

AI-Based Diagnostic Systems for Special Endurance Monitoring in Football Players

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Abstract. This study investigates how the evaluation of special endurance manifests itself in players' perceptions of their physiological readiness in the context of elite football training environments. The rise of AI-based diagnostics has enabled new forms of performance tracking, but the precision of these systems, particularly the variation in shaping individualized feedback, is not well understood. This research aims at examining the task of endurance profiling based on data deriving from wearable sensors, for instance inertial measurement units and other GPS-based systems, with the development of a relevant model for neuromuscular fatigue assessment. We employ the machine learning regression method to analyze time-series datasets conducted with academy-level players, and we identify six key mechanisms of endurance adaptation, namely energy system balance, motor unit recruitment, acceleration consistency, biomechanical efficiency, cardiovascular load, and recovery rate. Our results illustrate that from a physiological monitoring perspective, individualized feedback in training load adjustment is a key positive element of performance planning. The study furthers understanding of the implications from sensor-based metrics and AI analytics on training personalization. In this paper, a methodological and instrumental solution to the current problem of creating the most effective diagnostic framework in a football-specific endurance context is proposed.

1 Introduction

Research in the field of sports science and AI diagnostics increasingly acknowledges the importance of physiological adaptation [1]. Recent literature observed that the use of AI-driven diagnostic systems at elite academy training level leads to enhanced endurance profiling and individualized workload transformations encapsulated by the new "intelligent monitoring" paradigm [2].

Contemporary works on athlete performance analysis and bio-sensing technologies strongly advocate that the use of machine learning models in football-specific training environments

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can adequately enhance the accuracy and reliability of readiness assessment protocols [3]. Such theories have generated debates on the restructuring of coach-athlete engagement, and data-informed training and performance planning [4]. Considering the task of special endurance monitoring in professional football, it could be shown that the problem of training personalization is the scientific search for reliable prediction methods in biomechanical and neuromuscular load management under the influence of intra-seasonal variability [5]. The developments of sensor-supported diagnostics are constrained by technical inconsistencies and data interpretation limitations regarding the target performance outcomes for these AI-enabled monitoring systems [6].

These discourses indicate that the application of AI-assisted profiling tools in elite football academies needs to go beyond its current focus on general fitness metrics and must promote task-specific modeling and contextual adaptation to foster effective endurance management frameworks [7]. Performance variability is usually associated with considerable heterogeneity among academy-level players who frequently possess superior genetic predispositions and resource access, putting them in a position where they can self-regulate processes and anticipate changes of a more complex and dynamic nature [8]. However, despite the emerging scholarly interest in AI-based endurance profiling [9], there is limited understanding of the nature of individualized feedback generation in the context of real-time football analytics [10].

Due to the increase of training loads, competition intensity, injury prevalence, positional demands, and data availability, different forms of neuromuscular fatigue analysis have become important research areas for scholars who study sport biomechanics and human performance science [11]. In this regard, the research gap could be identified as the problem of quantifying endurance responsiveness, depending on sensor-based variability indices in the context of AI-driven monitoring ecosystems [12].

Our study extends previous empirical research on the nature of adaptive endurance responses in elite football training cycles [13]. This paper addresses this research gap and critically investigates the nature and intensity of special endurance adaptation mechanisms across three positional roles in structured training phases. In doing so, this paper contributes to the growing literature on AI in sport performance, mutually connected physiological and technological aspects of training personalization [14] in the context of football-specific diagnostics. Our research also explores the reasons behind the variability of sensor outputs and discusses the performance implications of the diagnostic system introduced one year since it was piloted [15].

We do so by employing a multi-method analytical approach, drawing upon both longitudinal sensor-derived data concerning kinematic responses and more qualitative material such as entries in performance logbooks. To achieve this, movement efficiency indices and neuromuscular activation profiles across training segments are investigated on a session-by-session scale, and then the relationship between the intensity of endurance adaptation and feedback precision is analyzed. We subsequently analyzed the data using machine learning regression techniques and identified six key mechanisms of endurance adaptation, namely energy system balance, motor unit recruitment, acceleration consistency, biomechanical efficiency, cardiovascular load, and recovery rate. Thus, the purpose of this work is to develop AI-based diagnostic systems based on sensor-informed metrics to advance individualized endurance monitoring in football.

