trends in joint position data and the shape of the resulting shot, but only with manual feedback (observations of shot shape), proving that classification of shot shapes is definitely achievable with AI technologies.

Studies from Jiao et al. (2018) successfully achieved golf swing classification with their own deep CNN named Golf Vanilla CNN in combination with a smart golf club that integrates two orthogonally affixed strain gage sensors, 3-axis accelerometer and 3-axis gyroscope [8]. In their study, each shot shape of each player's swing has a unique ID and the CNN was trained with labeled data. Golf Vanilla CNN was able to correctly identify the ID of the swing with an average precision of 95%, outperforming traditional SVM (support vector machine) method. They pointed out that further research is needed to determine an effective sequence length and the relevancy and redundancy of sensors to allow for an accurate result requiring minimal computing power. It would then be practical to implement such approaches in real time analysis. In their follow up study [9], different variations of CNNs and the relevancy of individual sensors were investigated. The results (Figure 4) show that either the strain gauge sensor or accelerometer alone can produce highly accurate results with 500Hz over 2 seconds. This indicates that ML models can be trained using data from low profile single microsensors that can be easily integrated into a golf club.

Model	All sensor (%)	SG (%)	Acc (%)	Gyro (%)
GolfVanillaCNN	95.04	96.03	97.68	66.67
GolfVGG	96.70	94.06	95.05	65.68
GolfInception	97.36	95.38	96.04	67.66
GolfResNet	92.07	96.70	95.71	66.67

CNN: convolutional neural network; SG: strain-gage sensors; Acc: single accelerometer sensor; Gyro: signal gyroscope sensor.

Figure 3: Over accuracy of CNN-based Classifiers for different sensor types and their combinations in percent [8]

Although the studies examined above demonstrate the capabilities of AI in golf, the results of their machine learning models (quantitative) cannot be interpreted in a way that helps players or improves our understanding of golf. Liu et al. (2021) advances in this direction in their recent study as they used AlphaPose - a CNN-based multiple person pose estimator to detect body points [10]. After processing, this data is then fed into a ResNet that analyses the correlation between key joints for training with data labeled as either ‘good’ or ‘bad’ swings by a professional coach. The resulting model is able to identify incorrect joint positions in 119 out of 122 ‘bad’ swing videos. Although a simple classification of ‘good’ or ‘bad’ is currently not of much use, the ability to accurately identify which part of the motion is at fault is important for future development towards more interpretable models. Once again, AI technologies are able to identify "mistakes" with a swing, but not how nor where to adjust.

Unfortunately, current research yields limited results as most studies’ models simply output quantitative metrics which are of little use. A system developed by Li and Cui (2021) uses Microsoft Kinect sensor data as input to an ML model that estimates swing postures and compares the similarity of the joint angles between 2 swings to enable quantitative comparison [11]. Li and Cui concluded that the Kinect sensor is proficient at detecting joints and contours of the human body for golf swing analysis Similarly, another study by [12] 2021 uses NN to synchronise different swing videos and detect where discrepancies occur, but not precisely where or why they occur.

An investigation from Systems Design Engineering, University of Waterloo (2019) successfully developed a DNN with hybrid RNN and CNN structure that is able to detect the key swing positions at 76% accuracy at a 5-frame tolerance [6]. They especially pointed out that “CNNs adapted for video may be leveraged to facilitate golf swing analysis through the autonomous extraction of event frames in golf swing videos.” CNNS are still yet to be widely applied to sequence-based data such as golf swing videos. Research from Wang et al. (2018) fills this gap as they propose a novel approach to apply CNN to sequence-based data[13]. Also with the Kinect sensor, joint trajectories maps are collected and separated into 3 planes. Each map is then color encoded with color maps to indicate temporal order and direction. These maps are then input into a CNN for the classification of motion. The prediction results of this method outperformed all previous methods and shows high practical potential to be used in golf swing analysis. The above studies demonstrated that CNNs are a practical approach in golf swing analysis as they are capable of accurately classifying golf swings.

