Undergraduate Research Journal for the Human Sciences

Volume 18
Issue 2025 *2025*

Article 6

July 2025

Integrating Artificial Intelligence and Wearable Technology in Soccer Training

Khush Dakwala
Piscataway High School, khushd2008@gmail.com

Vincent Chen Dr.
Georgian Court University, vchen@georgian.edu

Integrating Artificial Intelligence and Wearable Technology in Soccer Training

Abstract

The integration of Artificial Intelligence (AI) with wearable sensors has revolutionized soccer training. Real-time data on various physical, physiological, and biomechanical metrics such as acceleration, heart rate, and movement patterns are collected by the Local Position Measurement (LPM) and Electronic Performance and Tracking Systems (EPTS) sensors. By inputting these data into Machine Learning (ML) algorithms, specifically Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Decision Trees (DT), coaches can precisely analyze performance, manage injury risks, and develop personalized training plans for their athletes. Additionally, coaches can optimize training intensity, improve tactical decisions, and reduce injury risks. Furthermore, these sensors track recovery features such as sleep quality, stress levels, and mood, resulting in a comprehensive approach to managing athletes. As AI and wearable sensors continue to improve, their applications in soccer training will also continue to advance, resulting in improvements in player development, injury prevention, and team dynamics. The present paper discusses the role of AI integration with wearable sensors in soccer training by emphasizing their effectiveness in improving player conditions and team success.

Keywords: Artificial Intelligence, Machine Learning, Soccer, Electronic Performance and Tracking Systems

Introduction

Soccer has been considered one of the most popular and exciting sports in the world (Reilly & Williams, 2003). Succeeding in soccer requires physiological demands, technical skills, and technical behavior (Francesco Sgrò et al., 2018). Specifically, an athlete requires both core physical capacities, such as cardiorespiratory endurance, muscular strength, muscular endurance, agility, coordination, balance, reaction time, and speed, which can be developed through strength and conditioning training without the ball, as well as technical skills like heading, kicking, controlling, dribbling, throwing in, and goalkeeping, which are usually practiced with the ball (Guzman et al., 2022) (Francesco Sgrò et al., 2018). It is common for coaches to use the training method of small-sided games (SSGs) for a variety of levels as it seems to be a valid method to train these skills for the intensity of a real game (Francesco Sgrò et al., 2018).

As Artificial Intelligence (AI) evolves at a rapid pace, many uses of it have been made within the health and fitness fields such as medicine and science. Machine Learning (ML), a subset of AI, has significantly contributed to the evolution of AI. ML is a core component of AI that enables deep, data-driven analysis of datasets through AI applications (Chmait & Westerbeek, 2021). ML enables computers and algorithms to improve and expand their capabilities as more data is provided. After collecting and cleaning the data, the algorithm creates relationships between variables either with or without human assistance, where humans set the parameters for each variable. As the algorithm operates, it will be able to identify and select certain variables, which are used alongside the dependent variable (Nassis et al., 2023). Commonly used ML methods include Neural Networks, Support Vector Machines, and Random Forests (Van Eetvelde et al., 2021). These ML algorithms can also be implemented in the sport of soccer using physical sensors; leading to not only improved accuracy in predicting results and player performance, but also providing clear and understandable insights for coaches, and players (Calderón-Díaz et al., 2024). Using ML, soccer analysts gain valuable quantitative insights; providing them with in-depth insight to assess the individual player while also allowing them to analyze tactical aspects of the game (Kusmakar et al., 2020). The data can also be used to scout for new prospects, while an important aspect of the data is to analyze the risk of injury within players (Rossi et al., 2022).

In soccer, sensors are commonly used to collect data on individual players. Analyzing this data is crucial for enhancing physical match performance and achieving competitive success (Pettersen et al., 2018). To perform this analysis, sensors are integrated into wearable devices, such as activity trackers. Through connectivity, such as Bluetooth or Wi-Fi, the sensors automatically transmit data to software installed on a connected device, without the need for human intervention. Wearable sensors have enabled and amplified self-monitoring, which is defined as the observation and record of one's individual activities and own behavior (Rapp & Cena, 2016). Furthermore, these electronic sensors provide a perfect platform for data transmission from sensors in a simplified manner (Dai et al., 2023). A key aspect of its use is for injury prevention. Considering that sport injury prediction and prevention are trending topics in sport science, the data collected using the ML algorithms within the sensor can be used to forecast injuries (Van Eetvelde et al., 2021).

