

AI AND NEURAL NETWORKS IN SPORTS ANALYTICS: A COMPREHENSIVE REVIEW OF TECHNIQUES AND APPLICATIONS

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Abstract. The explosive growth of sports data, including event logs, tracking streams, video records, wearable signals, and biomechanics-related measurements, has fundamentally changed the way athletic performance is studied, interpreted, and optimized. What previously relied on manual observation and conventional statistics is now increasingly supported by artificial intelligence capable of extracting patterns from large, heterogeneous, and high-frequency datasets. This review aims to systematize the principal machine learning and deep learning approaches used in contemporary sports analytics, with a particular focus on three major application domains: match outcome prediction, tactical and spatiotemporal analysis, and injury risk assessment and prevention. The article synthesizes the use of widely adopted methods, ranging from regression, decision trees, random forests, support vector machines, and gradient boosting to artificial neural networks, convolutional neural networks, recurrent architectures, and graph-based models. Special attention is given to the relationship between data modality and model selection, especially in studies using tracking data, event data, physiological inputs, and biomechanical indicators. In addition to summarizing methodological trends, the review examines how AI-driven systems contribute to coaching support, player evaluation, workload monitoring and tactical decision-making. The evidence suggests that AI and neural networks have moved beyond experimental use and are becoming a central analytical infrastructure in modern sport. At the same time, persistent limitations remain, including data heterogeneity, limited interpretability, inconsistent validation protocols, and difficulties in transferring results from controlled settings to real competitive environments. Overall, this review positions AI-based sports analytics as a rapidly evolving field with strong practical value and clear relevance for the development of next-generation intelligent systems in sport.

Key words: sports analytics, artificial intelligence, tracking data, event data, match outcome prediction, tactical analysis, injury prevention.

Introduction

Sports analytics has moved far beyond its early association with box scores, hand-kept notes, and post-match summaries. Match events, player trajectories, wearable outputs, biomechanical signals, medical records, and video feeds now form a data environment that is both richer and more demanding than the one addressed by conventional descriptive statistics. This shift emerged at the intersection of sports science, information technology, computer vision, and mathematical modeling, where advances in sensing, storage, and computation made it possible to treat sport not merely as a sequence of isolated outcomes, but as a high-frequency, multivariate, and deeply contextual process [1; 2; 3].

In practical terms, the rise of data-intensive sport is tied to the real needs of clubs and performance departments. Elite organizations increasingly rely on tracking systems, embedded sensors, semi-automated event coding, and large commercial data platforms to monitor in real time. As a result, the analytical problem involves detecting patterns, forecasting what is likely to happen next, and translating complex evidence into decisions that matter on the training ground and on match day [1; 2; 3].

That development also exposes the limits of traditional methods. Classical statistical tools remain valuable for transparent summary reporting and hypothesis-driven analysis, yet they often struggle when the underlying process is nonlinear, sequential, interactive, and context-dependent. Manual observation and basic statistics rarely capture the full complexity of real-time movement,

tactical interaction, or evolving game states [2; 3; 4].

The present article offers a structured review of AI and neural-network-based methods in sports analytics, with particular attention to how the field moved from traditional descriptive statistics to data-intensive, model-driven analysis. More specifically, this review pursues four aims. First, it clarifies why contemporary sport requires analytical tools that can handle multimodal, spatio-temporal, and context-dependent data. Second, it synthesizes the major methods currently used in the field. Third, it organizes the literature around three application domains that recur across sports and datasets: outcome prediction, performance analysis, and injury prevention. Finally, it identifies the tensions that continue to shape the field, especially those related to interpretability, generalizability, data heterogeneity, and decision support in real sporting environments [1; 2; 3; 4].

Taxonomy of AI Applications in Sports.

The methodology of modern sports analytics has split into two primary paradigms: the transparent, feature-engineered world of classical machine learning (ML) and the high-dimensional, representation-heavy landscape of deep learning (DL). While the industry often chases the newest neural innovations, empirical evidence suggests that the «best» technique is frequently a function of data density and the specific need for interpretability.