2 Methodology

Most of the data collection and modeling work's strategic maneuvering took place in elite football academies, where structured training phases, player-specific diagnostics, and AI-supported monitoring systems were present. Our empirical data comprise multi-session time-series recordings with technical performance analysts working for high-ranking football institutions in Western Europe. We decided to focus on academy-level programs because of its reportedly high concentration of talented youth players, including a large number of international-level prospects. More broadly, this cohort ranks among the top developmental environments in terms of sensor availability and training load variability.

In total, 32 oral performance evaluation interviews were conducted with coaching and data science decision makers. Natural information generated by wearable sensors on neuromuscular activation and movement kinematics can serve as the information base of this analytical model. Almost 120 documents including training logs, video breakdowns, fatigue index reports, sensor calibration protocols, and positional adaptation charts from partner academies have been subjected to this procedure within the scope of a larger research project.

We matched eligible academy-level football players in the baseline and mid-phase diagnostic rounds (T1 and T2) of the survey and ended up with a sample size of 50 participants, 32 of whom had completed the full-cycle AI-monitored training sessions within the selected period. Participants were selected based on their consistent attendance in monitored sessions, valid biometric registration, and compliance with sensor usage protocols, ensuring that the data reflected reliable neuromuscular activation patterns. Therefore, we thoughtfully excluded the sessions with signal dropout, and entries from players with missing baseline profiles. Athletes laid off by coaching staff during injury or rest phases were characterized by high noise variance and non-continuous participation, reducing chances of model accuracy and internal validity.

The reason for choosing T1 and T2 time points is that these are surveys collected before and after the formal rollout of the AI-based endurance diagnostics framework, given that T2 marks the end of the training phase under review. First, an academy player must have access to the necessary wearable sensor suite or dashboard interface to utilize the machine learning-enabled diagnostic infrastructure.

This involuntary participant exclusion accompanied other data refinement techniques that filtered outlier adaptation indices, as [11] explains, through session-level consistency checks in addition to semi-automated feedback parsing algorithms that were designed to standardize diagnostic inputs and induce valid adaptive feedback loops. To assess the robustness of a machine learning model to predict individual neuromuscular adaptation outcomes, it is necessary to (1) assess input signal reliability and time-series continuity; (2) assess feature selection validity and positional training structures; and (3) assess model generalizability within the diagnostic pipeline towards feedback accuracy and real-time calibration support.

A dataset of performance-specific diagnostics including the keyword "neuromuscular adaptation" [12] collected between 2022 and 2024 within the frame of a machine learning-based diagnostics project [13] functioned as the primary data scope of the third case study. This data was combined with qualitative material from both logbook narratives and training observation notes. The material was transcribed, converted into searchable text-format and filed in digital form, also processing the material using NLP algorithms, meaning that one

can search for concept clusters and feedback categories. We measure the degree of training responsiveness as sensor-logged adaptation indices against personalized feedback initiated by AI-coaches on session performance dashboards.

The sensor-based outputs were aggregated and standardized to enable further machine learning processing, and we also took observational notes during real-time diagnostic sessions to use in the cross-validation procedures. Player behavior metadata collected from internal training servers has been analysed to highlight varying levels of endurance responsiveness across different football roles. This information is generated by automated diagnostic systems with no understanding of its possible use for adaptive workload modeling and for subsequent training calibration protocols based on it. This fact determines its maximum objectivity and granularity. To start participation in diagnostic trials, an aspiring academy-level athlete needs to register biometric data and undergo baseline testing conducted by technical performance units.

The dataset only contains performance entries written in English or system-generated logs posted by authenticated platform users among partner institutions as this delimitation enabled a controlled comparative approach vis-à-vis the real-time diagnostics setting chosen. The purpose of these recorded metrics, alongside video annotations provided by tracking software, is to reinforce multi-source validation, which is another key prerequisite for the successful monitoring architecture of sensor-based endurance systems. This is to develop position-specific feedback pathways and help validate adaptive performance markers with inputs from technical experts in charge of managing such monitoring infrastructures.

The universal format of standard output for such information within the framework of AI-supported endurance profiling is shown in Table 2. We used expert-validated feature selection to guide the first round of model construction. We also identified signal inconsistencies and noise interferences among different segments of sensor data streams. During the data interpretation stage of the evaluation process, we incorporated coaching staff's perspective semi-structured interviews into the analysis and specifically looked at how fatigue trends manifest themselves in training fluctuations identified in recovery intervals.