A majority of the data used to analyze soccer performance comes from wearable devices and sensors for quantification of sport and physical activity. In soccer today, the Electronic Performance and Tracking Systems (EPTS) sensor is approved by FIFA to be used in official matches (Pettersen et al., 2018). Using EPTS, soccer analysts can gain biometric data for the player which includes many metrics like acceleration, angular speed, temperature, pulse rate, etc. (Kos & Kramberger, 2017). Furthermore, another evolving type of sensor used by analysts to gain data from players is the Local Position Measurement (LPM) system. LPM systems operate by having the wearable technology emit signals to local receivers, which perform the actual triangulation. Compared to traditional GPS sensors, LPM systems are becoming more commonly used within soccer as they provide more depth of data (Pettersen et al., 2018).

Sensor Data Acquisition

In soccer training internationally, many teams commonly use the LPM sensor to gain data from a player. The LPM sensor collects fast and accurate measurements of object positions based on active movement. The LPM system can be viewed as an inverse of the GPS system, as the active transponders are used to measure positions while fixed passive base stations are strategically placed around the covered field of view (Pourvoyeur et al., 2006). On the other hand, GPS systems rely on satellites to track players' positions, making it usable in various locations. While the accuracy of the data collected by GPS can be affected by the number of satellites nearby along with the presence of obstacles and buildings, LPM uses fixed base stations specific to a location, providing higher accuracy and more frequent measurements. Due to its unique attributes, LPM sensors can be viewed more precisely, especially for tracking movement patterns in team sport (Fischer-Sonderegger et al., 2021).

Electronic Performance and Tracking Systems (EPTS) operate using a combination of hardware and software, which facilitates the collection, storage, analysis, and management of professional athletes' fitness and health data. EPTS are used nowadays in soccer to monitor and improve the performance of players. While EPTS mainly track player positions, they can also be used in combination with microelectromechanical devices, such as heart rate trackers and other devices to measure physiological performance (Bitilis et al., 2021). EPTS consist of two parts. The wearable part of EPTS uses camera-based and wearable technologies that are worn between the shoulder blades supported by a vest, which looks like a sports bra. It has various sensors that measure velocity, distance covered, parts of the field where the player was moving, heartbeat, and the impact of a jump or a tackle (Seçkin et al., 2023). EPTS sensors are gaining more exposure on the soccer field since they ensure that every game and training behavior of every player on the pitch is recorded, and all technical tactical and physical parameters are assessed (Bitilis et al., 2021).

EPTS sensors can also be extremely beneficial for coaches as it allows them to track various important factors for their athletes such as injuries, illnesses, sleep, stress, and mood (Bitilis et al., 2022). With coaches given the ability to monitor these factors in real-time, it accurately enables coaches to provide more proactive and personalized interventions for athletes, which may lead to better performance and well-being of the athletes (Düking et al., 2018). Additionally, data acquired from EPTS sensors can also be used to create specific training programs that meet the needs of individual athletes, optimizing training load and recovery periods (Bourdon et al., 2017). This personalized approach doesn't just enhance athletic performance, but it also reduces risk of overtraining and injury (Saw et al., 2016). For example, athletes who are identified as being at risk for overtraining can have their training load adjusted to their specific need so they can ensure recovery, prevent burnout and enhance performance on the field (Bourdon et al., 2017).

It is essential for coaches to ensure their athletes are getting enough rest. Lack of sleep or poor sleep quality can negatively impact the athlete's reaction time, decision-making, and physical performance (Fullagar et al., 2015). Being able to track sleeping patterns through the data acquired through the EPTS sensor provides insights into the recovery status of athletes, as sleep is a key factor for recovery, including muscle repair, cognitive function, and the overall health of athletes (Fullagar et al., 2015). Additionally, by understanding the sleep habits of their athletes, coaches can schedule training sessions and competitions at optimal times to maximize performance among athletes (Fullagar et al., 2015). Monitoring stress levels and mood states is also vital as these psychological factors hold a massive significance among athletic performance and risk of injury (Kellmann et al., 2018). High levels of stress can potentially cause increased muscle tension, leading to a higher risk of injury, while negative mood states can reduce motivation and focus (Kellmann et al., 2018). Using EPTS sensors to monitor these factors allows for timely psychological interventions and support, ultimately contributing to a more holistic approach to athlete management (Kellmann et al., 2018).

By having a comprehensive understanding of both the physical and psychological states of their athletes, coaches can make more informed decisions and provide better support to their teams (Moesch et al., 2018). This holistic approach is crucial in soccer since the margin between success and failure is often very small (Williams et al., 2018). By acquiring and utilizing data from EPTS sensors and implementing it into coaching strategies, coaches can not only enhance performance but also contribute to the health and career longevity of their athletes (Williams et al., 2018). Furthermore, it improves communication between athletes and coaches, creating a more supportive and understanding relationship (Moesch et al., 2018). This can lead to higher levels of trust and cooperation, which are essential for achieving peak performance in a team sport such as soccer.