Classical AI/ML Methods: The Interpretable Baseline

Classical AI and machine learning methods still form the backbone of a large share of sports analytics studies. In many sports settings, the available data are match logs, player statistics, role-based indicators, workload summaries, or manually derived contextual features rather than raw video or dense tracking streams. Under those conditions, regression-based models, tree methods, margin-based classifiers, probabilistic learners, and clustering techniques remain not only viable but often preferable because they are easier to train, easier to interpret, and easier to deploy in decision-support environments [1; 2].

Table 1. Classical AI/ML techniques in sports analytics

Method family	Typical inputs	Representative tasks	Main strengths	Main limitations
Regression	Match statistics, player/team attributes, form, workload, context variables	Outcome prediction, win probability, player valuation, performance modelling	Interpretable, probabilistic, strong baseline for structured data	Weak on complex nonlinear relations; depends on feature engineering
Decision trees	Tabular match, session, GPS, screening, and tactical data	Winner classification, player categorization	Easy to interpret, visual, useful for rule-based decisions	Prone to overfitting; less stable than ensembles
Random forests	Engineered match features, player stats, wellness and injury-history data	Match prediction, injury modelling	Robust, handles nonlinearities, strong on structured datasets	Less transparent than single-tree models
SVM	High-dimensional structured features, player/session records	Outcome classification, injury prediction, tactical-state classification	Effective in nonlinear classification	Harder to tune and explain; weaker scalability
k-NN	Historical match descriptors, player data, similarity-based vectors	Baseline prediction, player grouping, similarity retrieval	Simple, non-parametric, useful baseline	Sensitive to scaling and irrelevant features
Boosting	Engineered match features, load indicators, wellness/RPE	Match prediction, fatigue forecasting, performance ranking	High predictive accuracy, captures interactions well	Lower interpretability; requires careful tuning
Clustering	Tracking, positional, movement, anthropometric data	Player profiling, formation discovery, workload segmentation	Useful for exploratory analysis and latent pattern discovery	Not a direct supervised prediction tool

Bayesian approaches	Match outcomes, ratings, dependency structures	Probabilistic prediction, dependency modelling	Handles uncertainty explicitly, interpretable probabilistic reasoning	Relies on model assumptions; often weaker on highly complex data
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Neural Network and Deep Learning methods

If classical machine learning remains the stable core of structured sports prediction, neural-network methods define the current frontier of methodological expansion. Their rise is closely tied to the changing form of sports data. Once analysts moved beyond hand-crafted summaries toward video, tracking coordinates, event streams, and multimodal athlete monitoring, models capable of learning hierarchical and nonlinear representations became much more attractive. This is precisely the context in which multilayer perceptrons, convolutional models, recurrent networks, graph neural networks, and more recently transformer-based systems became central to the field [1; 2; 3].

Multi-Layer Perceptrons (MLP/ANN): The simplest member of this family is the multilayer perceptron, often referred as an artificial neural network. MLP-style models are still widely used when the input remains tabular but the analyst expects nonlinear interactions that are difficult to specify manually. In that sense, they represent the neural counterpart to boosted trees or nonlinear SVMs. MLPs have been used since the 1990s to predict NFL outcomes with 61–75% accuracy [5]. NFL and football studies have used feedforward ANNs for winner classification and score-related prediction but their usefulness depends on data volume, feature representation, and the stability of the task definition [1].