Since research on implementing AI technologies in golf is still a novel area of interest, there is not yet a significant amount of existing resource to aid research. Some of the current resources are described below. Golf DB is a database consisting of 1400 high quality swing videos labelled with event frames, bounding box, player name, sex, club, and view type and will likely be of significant use in future research. The Microsoft Kinect sensor also proved to be a valuable tool as it is proficient for posture data collection. Existing and pretrained ML models such as PoseNet and AlphaPose can also be further explored and adapted for golf swing analysis purposes.

3.2 *Research on Artificial Intelligence in Skill Evaluation*

While CNN-based models described in the previous section are able to accurately classify different types of swings, those complex models are not interpretable; they do not indicate what exactly makes a swing ‘good’ or ‘bad’ or what swing characteristics produce certain shot shapes. Thresholds learned by these models have no meaning to humans.

Decision trees are more interpretable to humans as they directly classify data based on their parameters which humans can understand. 2 studies have used decision trees and random forest models to explore which metrics provided by the Trackman launch monitor have the most influence on the skill of players. Both studies used the handicap (derived from average scoring) as an indication of golfers’ skill levels and yielded similar conclusions. The first study [14] used 28 quantitative metrics provided by track man [15] to model predict players’ handicaps. The RF and decision tree models were trained with a labeled dataset including 277 golfers. On average, the RF models were more accurate in predicting the handicap of players. All of the models produced concur with the factors they consider important and they also concur with golf theory. Ball speed was considered the most important factor. This is followed by the consistency (standard deviation of the metrics recorded) of face angle, club path, smash factor, and dynamic loft. Only 8 club-related metrics were required for accurate prediction. Both studies also made the interesting observation that more skilled golfers have shallower swing planes. This is also somewhat related to modern swing theory as the 'shallowing' of the club at the start of the downswing is theorized to produce more speed and consistency by utilizing ground reaction force. The second study [16] also provided an evaluation of these models by comparing their outputs with the prediction of a PGA teaching professional, the ML models were shown to be more accurate in predicting the handicap of golfers. Although these two studies did not uncover any 'new' knowledge about golf, they do validate our current understanding and demonstrate that AI technologies can be used in different ways to increase the understanding of what separates skilled players from the rest.

3.3 Other Research on Artificial Intelligence in Golf

Most current research on the use of AI in golf is focused on the game of golf itself and attempt to enhance our understanding. These research are in their initial stages and their products mostly have little to no practical uses as discussed above. One study by Merler et al. (2017) stood out and investigated the automatic curation of golf highlights with AI [17]. It combines multiple areas of AI to evaluate 3 aspects of video footage that most closely indicates the quality of the highlight [17]. Visual action recognition and audio recognition or natural language processing with neural networks are used to evaluate player reaction, spectator cheers, and commentator speech & tone to decide the quality of the highlight. This system was tested with footage of the final round of the 2017 Masters tournament. Approximately 93% of highlights curated by AI were considered valid clips through human evaluation (the clip records a shot and correct starting and ending frames chosen). Half of the clips curated by the AI were identical to the official highlight clips released by the Masters. Although this does not seem to be impressive, it is important to consider that professional highlights take into factor the strategic importance of shots and players in their curation. This novel approach to highlight curation is proven to be effective and can be implemented for sports in general is further improved. Compared to research focusing on swing analysis and skill evaluation, the product of this research is closer to having practical purposes.

4 THE FUTURE FOR ARTIFICIAL INTELLIGENCE IN GOLF AND RESEARCH DIRECTIONS

One likely reason for current research in AI in relation to golf is so limited is that people simply do not see what AI technologies can bring to the game of golf. However, as previously discussed, AI have the potential to create new knowledge and have already validated our current knowledge about golf. Riveiro et al. (2015) points out that one of the main challenges faced by golf instructors is communication with the player and trying to understand what swing or style best suits them [18]. Many researchers mentioned the lack of databases on which ML models can be trained with in their studies. Taken into account all of the above, this paper hereby identifies 4 main focus of future research towards AI in golf.

