International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 3, March 2026)

Holistic Athlete Performance Analyzer with Real-Time Fatigue Prediction

Priyanga G[1], Hemanth Krishna G[2], Mithun S[3], Nishanth C[4], Syed Farook S[5]

[1]*Dept. of Information Technology, Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India*
[2]*Dept. of Information Technology, Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India*
[3]*Dept. of Information Technology, Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India*
[4]*Dept. of Information Technology, Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India*
[5]*Dept. of Information Technology, Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India*

***Abstract*— Athlete performance evaluation is traditionally based on subjective observation and isolated performance metrics, which may not accurately reflect real-time physiological conditions. This paper presents a holistic athlete performance analyzer with real-time fatigue prediction using an integrated multi-sensor system. The proposed system combines ECG, GPS, IMU, and pressure sensors with an ESP32 microcontroller to collect and process physiological and motion data simultaneously. Timestamp-based synchronization ensures accurate multi-sensor data fusion for reliable analysis. The collected data are processed using Principal Component Analysis (PCA) and machine learning techniques to classify fatigue levels and cluster player performance patterns. The system provides an objective, data-driven approach for monitoring athlete performance, supporting coaches in decision-making, injury prevention, and optimized training strategies. Designed as a low-cost and scalable solution, the proposed model enables efficient real-time monitoring and performance assessment in sports environments.**

***Keywords*—Athlete Monitoring, Biomechanical Analysis, ECG-Based HRV Fatigue Detection, Edge Computing, Embedded Systems, FSR, Gait Analysis, GPS Tracking, IMUSensor, Machine Learning, Multi-Sensor Fusion Performance Profiling, PCA, Real-Time Data Synchronization, Sports Analytics, Wearable IoT, and GMM.**

I. INTRODUCTION

The monitoring of athletes in competitive sports has changed due to the quick development of wearable sensor technologies. In addition to physiological indicators like heart rate and cardiovascular strain, contemporary monitoring systems gather comprehensive biomechanical data like speed, acceleration, sprint distance, and geographical coordinates. The efficiency of these systems for quick tactical adjustments is limited because most performance evaluations are carried out after training sessions, despite the fact that they offer extensive datasets. Because sports performance is multifaceted and dynamic, real-time interpretation of complex sensor data continues to be a significant difficulty. One important aspect affecting injury risk, performance decrease, needs is athlete weariness.

It is necessary to examine both internal physiological reactions and external workload indicators in order to accurately predict weariness. Nevertheless, current monitoring methods frequently handle these factors separately, which lowers the forecasting accuracy of the data. The demand for integrated systems that can glean valuable insights from ongoing data sources is rising. Coaching decisions can be supported and performance transparency increased using a comprehensive analytical framework that integrates statistical modelling, machine learning, and explainable AI. This study offers a paradigm for dynamically predicting tiredness and assessing performance during high-intensity exercises.

A. Purpose of the Research

The primary purpose of this research is to develop an integrated and intelligent framework capable of evaluating athlete performance and predicting fatigue in real time through the fusion of multiple data modalities. Modern sports environments generate large volumes of sensor data, yet the lack of unified analytical models limits their practical utility. The research aims to bridge this gap by combining biomechanical movement metrics, physiological indicators, and temporal performance trends into a single interpretable performance index. By leveraging dimensionality reduction techniques and machine learning algorithms, the system seeks to transform raw sensor streams into structured insights that can support tactical decision-making during live sessions. suitable for professional and competitive sport environments.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 3, March 2026)

Coaches often depend on visual assessment and experience to judge fatigue levels, which may lead to inconsistencies or delayed interventions. The proposed framework introduces automated, data-driven fatigue prediction capable of identifying early performance decline.