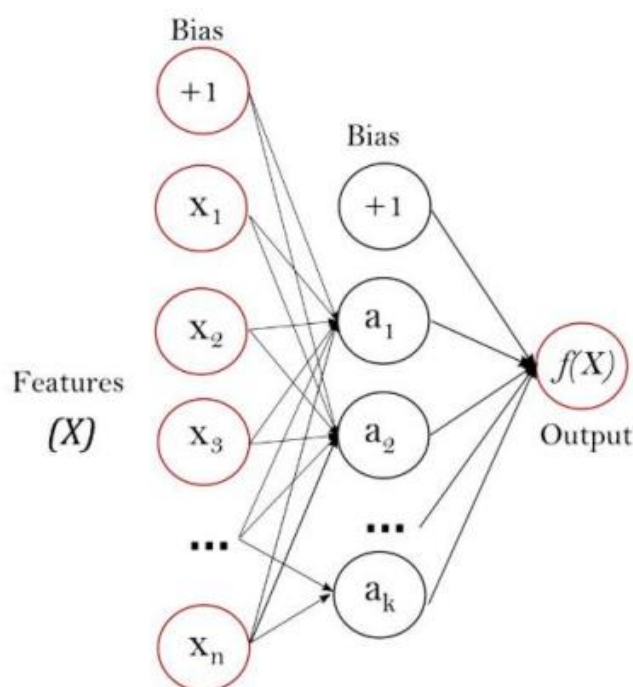


Figure 1. Basic architecture of a multilayer perceptron (MLP)

Convolutional Neural Networks (CNN): Convolutional neural networks became influential when sports analytics began to engage more seriously with image-like and video-derived inputs. CNNs are especially effective at extracting local spatial patterns, which makes them suitable for pose estimation, action recognition, technique analysis, and event detection from visual data. CNNs have revolutionized visual analysis, enabling automated action recognition from broadcast footage with accuracies exceeding 95% [6]. By transforming sensor time-series into 2D «images», CNNs can detect abnormal movement patterns that precede knee injuries [7].

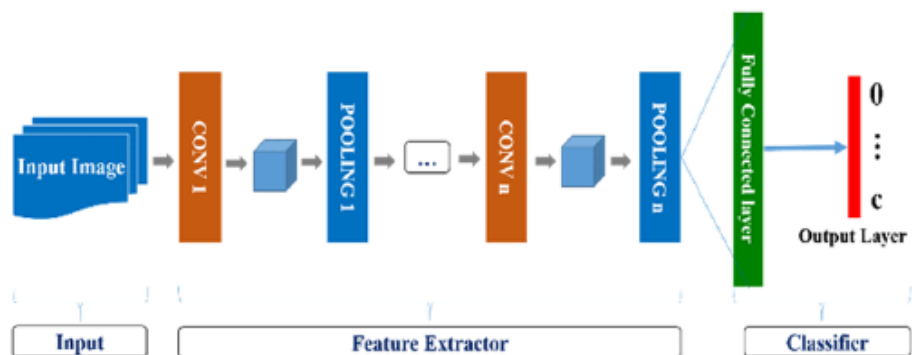


Figure 2. CNN classifier used in sports for injury prediction

Recurrent Neural Networks (RNN/LSTM/GRU): Since match results are inherently sequential, LSTMs are the gold standard for modeling a team's «form» over a season. LSTM and GRU variants, were adopted because many sports processes are inherently sequential. Match events unfold over time, workload signals evolve across sessions, and tactical behavior depends on prior states rather than isolated observations. Zhang et al. [8] proposed an attention-based LSTM for sports match prediction, combining temporal sequence learning with an attention mechanism and a sliding window to improve timeliness in football forecasting. Zhou and Zhu [9] similarly describe RNNs, LSTMs, and GRUs as suitable for sequential inputs such as positional data, event logs, and physiological streams, emphasizing their value in fatigue prediction, tactical pattern discovery, and performance forecasting.