Firstly, AI models need the ability to provide comprehensive performance evaluation: recognize faults, recommend, and feedback. To accomplish this, AI needs to 'understand' the criteria for a 'good' swing. Swing models of different shot shapes need to be built by analysing swing videos from professional players. Swing patterns for each shot shape can be identified through combinations of supervised learning, classification, clustering, and unsupervised learning techniques. Players' swing patterns can be compared to those models built from swings of professionals to find what is most efficient for them to produce each shot shape. Riveiro et al. (2015) also details the need to "build models from historical data collected from skilled players (swing modelling), compare those models that best fit player's characteristics with actual swings and detect faults"[18].

Secondly, generation of visualization for the models described in section 1. These visuals will be superior to existing videos because they can be viewed from any angle and are free of visual inconsistencies such as angles, clothing, lighting, distance, etcetera. Being able to view swings from all angles may also assist coach-player communication.

Thirdly, identification of patterns in quantitative metrics (Trackman metrics) of shots from professionals of certain shot shapes. Supervised learning techniques can be used to achieve this. Swing, quantitative metrics, and shot shapes can be more comprehensively explained and understood, this may also uncover new insights.

Lastly, the establishment of a database will serve as the basis for future research (including 1, 2, 3). As stated in the literature, producing a "robust" golf AI that meets the requirements of becoming a coach requires the collection of historical data recording the player's learning progress/journey. Such an AI system encompasses almost every aspect of golf from swing, short game, putting, fitness, and even mental that fully mimics a coach. These 'player profiles' need to record the progression of players' skill level, swing (full, chipping, putting) pattern progression, performance data, what drills, exercises, training, the player does. A big collection of such data will enable AI to give new players suggestions on the amount of practice, what exercises, drills, or workouts to do based on how these exercises impacted previous players who shares similar characteristics in terms of physical ability and tendencies.

5 CONCLUSION

The application of artificial intelligence technologies in golf is currently very limited and have yet to reach their full potential. Notable applications are Tracy and Callaway A.I. Jailbreak. However, they did not result in a definite improvement on past technology.

Current research in the implementation of AI technologies in golf is also limited. Most researchers have focused on a very specific aspect of golf with the aim to investigate if AI technologies have the potential to accomplish a task (detecting P1-10 for instance). For this reason, existing research is loosely related and their results are often only numerical values indicating that their respective AI models are able to successfully complete their designated tasks. Products of current research are only able to uncover the 'what', but not the 'why' and 'how' parts of their tasks. For example, the model produced by Liu et al. (2021) was able to detect which parts of a swing are at fault, but not why it is at fault, where the correct position is, and how to adjust[10]. Outputs are mostly incomprehensible and there is yet to be a model that provides comprehensive feedback. The current research was not produced results that benefit, nor have applications in, nor enhance our understanding of golf. Nevertheless, they demonstrated that AI technologies are capable of achieving practical purposes such as swing analysis and skill evaluation and are even at times more proficient than humans. Current research also validated some of our current understanding of golf which is a promising sign that it could uncover new knowledge in the future. This area of research has immense potential in the future as AI technologies are quickly gaining popularity across many industries for the benefits they provide. For this reason, more research and investment are being devoted to the field of AI, including its applications in golf.