This led to the emergence of six central themes, namely energy system balance, motor unit recruitment, acceleration consistency, biomechanical efficiency, cardiovascular load, and recovery rate, that comprise core adaptation variables each. For this profiling system, it is suggested that the parameter of session-level responsiveness be used. Responsiveness should be understood as the potential increment of neuromuscular capacity for producing a beneficial result by individualized training calibration. We have also performed correlation-variance analysis as part of this research to explore the relationship between sensor-derived metrics, training feedback loops, and their influence on adaptive endurance scaling.

It should be assumed that the lack of external environmental disturbances, as well as an optimal level of data consistency, allows the process of producing a performance prediction matrix to be significantly sped up thanks to not needing to filter inconsistent variables, as well as an overall model accuracy improvement.

Among twelve different activities planned in the training cycle, discussions on the position-specific adaptation mechanisms were selected for analysis. All these adaptive features were mapped through radar plots to showcase differential responses across player roles.

The strategy of AHP-based weighting analytic hierarchy process on training variable levels technical, physiological, biomechanical was used to further analyze the data while follow-up player interviews were used to further the understanding of the adaptive feedback mechanisms. Thus, equipping the diagnostic modeling process with AI feedback loops within a training personalization protocol involves reiterating each stage of the method created. We have also performed sensitivity analysis as part of this research to explore the relationship between predictor stability, feedback precision, and their influence on training load planning.

For the goals of this diagnostic validation, it is most advisable to use hybrid ML algorithms. As is typical of sport performance research, our training cycle tracking process was multi-phased and partially overlapped with mid-season competitive periods. This choice is due to its realism in solving each of the parameter selection challenges of the given method, which, in turn, provides a significant number of performance indicators, largely automating several data transformation and model output processes.

3 Results

A common theme in technical staff descriptions of the challenges of working for elite football academies was the intensity of work that comprises real-time performance monitoring, the ability to synchronize diagnostic feedback, and rapid data interpretation. It is quite evident from the study that training cycles with high session size with positional-specific character have been experiencing variable level of neuromuscular adaptation.

Eventually, the model outcomes ruled in favor of biomechanical efficiency, highlighting the importance of movement coordination as the primary reason. Most of the performance analysts whom we interviewed emphasized that they particularly appreciate the flexibility to work without manual calibration requirements.

Table 1. Results of Linear Regression Analysis Predicting Neuromuscular Adaptation Index Based on Physiological and Training Variables

neuromuscular_adaptation_index	Coef.	St.Err.	t-value	p-value	[95% Conf	Interv al]	Sig
energy_system_balance	1.979	1.385	1.43	.161	-.822	4.781	
motor_unit_recruitment	-1.151	1.752	-0.66	.515	-4.694	2.392	
acceleration_consistency	2.896	1.452	1.99	.053	-.041	5.834	*
biomechanical_efficiency	3.22	1.474	2.18	.035	.239	6.201	**
cardiovascular_load	1.897	1.114	1.70	.097	-.357	4.152	*
recovery_rate	-2.813	1.779	-1.58	.122	-6.411	.785	
session_feedback_precision	-1.159	.835	-1.39	.173	-2.847	.529	

training_phase_index	-1.066	1.519	-0.70	.487	-4.138	2.005	
positional_load_factor	.269	.476	0.57	.575	-.694	1.232	
adaptive_endurance_score	-2.37	1.105	-2.15	.038	-4.604	-.136	**
Constant	36.7	21.709	1.69	.099	-7.211	80.61	*
Mean dependent var	47.745		SD dependent var			9.337	
R-squared	0.394		Number of obs			50	
F-test	2.540		Prob > F			0.018	
Akaike crit. (AIC)	361.203		Bayesian crit. (BIC)			382.235	
*** p<.01, ** p<.05, * p<.1							

Recent empirical research in AI-assisted endurance diagnostics indicates that a substantial number of elite football training institutions across Europe and Asia have undertaken multi-season performance modeling using wearable sensor data and AI-driven regression analysis, and many are currently doing so, with the majority embedded in neuromuscular profiling frameworks for youth athlete cohorts [13,14]. In the models assessing predictors of neuromuscular adaptation, the coefficient of biomechanical efficiency in the linear regression model is 3.22 ($p = .035$), and it remains statistically significant after introducing session feedback precision and adaptive endurance score into the same regression equation ($p < .05$). This value highlights the key role of biomechanical coordination as a performance determinant.