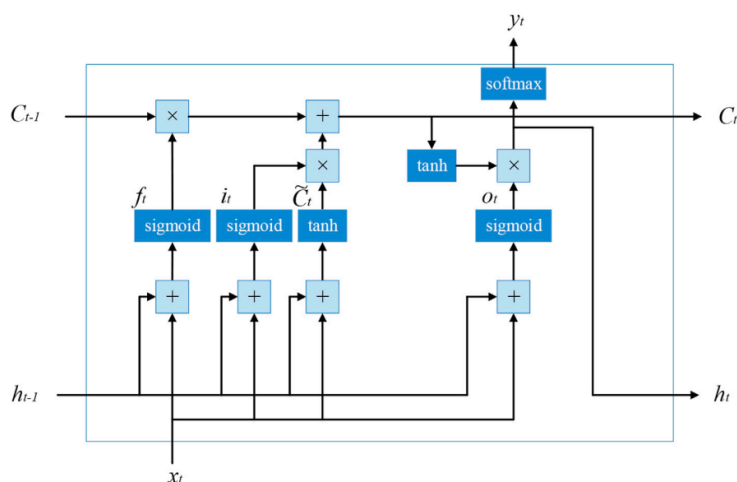


Figure 3a. LSTM unit for sports time-series modeling

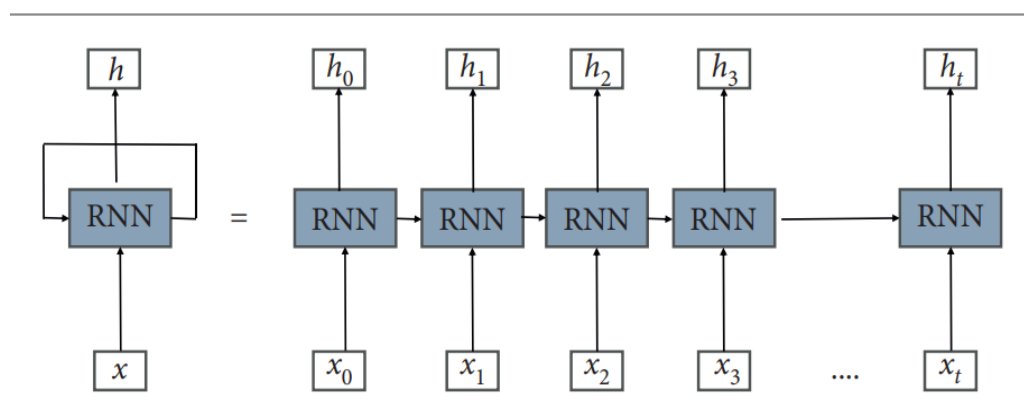


Figure 3b. RNN architecture for sequential sports data

CNN-LSTM and GNNs: Hybrid CNN-LSTM models capture both the spatial arrangement of players and the temporal evolution of a play, reaching up to 97% accuracy in movement recognition [7]. Their logic is straightforward: convolutional blocks learn spatial or local visual features, while recurrent units model how those features evolve through time. Pietraszewski et al. [6] explicitly note the growing use of CNN-LSTM hybrids for motion recognition and performance prediction across sports. Graph neural networks are especially suitable for team sports, where players are not independent units but connected agents whose influence is shaped by proximity, coordination, and opposition. Xenopoulos and Silva [4] report statistically significant gains from graph-based models over state-of-the-art baselines in both American football and esports, while also emphasizing their usefulness for «what-if» analysis and the visualization of interaction patterns. Systems like TacticAI use geometric deep learning to model symmetries on the pitch, allowing Liverpool FC to simulate «what-if» tactical adjustments for corner kicks [6; 9; 10].