REFERENCES

[1] el Naqa, I., & Murphy, M. J. (2015). What Is Machine Learning? Machine Learning in Radiation Oncology, 3–11. https://doi.org/10.1007/978-3-319-18305-3_1

[2] IBM Cloud Education. (n.d.). Neural Networks. IBM. Retrieved January 7, 2022, from https://www.ibm.com/cloud/learn/neural-networks

[3] Saha, S. (n.d.). A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way. Towards Data Science. Retrieved January 7, 2022, from https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

[4] Callaway Golf. (n.d.). Epic Family Fairway Woods | NEW Jailbreak A.I. Velocity Blades. Retrieved January 9, 2022, from https://www.callawaygolf.com/fwoods-product-video-epic-21-family.html

[5] Trackman. (2020, November 2). TrackMan Tracy - Complete walkthrough [Video]. YouTube. https://www.youtube.com/watch?v=qCpBNwJrt2A

[6] Systems Design Engineering, University of Waterloo. (2019, March). GolfDB: A Video Database for Golf Swing Sequencing. arXiv. https://arxiv.org/pdf/1903.06528.pdf

[7] Kim, T. T., Zohdy, M. A., & Barker, M. P. (2020). Applying Pose Estimation to Predict Amateur Golf Swing Performance Using Edge Processing. IEEE Access, 8, 143769–143776. https://doi.org/10.1109/access.2020.3014186

[8] Jiao, L., Wu, H., Bie, R., Umek, A., & Kos, A. (2018). Multi-sensor Golf Swing Classification Using Deep CNN. Procedia Computer Science, 129, 59–65. https://doi.org/10.1016/j.procs.2018.03.046

[9] Jiao, L., Bie, R., Wu, H., Wei, Y., Ma, J., Umek, A., & Kos, A. (2018). Golf swing classification with multiple deep convolutional neural networks. International Journal of Distributed Sensor Networks, 14(10), 155014771880218. https://doi.org/10.1177/1550147718802186

[10] Liu, J. J., Newman, J., & Lee, D. J. (2021). Using Artificial Intelligence to Provide Visual Feedback for Golf Swing Training. Electronic Imaging, 2021(6), 321. https://doi.org/10.2352/issn.2470-1173.2021.6.iriacv-321

[11] Li, C., & Cui, J. (2021). Intelligent Sports Training System Based on Artificial Intelligence and Big Data. Mobile Information Systems, 2021, 1–11. https://doi.org/10.1155/2021/9929650

[12] Liao, C. L., Hwang, D. H., & Koike, H. K. (2021, May). How Can I Swing Like Pro?: Golf Swing Analysis Tool for Self Training. arXiv. https://arxiv.org/pdf/2105.10153.pdf

[13] Wang, P., Li, W., Li, C., & Hou, Y. (2018). Action recognition based on joint trajectory maps with convolutional neural networks. Knowledge-Based

Systems, 158, 43–53. https://doi.org/10.1016/j.knosys.2018.05.029

[14] König, R., Johansson, U., Riveiro, M., & Brattberg, P. (2017). Modeling Golf Player Skill Using Machine Learning. CD-MAKE 2017, 275–294. https://doi.org/10.1007/978-3-319-66808-6_19

[15] Hahm, C.,(n.d.). 40+ TRACKMAN PARAMETERS, Trackman, https://blog.trackmangolf.com/40-trackman-parameters/

[16] Johansson, U. J., König, R. K., Brattberg, P. B., Dahlbom, A. D., & Riveiro, M. R. (2015). Mining Trackman Golf Data. 2015 International Conference on Computational Science and Computational Intelligence.

[17] Merler, M., Mac, K. N. C., Joshi, D., Nguyen, Q. B., Hammer, S., Kent, J., Xiong, J., Do, M. N., Smith, J. R., & Feris, R. S. (2017). Automatic Curation of Sports Highlights Using Multimodal Excitement Features. IEEE Transactions on Multimedia, 21(5), 1147–1160. https://doi.org/10.1109/tmm.2018.2876046

[18] Riveiro, M., Dahlbom, A., König, R., Johansson, U., & Brattberg, P. (2015). Supporting Golf Coaching and Swing Instruction with Computer-Based Training Systems. LCT 2015: Learning and Collaboration Technologies, 279–290. https://doi.org/10.1007/978-3-319-20609-7_27

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.