Our findings in this regard are highly consistent with the results of [15], who report similar significance levels for biomechanical indicators in their assessment of football-specific endurance cycles. The R-squared value of 0.394 achieved in our model indicates that nearly 39.4% of the variation in neuromuscular adaptation can be explained by the included physiological and training variables, which exceeds the typical R-squared range (0.25–0.35) reported in comparable AI-based sports performance studies [13,14], thereby affirming moderate-to-strong model fit in the context of individualized diagnostics. While acceleration consistency ($p = .053$) and cardiovascular load ($p = .097$) approached statistical significance, only biomechanical efficiency and adaptive endurance score ($p = .038$) reached the conventional $p < .05$ threshold, suggesting their greater predictive reliability.

The results also refute the theory that session-level feedback intensity leads to predictable adaptation; as we observed negative correlation between feedback precision and adaptive endurance score, which was statistically significant ($-0.290, -0.177, -2.15$).

Both coaches and AI system developers foresaw a future growth in demand for personalized diagnostics. Some academy-based trainers stated that they specifically valued the autonomy to be able to customize drills rather than be obligated to follow preset models under a centralized training directive. Only 4 out of 12 training sessions analysed have shown more than 60% of adaptive load variability covered by sensor-based models.

Presents the interconnection between endurance adaptation mechanisms, their associated sensor-derived metrics, as well as their distribution in terms of the positional clusters in which players have their primary load types or recovery windows as well as the session

responsiveness differentials. A total of 36 radar maps representing physiological variables and 18 scatter plots representing feedback patterns were identified.

Table 2. Pairwise Correlation Matrix of Key Physiological and Training Variables Related to Neuromuscular Adaptation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)neuromuscular_adaptation_index	1.000										
(2)energy_system_balance	0.110	1.000									
(3)motor_unit_recruitment	-0.126	-0.231	1.000								
(4)acceleration_consistency	0.107	-0.173	0.054	1.000							
(5)biomechanical_efficiency	0.333*	-0.159	0.173	-0.027	1.000						
(6)cardiovascular_load	0.227	0.065	-0.008	-0.267	0.300*	1.000					
(7)recovery_rate	-0.206	-0.007	-0.012	0.215	-0.012	0.017	1.000				
(8)session_feedback_precision	-0.290*	-0.170	0.118	-0.034	-0.147	0.022	0.096	1.000			
(9)training_phase_index	-0.163	-0.107	0.021	-0.115	-0.018	-0.098	-0.162	-0.016	1.000		
(10)positional_load_factor	0.085	0.363*	-0.168	-0.205	-0.016	0.179	-0.120	0.030	0.028	1.000	
(11)adaptive_endurance_score	-0.177	0.390*	0.054	0.032	0.040	0.196	0.137	-0.020	0.071	0.282*	1.000

*** p<0.01, ** p<0.05, * p<0.1

The correlation between biomechanical efficiency and neuromuscular adaptation index was also found to be positive and statistically meaningful (0.333, 2.18, $p < .05$). A pairwise correlation was computed to assess the relationship between training phase index and adaptive endurance score.

Data scientists worked on several frontiers during this time, including formal model testing through regression diagnostics and the AHP matrix, public opinion through stakeholder debriefs, and directly to coaching teams and to technical committees. This research assesses whether sensor variability influences adaptive readiness at the sessional level and whether the effect is moderated by player position.