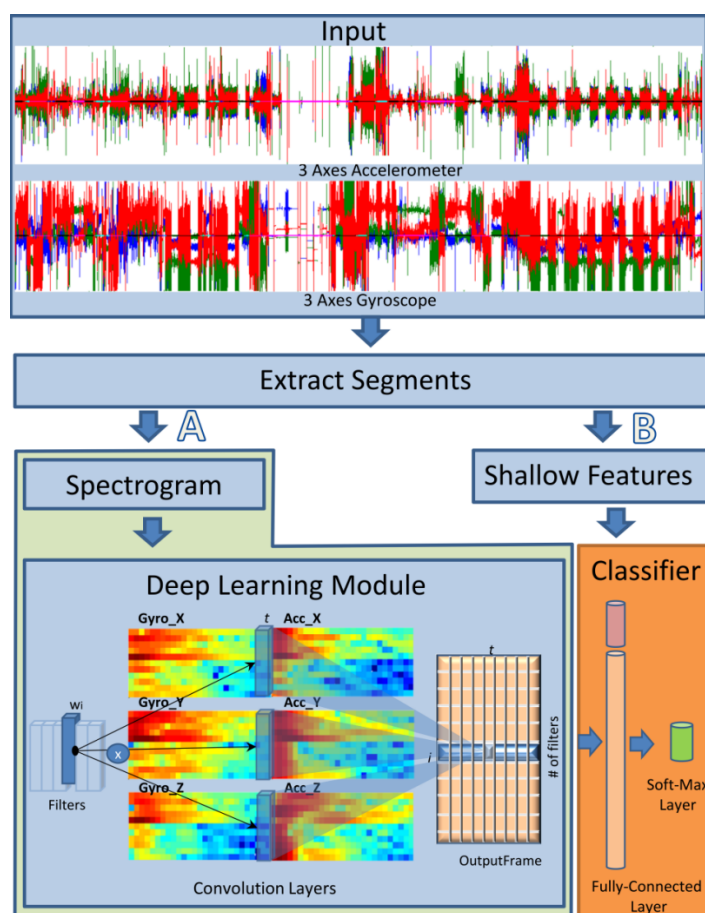


Figure 4a. Hybrid deep learning architecture for movement recognition

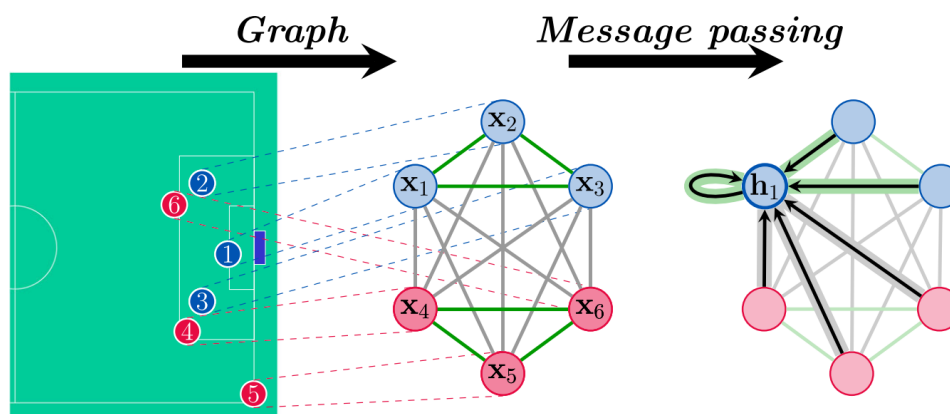


Figure 4b. Graph-based representation and message passing in team sports

Comparative synthesis: What works best, where, and why?

The rapid proliferation of algorithmic solutions in sports analytics has created a fragmented landscape where the «state-of-the-art» (SOTA) is often context-dependent. The central pattern is not that one model family dominates all tasks, but that performance depends on the match between data structure, sport context, and decision objective. In that sense, they ask which technique is best suited to a particular analytical problem, under particular data conditions, and with what trade-off in transparency, generalizability, and practical usability. Recent review work by Pietraszewski et al. [6] supports exactly this interpretation: across sports, deep learning tends to achieve higher pooled performance than classical machine learning, yet its advantages are uneven and strongly dependent on input modality, methodological rigor, and the realism of the evaluation setting.

Classical ML vs. Deep Learning: A recurring theme is that Artificial Neural Networks (ANNs) do not consistently outperform classical methods in every domain [4, 11]. In match outcome prediction using tabular historical data, classical classifiers like Random Forest (RF) and XGBoost frequently match or exceed the accuracy of Multi-Layer Perceptrons (MLP), particularly when datasets are structured and relatively small [12]. Roumani [11] demonstrated that RF was superior in identifying Super Bowl winners, while Markopoulou [12] found XGBoost to be the most effective for minimizing error in player scoring statistics. However, the balance of power shifts decisively toward Deep Learning when the task involves unstructured high-dimensional inputs, such as raw video or high-frequency tracking data [13; 14]. Meta-analyses indicate a pooled classification accuracy of 92.3% for DL architectures compared to 78.6% for classical ML across movement-intensive tasks [6]. This performative gap is most pronounced in action recognition, where CNNs achieve near-perfect classification [15; 16].