ML Algorithms Utilization

By utilizing ML algorithms, electronic sensors can analyze the collected data thoroughly, leading to more accurate predictions by integrating different types of sensor data and adjusting algorithm parameters (Dai et al., 2023). These systems, which include devices like accelerometers, gyroscopes, and force sensors, generate a large amount of data, which can be difficult to analyze using typical statistical methods. By utilizing ML appropriately, these systems can identify complex patterns and correlations within the data, leading to more precise insights into athletic performance (De Fazio et al., 2023). Additionally, the use of ML can allow for real-time monitoring and feedback, enhancing the adaptability of training programs based on immediate performance metrics (De Fazio et al., 2023).

For electronic sensors such as EPTS and LPM sensors, traditional ML algorithms such as artificial neural networks (ANN), support vector machines (SVM), and decision trees (DT) are used, and they show better performance when there are fewer input data (Dai et al., 2023). In situations where data is limited, these algorithms can still be utilized to extract meaningful patterns and provide accurate predictions.

Artificial Neural Networks (ANNs) are known for their ability to model complex, non-linear relationships, making them suitable for applications where the sensor data may not follow direct trends (Phatak et al., 2021). Multiple studies have implemented or proposed ANN to predict sports results (Phatak et al., 2021). In addition to predictive modeling, ANNs have been utilized for tasks such as classification and anomaly detection in sports data. For example, an ANN can be trained to classify different types of movements or detect unusual patterns that could indicate the risk of injury (Dai et al., 2023). Additionally, ANNs are adaptable because they can be specifically configured to improve performance over time for athletes by adjusting parameters such as learning rate and network architecture (De Fazio et al., 2023).

The use of Support Vector Machines (SVMs) is beneficial in sports technology as they are effective in small-sample datasets and can handle noisy data. This makes SVMs ideal for recognizing activities with motion patterns such as soccer (Wang, 2024). SVMs are advantageous because they create decision boundaries which maximize the margin between different classes of data, and this is essential for accurately classifying movements in sports where the data may overlap or be difficult to separate (De Fazio et al., 2023). This capability makes SVMs useful in sports like soccer, where distinguishing between different types of player movements can be complex (Dai et al., 2023).

Decision Trees (DT) algorithms provide clear interpretation of the data and offer the ability of visualization (Marynowicz et al., 2022). DT are favored by analysts for their simplicity and interpretability since they allow coaches to visualize the decision-making process behind predictions (Phatak et al., 2021). This feature is crucial in a sports context since it allows the coaching staff to understand how different factors, such as speed or angle of motion, contribute to outcomes (De Fazio et al., 2023). Furthermore, DT can be easily integrated with other ML algorithms to create group methods, such as random forests, which further enhance prediction accuracy while maintaining interpretability (Marynowicz et al., 2022).

Conclusion

Wearable sensor technology combined with machine learning algorithms has significantly enhanced methods of soccer training. Specifically, LPM sensors and EPTS, integrated with ML algorithms involving ANNs, SVMs, and DTs, provide the coaches with precise details of player performance and health which was not possible earlier. These systems provide real-time monitoring of physical and physiological parameters for athletes, resulting in personalized training programs with better strategies for injury prevention for each individual athlete.

Since the technology can process large quantities of data about the performances of players, coaches now benefit even more when making informed decisions on the training, recovery, and tactics that need to be adopted for a particular game. While machine learning algorithms are especially good at finding patterns in player movements and performance, each algorithm type is useful in different ways. ANN brings pattern recognition, SVM deals well with less data, while DT yield interpretable outcomes for the coaching staff. This deep analysis of data has completely changed the soccer teams' approach to developing players and preparing for matches.

These technologies are not only being implemented for physical performance metrics but also extend into monitoring sleep, stress levels, and other recovery factors, allowing coaches to be more responsive to players' overall well-being. The holistic monitoring system has particularly appealed to young players for its ability to improve proper development while preventing injuries. It enables coaches to track and analyze all these parameters for better, more balanced training programs that optimize performance while reducing the risk of burnout or injury.

As this technology is continuously improving, it will continue to be used by coaches for their soccer teams as it opens new pathways toward performance optimization and player development. ML algorithms continue to grow in sophistication, and with more advanced sensor technologies, potential applications might delve even deeper into player performance and team dynamics. This is a big step in the methodology of training for modern soccer as it puts a quantitative approach on traditional coaching methodology while staying in line with player welfare. The success of such systems only proves how well technology has contributed to sports development, with athletes being able to maintain peak performances across all levels of the game.