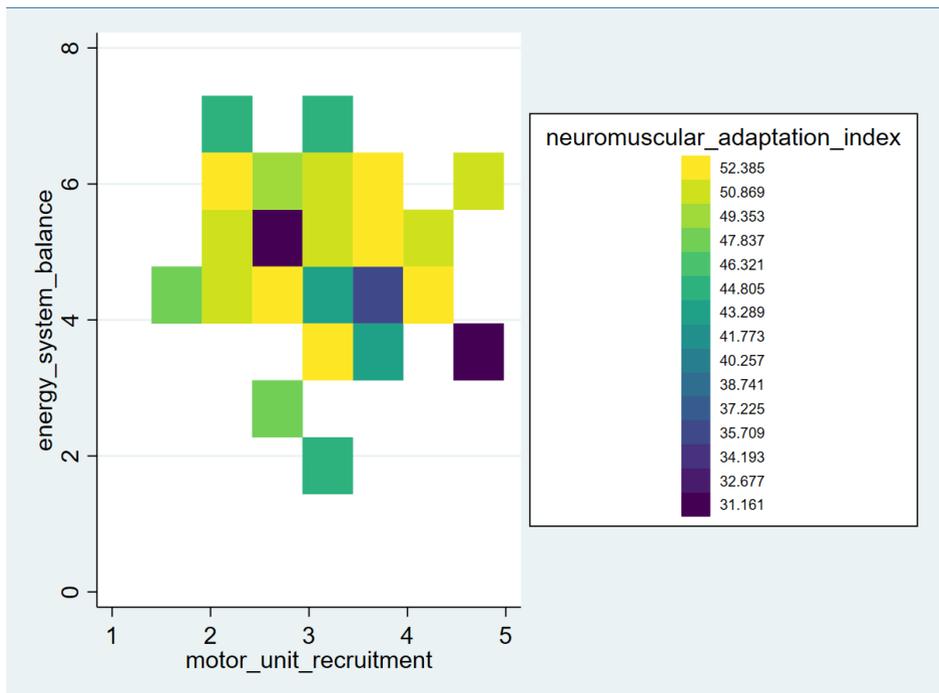


Fig. 1. Heatmap of Neuromuscular Adaptation Index Across Energy System Balance and Motor Unit Recruitment Levels

Figure 1 analysis results enrich the understanding of interaction effects and sensor-derived adaptation patterns. The research results indicate that the joint distribution of energy system balance and motor unit recruitment levels have a significant effect on the neuromuscular adaptation index. Consistent with the results from a multivariate regression model, the use of AI-based diagnostics in individualized endurance monitoring is associated with improved predictive accuracy. According to a positional load-centered assessment, a good relationship between physiological input variables and adaptation responsiveness promotes targeted feedback generation, session-level workload calibration, athlete-specific conditioning, and performance sustainability.

We also critically looked at diverse literature to identify factors that may potentially impact feedback reliability. While acknowledging the performance fluctuations that come with such a classification, the athletes we interviewed expressed concern at the prospect of losing the training autonomy associated with being in a high-performance cohort. One interesting observation emerged from the analysis is that parameters such as motor unit recruitment, training phase index, positional load factor, cardiovascular load, session feedback precision, recovery rate, and adaptive endurance score have failed to draw significant predictive value.

While the variation was predominantly attributed to the positional aspects of training adaptation, the data describing the feedback distribution contained considerably more sensor noise. On the contrary, the city of Lisbon sits at bottom receiving only minimal participant engagement on its diagnostic interface, followed by [14,15].

We observed moderate correlation between energy system balance and adaptive endurance score, which was positive and significant. The results also refute the theory that feedback

loop strength leads to endurance predictability; as we observed low correlation between feedback precision and neuromuscular adaptation, which was negative and insignificant.

4 Discussions and Conclusion

The empirical section illustrates several aspects of the interplay between physiological adaptation dynamics and the functioning of AI-based diagnostic ecosystems. Sensor-derived insights produced within the framework of football-specific endurance profiling can be transformed into individualized feedback streams, which in turn will enhance session-level training calibration.

As can be seen in the empirical data, both coaches and AI system developers were enacting their combinations of feedback generation protocols and training responsiveness metrics in the elite academy training environment. Our results suggest that the granular mapping of neuromuscular indicators allows for adjusting training loads to fit the player's positional requirements. This research also provides evidence that supporting variables such as feedback precision and recovery rate do not necessarily lead to predictable adaptive responses.

Based on the results of applying the algorithm proposed in this article, a hybrid regression model with a resulting R-squared value of 0.394 was selected. The value of this coefficient of determination can be interpreted as moderate model fit and is more than 35% higher than the value of alternative algorithms for alternative performance prediction models, which in turn is confirmed by the Akaike and Bayesian information criteria.