Table 2. Methodological Suitability Matrix Based on Data and Task Type

Data Modality	Leading Technique	Primary Strength	Accuracy Potential
Tabular/Historical	XGBoost / Random Forest	Interpretability & Handling Imbalance	~65% - 75% (Match Outcome)
Spatio-Temporal	GNN / TITAN	Preserves Relational Context	~85% - 90% (Tactical Analysis)
Video/Visual	CNN-LSTM / Swin Transformer	Automatic Feature Extraction	>95%(Action Recognition)
Wearable/Sensor	AS-LSTM / RNN	Models Sequential Fatigue	~90% (Injury Risk)

Tabular vs. Spatio-Temporal: While traditional models treat player variables as independent vectors, team sports are inherently relational. This insight marks the primary limitation of classical ML. Standard vector representations — which rely on keypoints or role assignments — often discard the local neighborhood information critical for tactical understanding. The emergence of GNN has bridged this gap. Xenopoulos and Silva [4] demonstrated that representing a game state as a fully-connected graph reduces test set loss by 9% in the NFL and 20% in esports. By treating athletes as nodes and interactions as edges, GNNs capture the micro-coordination that «box score» models miss. This trend culminates in architectures like TITAN, which utilizes dual-stream encoders to jointly model temporal event sequences and player interaction graphs, capturing both short-term shifts and long-range game dynamics [9].

Team vs. Individual sports: Team sports exhibit higher model performance (89.7%) compared to individual sports (81.2%), likely due to the richer data environments and the multi-agent nature of the feedback loops [6]. In contrast, individual sports focus heavily on pose estimation and biomechanics. For instance, computer vision models achieve up to 98.6% accuracy in tennis shot classification [17], whereas match outcome prediction in baseball remains methodologically challenging when based on statistics alone, particularly because performance is shaped by complex game structure and context [18].

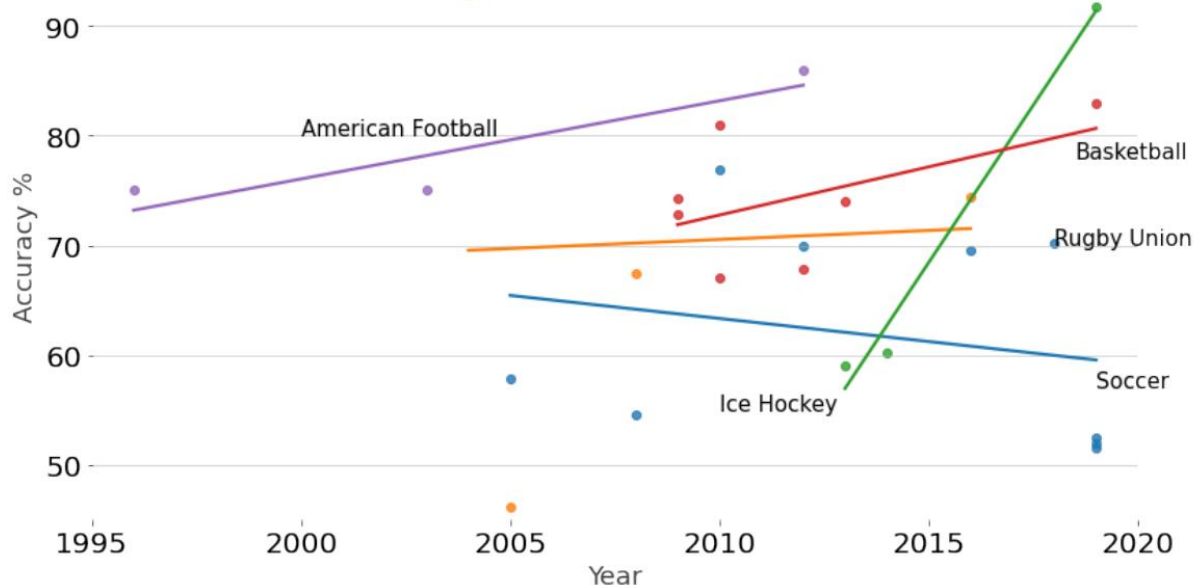


Figure 5. Historical Accuracy Trends for Match Outcome Prediction

What works best?