References

Bitilis, P., Chatzipanagiotou, N., Kosmalla, F., Lukosch, S., Niess, J., Niforatos, E., Wozniak, P. W., & Zancanaro, M. (2022). *Digitalizing the Football Experience: A study on Electronic Performance and Tracking Systems (EPTS) from the perspective of football athletes and training staff Digitalizing the Football Experience A study on Electronic Performance and Tracking Systems (EPTS) from the perspective of football athletes and training staff*. http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-122823

Bitilis, P., Chatzipanagiotou, N., Mirijamdotter, A., & Jokela, P. (2021). *Electronic Performance and Tracking Systems (EPTS) Perceptions, Benefits and Challenges of Professional Football Athletes and Training Staff*.

Bourdon, P. C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M. C., Gabbett, T. J., Coutts, A. J., Burgess, D. J., Gregson, W., & Cable, N. T. (2017). Monitoring athlete training loads: Consensus statement. *International Journal of Sports Physiology and Performance*, *12*, 161–170. https://doi.org/10.1123/IJSPP.2017-0208

Calderón-Díaz, M., Silvestre Aguirre, R., Vásconez, J. P., Yáñez, R., Roby, M., Querales, M., & Salas, R. (2024). Explainable Machine Learning Techniques to Predict Muscle Injuries in Professional Soccer Players through Biomechanical Analysis. *Sensors*, *24*(1). https://doi.org/10.3390/s24010119

Chmait, N., & Westerbeek, H. (2021). Artificial Intelligence and Machine Learning in Sport Research: An Introduction for Non-data Scientists. *Frontiers in Sports and Active Living*, *3*. https://doi.org/10.3389/fspor.2021.682287

Dai, N., Lei, I. M., Li, Z., Li, Y., Fang, P., & Zhong, J. (2023). Recent advances in wearable electromechanical sensors—Moving towards machine learning-assisted wearable sensing systems. In *Nano Energy* (Vol. 105). Elsevier Ltd. https://doi.org/10.1016/j.nanoen.2022.108041

De Fazio, R., Mastronardi, V. M., De Vittorio, M., & Visconti, P. (2023). Wearable Sensors and Smart Devices to Monitor Rehabilitation Parameters and Sports Performance: An Overview. In *Sensors* (Vol. 23, Issue 4). MDPI. https://doi.org/10.3390/s23041856

Düking, P., Holmberg, H. C., & Sperlich, B. (2018). The potential usefulness of virtual reality systems for athletes: A short SWOT analysis. In *Frontiers in Physiology* (Vol. 9, Issue MAR). Frontiers Media S.A. https://doi.org/10.3389/fphys.2018.00128

Fischer-Sonderegger, K., Taube, W., Rumo, M., & Tschopp, M. (2021). How far from the gold standard? Comparing the accuracy of a Local Position Measurement (LPM) system and a 15 Hz GPS to a laser for measuring acceleration and running speed during team sports. *PLoS ONE*, *16*(4 April). https://doi.org/10.1371/journal.pone.0250549

Francesco Sgrò, Salvatore Bracco, Salvatore Pignato, & Mario Lipoma. (2018). Small-Sided Games and Technical Skills in Soccer Training: Systematic Review and Implications for Sport and Physical Education Practitioners. *Journal of Sports Science*, *6*(1). https://doi.org/10.17265/2332-7839/2018.01.002

Fullagar, H. H. K., Skorski, S., Duffield, R., Hammes, D., Coutts, A. J., & Meyer, T. (2015). Sleep and Athletic Performance: The Effects of Sleep Loss on Exercise Performance, and Physiological and Cognitive Responses to Exercise. In *Sports Medicine* (Vol. 45, Issue 2, pp. 161–186). Springer International Publishing. https://doi.org/10.1007/s40279-014-0260-0

Guzman, D., Young, M., Howard, T., & National Strength & Conditioning Association (U.S.). (2022). *Strength training for soccer*.