B. *Need for tri – modal system*

Effective athlete performance analysis requires comprehensive monitoring of both external workload and internal physiological response. A tri-modal sensor approach integrates three complementary data streams: biomechanical movement data, physiological heart rate signals, and temporal progression patterns. Each modality captures a distinct dimension of performance, and their integration provides a more accurate and holistic assessment than any single source alone. The first modality, biomechanical sensing, typically obtained through GPS and inertial measurement units, captures metrics such as speed, acceleration, sprint distance, and positional changes. These indicators quantify external load and mechanical stress applied during activity. However, external workload alone does not reflect the athlete's internal physiological strain. The second modality, physiological sensing, primarily through heart rate monitoring, provides insight into cardiovascular response, exertion levels, and recovery capacity. Heart rate variability and time spent in high-intensity zones reveal internal load, which is critical for fatigue assessment. Nonetheless, physiological data without movement context may not fully explain performance variations.

The third modality involves temporal modeling of performance evolution across sequential time windows. Performance and fatigue are dynamic processes that develop progressively during activity. By incorporating time-series analysis, the system captures trends, volatility, and rate of decline, enabling predictive fatigue estimation rather than static evaluation.

C. *Existing System*

Athlete monitoring systems primarily rely on single-sensor devices such as GPS trackers or heart-rate monitors. These systems measure either external workload, like speed and distance, or internal physiological response, such as heart rate, but rarely integrate both in a unified framework. As a result, performance evaluation remains fragmented and incomplete. In many cases, fatigue assessment depends heavily on subjective observation by coaches, leading to variability and potential bias in decision-making. Most current platforms provide post-session reports rather than real-time insights, limiting their usefulness for immediate tactical adjustments during training or competition. Additionally, synchronized analysis between biomechanical and physiological parameters is often lacking, reducing the ability to accurately detect fatigue patterns or injury risk. Many commercial systems are expensive and designed for specific sports, restricting scalability and broader adoption. These limitations highlight the need for a more integrated, real-time, and data-driven performance analysis approach.

D. *Proposed System*

A tri-modal wearable framework that integrates ECG, GPS, IMU, and pressure sensors to capture both physiological and biomechanical performance indicators. Unlike traditional single-sensor systems, this approach enables synchronized multi-sensor data fusion using timestamp-based alignment, ensuring accurate correlation between internal and external workload parameters. Dimensionality reduction techniques such as Principal Component Analysis are applied to extract dominant performance features, while machine learning algorithms, including Gaussian Mixture Models, are used for fatigue profiling and player clustering. The architecture is designed as a low-cost and scalable solution built on ESP32-based edge devices, enabling efficient on-device preprocessing. The framework supports real-time performance monitoring, scouting analysis, and early injury risk detection, making it suitable for continuous and intelligent athlete management in modern sports environments.

II. BACKGROUND AND MOTIVATION

The increasing competitiveness in modern sports and the demand for peak athlete performance have intensified the need for accurate and continuous performance monitoring systems. Traditional performance assessment methods rely heavily on manual observation, post-match analysis, and isolated metrics such as total distance covered or average heart rate. These approaches often fail to capture the dynamic interaction between physiological strain and biomechanical workload during high-intensity activities. As competitions become faster and more physically demanding, delayed identification of fatigue can increase injury risk and negatively affect team performance.

The advancement of wearable technologies and wireless sensor networks provides an opportunity to transform athlete monitoring into a data-driven and real-time process. By integrating ECG, GPS, and IMU sensors, it becomes possible to continuously monitor heart-rate response, movement intensity, and acceleration patterns

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 3, March 2026)

simultaneously. A holistic performance analyzer enables synchronized multi-sensor data fusion, automated fatigue prediction, and objective performance evaluation. The motivation behind this system is to develop a scalable, cost-effective, and intelligent framework capable of supporting precision training, reducing injury risk, and enhancing overall athletic performance through real-time insights.

III. OBJECTIVES

1. To study existing athlete monitoring systems and identify their limitations in single-sensor and post-session analysis approaches.
2. To understand the requirements for developing a tri-modal sensor-based athlete performance monitoring system capable of synchronized physiological and biomechanical data fusion.
3. To design and develop a comprehensive framework for real-time athlete performance evaluation and fatigue prediction using PCA, machine learning, and explainable artificial intelligence techniques.