In summary, XGBoost and Random Forest remain the gold standard for match forecasting where data is tabular and experts require transparency [11; 12]. CNN-LSTM hybrids and GNNs are unrivaled for tactical modeling and action recognition, provided high-fidelity tracking data is available [4, 6]. The future of the field belongs to hybrid architectures like TITAN and TacticAI, which merge the representational power of deep learning with domain-specific knowledge to provide insights that are not only accurate but also actionable and trustworthy [19; 20].

Conclusion

The comprehensive synthesis of literature confirms that sports has undergone a permanent metamorphosis: it is no longer just a game of intuition, but a high-stakes «game of data». This review has demonstrated that Artificial Intelligence and Neural Networks have moved from the periphery of sports science to its very center, providing the computational «eyes» needed to decode the complexities of elite performance.

Two primary conclusions emerge from analysis:

- While classical ML methods remain superior for small, tabular datasets, deep learning architectures are unrivaled in processing high-dimensional spatio-temporal data, consistently achieving recognition accuracies [13; 14].
- The emergence of GNNs represents a paradigm shift. By treating teams as dynamic, interconnected graphs rather than independent vectors, AI can finally capture the coordinative nuances that define winning tactics [6; 10].

In the final analysis, AI is not intended to replace the human element of coaching but to augment it, stripping away cognitive biases and replacing them with objective, probabilistic insights. By addressing the current research gap we can ensure that the next generation of sports analytics is not only more accurate but also more transparent, ethical, and actionable. This review provides the fundamental evidence-based foundation for that development, charting a course toward a truly intelligent future for professional sports.

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ЖАСАНДЫ ИНТЕЛЛЕКТ ПЕН НЕЙРОНДЫҚ ЖЕЛІЛЕР АРҚЫЛЫ СПОРТТЫҚ АНАЛИТИКАНЫ ЖАҚСARTУҒА АРНАЛҒАН ЖҮЙЕНІ ӘЗІРЛЕУ

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Андатпа. Оқиғалар журналдары, трекинг ағындары, бейнежазбалар, киілетін құрылғылар сигналдары және биомеханикаға қатысты өлшемдерді қамтитын спорттық деректер көлемінің қарқынды өсуі спорттық нәтижелілікті зерттеу, түсіндіру және оңтайландыру тәсілдерін түбегейлі өзгертті. Бұрын қолмен бақылау мен дәстүрлі статистикаға негізделген талдау бүгінде үлкен, гетерогенді және жоғары жиілікті деректер жиынтықтарынан заңдылықтарды анықтай алатын жасанды интеллект әдістерінің қолдауына көбірек сүйенеді. Осы шолу мақаласының мақсаты — қазіргі спорттық аналитикада қолданылатын машиналық оқыту мен терең оқытудың негізгі тәсілдерін жүйелеу, әсіресе үш негізгі қолдану саласына назар аудару: матч нәтижелерін болжау, тактикалық және кеңістіктік-уақыттық талдау, сондай-ақ жарақат қаупін бағалау мен оның алдын алу. Мақалада регрессия, шешім ағаштары, кездейсоқ ормандар, тірек векторлар әдісі және градиенттік бустингтен бастап жасанды нейрондық желілерге, сверткалық нейрондық желілерге, рекурренттік архитектураларға және графтық модельдерге дейінгі кең таралған әдістерді қолдану жинақталып қарастырылады. Әсіресе трекинг деректері, оқиға деректері, физиологиялық көрсеткіштер және биомеханикалық индикаторлар пайдаланылатын зерттеулерде деректер модальдігі мен модель таңдауының өзара байланысына ерекше назар аударылады. Әдіснамалық үрдістерді жалпылаумен қатар, шолу жасанды интеллектке негізделген жүйелердің жаттықтырушылық шешімдерді қолдауға, ойыншыларды бағалауға, жүктемені мониторингтеуге және тактикалық шешім қабылдауға қалай ықпал ететінін қарастырады. Жинақталған дәлелдер жасанды интеллект пен