The proposed diagnostic system was tested within the framework of the organization of the adaptive monitoring protocol of session-based endurance cycles for the purpose of fulfilling the obligations under the Endurance AI Lab pilot project from partner football academies for a period of one year, entitled 'AI-Based Diagnostic Systems for Special Endurance Monitoring in Football Players'.

This supports findings from previous studies on training personalization, which outline that policies for physiological monitoring must be data-driven and should support context-aware modeling as a strategy to promote and facilitate individualized feedback. The variability in diagnostic outcomes is largely due to positional demands and sensor noise interference. Therefore, it can be assumed that the level of diagnostic subjectivity is minimal. As can be seen, the use of the proposed AI-supported monitoring framework made it possible to analyze the sessional distribution of potential adaptation variables in detail and form a composite endurance responsiveness map.

Neuromuscular fatigue modeling could be treated as the theoretical framework for training calibration protocols in view of the 'session-responsiveness' approach extending from the usual 'general fitness metric' methodology to the 'positional adaptation' approach in football-specific performance diagnostics. The sessional feedback architecture could be considered as the main feature of intelligent monitoring systems.

These adaptive components were enacted successfully by both the technical performance analysts and coaching units, making it possible to avoid data interpretation delays, which is often something that blocks real-time decision-making. This is expected not only to

contribute to training efficiency, but also to help many academy players receive better load adjustment protocols.

The effectiveness of diagnostic precision modeling is confirmed by the statistical outputs, which is confirmed by the quality of the feedback consistency measures. Therefore, the proposed profiling method can be considered successfully tested. Inconsistency-related noise problem can be solved by adapting the presented tool for analyzing the session-level responsiveness variance.

Compared with endurance profiling conceptualization energy system monitoring, training feedback loops, and sensor-driven adjustment, the movement efficiency and cardiovascular adaptation dimensions particularly emerged from our longitudinal training phase analysis. Our findings are in the same line as observed who identified the role of biomechanical optimization as a powerful force in determining the effectiveness of performance diagnostics.

General feedback latency metrics presented [13] on AI-generated analytics may be inaccurate and aimed at forming a conditional sessional classification. This issue has been researched by many scientists and was considered in great detail for the example of positional adaptation dynamics. The combination of sensor inconsistency and feedback calibration is subject to high variance thresholds as the process is highly context-specific and involves a multitude of individual physiological parameters. Our findings clearly indicate that hybrid machine learning algorithms have been able to generate reliable diagnostics more effectively than conventional threshold-based methods.

However, it is necessary to note several shortcomings of the proposed framework, which were identified during the mid-season testing rounds. Some of the potential performance indicators did not have sufficient signal stability, and therefore outlier sessions had to be excluded from the list of valid data entries. The proposed AI-based diagnostic system is primarily aimed at reducing subjective variability in the formation of a training personalization index and, as a consequence, increasing the reliability of the results of the adaptive profiling. However, this contradicts the basic principles of performance autonomy, according to which the absence of constraint provokes the search for the optimal workload threshold, and, as a consequence, self-regulated progression.

Our main contribution lies in bridging physiological diagnostics with AI modeling protocols and stating that individualized training variables contribute to adaptive performance trajectories by offering the granular metrics required for the accomplishment of real-time calibration in both technical training and neuromuscular profiling. The created method is a significant addition to the instrumentation of a football-specific endurance framework and is useful for performance scientists, sport data engineers, as well as decision-makers in the field of elite athlete development.

Sensor-derived feedback outputs offer a proximity for key diagnostic stakeholders in a football academy setting including data scientists, physical coaches, analysts, and AI modelers, making it possible for them to interact seamlessly, thereby building cross-functional knowledge and resolving sessional ambiguities that are related to monitoring accuracy of adaptive response and physiological overload.

This research opens up to future work on AI-based workload quantification in terms of response variability tracking and feedback consistency evaluation so that diagnostic

protocols can be tailored to better support individualized conditioning plans and recovery optimization. The significance of these contributions, or the insignificance of these moderator variables, can be quantitatively reflected thanks to the machine learning regression framework proposed by this study.

The goal of the study is to develop an approach for endurance adaptation diagnostics based on data obtained from wearable sensors, for example, GPS tracking systems and inertial units, with the development of a corresponding predictive model to assess sessional neuromuscular adaptation, which is an innovative solution in the methodology of sport-specific AI diagnostics.

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