Kellmann, M., Bertollo, M., Bosquet, L., Brink, M., Coutts, A. J., Duffield, R., Erlacher, D., Halson, S. L., Hecksteden, A., Heidari, J., Wolfgang Kallus, K., Meeusen, R., Mujika, I., Robazza, C., Skorski, S., Venter, R., & Beckmann, J. (2018). Recovery and performance in sport: Consensus statement. *International Journal of Sports*

Physiology and Performance, *13*(2), 240–245. https://doi.org/10.1123/ijspp.2017-0759

Kos, M., & Kramberger, I. (2017). A Wearable Device and System for Movement and Biometric Data Acquisition for Sports Applications. *IEEE Access*, *5*, 6411–6420. https://doi.org/10.1109/ACCESS.2017.2675538

Kusmakar, S., Shelyag, S., Zhu, Y., Dwyer, D., Gastin, P., & Angelova, M. (2020). Machine Learning Enabled Team Performance Analysis in the Dynamical Environment of Soccer. *IEEE Access*, *8*, 90266–90279. https://doi.org/10.1109/ACCESS.2020.2992025

Marynowicz, J., Lango, M., Horna, D., Kikut, K., & Andrzejewski, M. (2022). Predicting ratings of perceived exertion in youth soccer using decision tree models. *Biology of Sport*, *39*(2), 245–252. https://doi.org/10.5114/BIOLSPORT.2022.103723

Moesch, K., Kenttä, G., Kleinert, J., Quignon-Fleuret, C., Cecil, S., & Bertollo, M. (2018). FEPSAC position statement: Mental health disorders in elite athletes and models of service provision. *Psychology of Sport and Exercise*, *38*, 61–71. https://doi.org/10.1016/J.PSYCHSPORT.2018.05.013

Nassis, G. P., Verhagen, E., Brito, J., Figueiredo, P., & Krustrup, P. (2023). A review of machine learning applications in soccer with an emphasis on injury risk. In *Biology of Sport* (Vol. 40, Issue 1, pp. 233–239). Institute of Sport. https://doi.org/10.5114/biolsport.2023.114283

Pettersen, S. A., Johansen, H. D., Baptista, I. A. M., Halvorsen, P., & Johansen, D. (2018). Quantified soccer using positional data: A case study. *Frontiers in Physiology*, *9*(JUL). https://doi.org/10.3389/fphys.2018.00866

Phatak, A. A., Wieland, F. G., Vempala, K., Volkmar, F., & Memmert, D. (2021). Artificial Intelligence Based Body Sensor Network Framework—Narrative Review: Proposing an End-to-End Framework using Wearable Sensors, Real-Time Location Systems and Artificial Intelligence/Machine Learning Algorithms for Data Collection, Data Mining and Knowledge Discovery in Sports and Healthcare. In *Sports Medicine - Open* (Vol. 7, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s40798-021-00372-0

Pourvoyeur, K., Gahleitner, T., Gassenbauer, G., Stelzer, A., & Schuster, S. (2006). Effects of motion models and sensor data on the accuracy of the LPM positioning system. *2006 9th International Conference on Information Fusion, FUSION*. https://doi.org/10.1109/ICIF.2006.301599

Rapp, A., & Cena, F. (2016). Personal informatics for everyday life: How users without prior self-tracking experience engage with personal data. *International Journal of Human-Computer Studies*, *94*, 1–17. https://doi.org/10.1016/J.IJHCS.2016.05.006

Reilly, T., & Williams, Am. (2003). *Science and Soccer, Second Edition*.

Rossi, A., Pappalardo, L., & Cintia, P. (2022). A narrative review for a machine learning application in sports: An example based on injury forecasting in soccer. In *Sports* (Vol. 10, Issue 1). MDPI. https://doi.org/10.3390/sports10010005

Saw, A. E., Main, L. C., & Gastin, P. B. (2016). Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. In *British Journal of Sports Medicine* (Vol. 50, Issue 5, pp. 281–291). BMJ Publishing Group. https://doi.org/10.1136/bjsports-2015-094758

Seçkin, A. Ç., Ateş, B., & Seçkin, M. (2023). Review on Wearable Technology in Sports: Concepts, Challenges and Opportunities. In *Applied Sciences (Switzerland)* (Vol. 13, Issue 18). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/app131810399

Van Eetvelde, H., Mendonça, L. D., Ley, C., Seil, R., & Tischer, T. (2021). Machine learning methods in sport injury prediction and prevention: a systematic review. In *Journal of Experimental Orthopaedics* (Vol. 8, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s40634-021-00346-x

Wang, S. (2024). SVM-based support vector type recognition machine for smart things in soccer training motion recognition. *Scalable Computing*, *25*(4), 2519–2531. https://doi.org/10.12694/scpe.v25i4.2923

Williams, T. L., Hunt, E. R., Papathomas, A., & Smith, B. (2018). Exercise is medicine? Most of the time for most; but not always for all. *Qualitative Research in Sport, Exercise and Health*, *10*(4), 441–456. https://doi.org/10.1080/2159676X.2017.1405363