нейрондық желілердің эксперименттік қолдану шегінен шығып, қазіргі спорттың орталық аналитикалық инфрақұрылымына айналып келе жатқанын көрсетеді. Сонымен бірге деректердің гетерогенділігі, интерпретацияның шектеулілігі, валидация хаттамаларының бірізді болмауы және бақыланатын ортадан нақты жарыс жағдайларына нәтижелерді көшірудегі қиындықтар сияқты елеулі шектеулер сақталуда. Жалпы алғанда, бұл шолу жасанды интеллектке негізделген спорттық аналитиканы жоғары практикалық маңызы бар және спорттағы жаңа буын интеллектуалдық жүйелерін дамыту үшін айқын өзектілігі бар қарқынды дамып келе жатқан сала ретінде сипаттайды.

Түйін сөздер: спорттық аналитика, жасанды интеллект, трекинг деректері, оқиға деректері, матч нәтижелерін болжау, тактикалық талдау, жараматтың алдын алу.

РАЗРАБОТКА СИСТЕМЫ ДЛЯ УЛУЧШЕНИЯ СПОРТИВНОЙ АНАЛИТИКИ С ПОМОЩЬЮ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА И НЕЙРОННЫХ СЕТЕЙ

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Аннотация. Стремительный рост объемов спортивных данных, включая журналы событий, потоки трекинг-данных, видеозаписи, сигналы носимых устройств и биомеханические измерения, фундаментально изменил способы изучения, интерпретации и оптимизации спортивной результативности. То, что ранее опиралось преимущественно на ручное наблюдение и традиционные статистические методы, сегодня всё в большей степени поддерживается системами искусственного интеллекта, способными выявлять закономерности в крупных, гетерогенных и высокочастотных массивах данных. Цель данного обзора — систематизировать основные методы машинного и глубокого обучения, применяемые в современной спортивной аналитике, с особым акцентом на трёх ключевых прикладных направлениях: прогнозирование исходов матчей, тактический и пространственно-временной анализ, а также оценка и предотвращение риска травм. В статье обобщается применение широко распространённых подходов — от регрессии, деревьев решений, случайных лесов, машин опорных векторов и градиентного бустинга до искусственных нейронных сетей, сверточных нейронных сетей, рекуррентных архитектур и графовых моделей. Особое внимание уделяется взаимосвязи между типом данных и выбором модели, особенно в исследованиях, использующих трекинг-данные, данные событий, физиологические показатели и биомеханические индикаторы. Помимо обобщения методологических тенденций, обзор рассматривает, каким образом системы на основе искусственного интеллекта способствуют поддержке тренерских решений, оценке игроков, мониторингу нагрузок и тактическому анализу. Представленные данные свидетельствуют о том, что искусственный интеллект и нейронные сети вышли за пределы экспериментального использования и становятся центральной аналитической инфраструктурой современного спорта. Вместе с тем сохраняются существенные ограничения, включая гетерогенность данных, ограниченную интерпретируемость, несогласованность протоколов валидации и трудности переноса результатов из контролируемых условий в реальные соревновательные среды. В целом данный обзор рассматривает спортивную аналитику на основе искусственного интеллекта как быстро развивающуюся область, обладающую высокой практической значимостью и очевидной актуальностью для разработки интеллектуальных систем нового поколения в спорте.

Ключевые слова: спортивная аналитика, искусственный интеллект, трекинг-данные, данные событий, прогнозирование исходов матчей, тактический анализ, предотвращение травм.