IV. LITERATURE SURVEY

Recent research in sports analytics highlights the growing importance of integrating wearable sensor data with machine learning techniques for performance evaluation. Traditional systems primarily rely on GPS tracking and heart-rate monitoring independently, focusing either on external workload metrics such as distance and speed, or internal physiological responses like cardiovascular strain. Several studies emphasize composite index construction using Principal Component Analysis (PCA) to summarize multidimensional performance variables into interpretable latent components. Advanced approaches incorporate temporal modelling and regression-based prediction techniques to estimate fatigue progression across sessions.

However, many existing models are retrospective in nature and designed for post-match analysis rather than real-time monitoring. While clustering techniques have been explored for player profiling, limited research integrates synchronized tri-modal sensor fusion, temporal sequence modelling, and explainable AI methods. The integration of heart-rate variability, acceleration zones, metabolic load, and PCA-derived composite indices into a unified fatigue prediction framework remains relatively underexplored.

This research addresses these gaps by combining multi-sensor fusion, PCA modelling, temporal machine learning, and SHAP-based explainability to deliver actionable insights for coaches and sports scientists.

V. PROPOSED METHODOLOGY

The proposed methodology consists of a multi-layered data acquisition, processing, and prediction framework designed for real-time athlete performance monitoring. The sensing layer integrates tri-modal wearable sensors including ECG for physiological load, GPS for spatial movement tracking, and IMU sensors for acceleration and biomechanical analysis. These sensors continuously collect high-frequency data during training or competition.

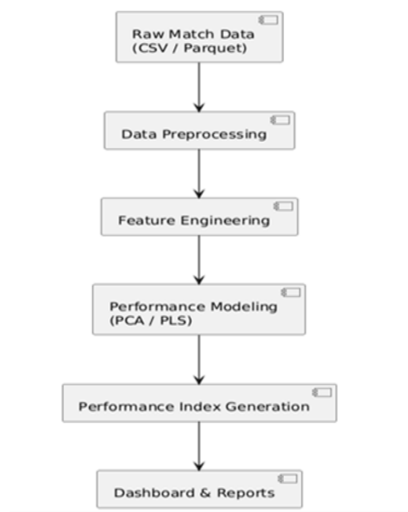

Fig. 1: Block Diagram of Proposed Methodology

The processing layer performs data cleaning, synchronization using timestamp alignment, and feature extraction. Movement metrics such as acceleration zones, speed zones, explosive distance, and high metabolic load are computed alongside cardiovascular indicators including HR mean, HR variability (RMSSD), TRIMP, and heart-rate zones. Principal Component Analysis is applied to reduce dimensionality and construct composite indices representing acceleration performance, high-intensity running, and medium-intensity activity.

VI. HARDWARE & SOFTWARE DESCRIPTION

The hardware architecture is centered around ESP32-based wearable edge devices designed for continuous physiological and motion monitoring.

The ESP32 microcontroller acts as the primary processing and communication unit, integrating an ECG sensor, GPS module, and IMU accelerometer into a compact wearable system. The ECG sensor captures cardiac electrical activity to derive heart rate, heart rate variability, and other stress-related indicators. The GPS module provides positional coordinates, distance, and speed data, while the IMU records acceleration, deceleration, and orientation patterns to analyze gait dynamics. All sensor signals are time-synchronized at the device level to ensure data consistency. The ESP32 performs preliminary signal conditioning and data structuring before transmitting synchronized packets through wireless communication protocols such as Wi-Fi or Bluetooth to a local processing unit or cloud server for advanced analysis.

The software framework is implemented using a Python-based data processing pipeline that ensures scalability and analytical robustness. Raw sensor data undergoes preprocessing steps including filtering, normalization, segmentation, and feature extraction using libraries such as NumPy and Pandas. Dimensionality reduction techniques like Principal Component Analysis (PCA) are applied to optimize feature space, while machine learning models from Scikit-learn, including Random Forest and Gradient Boosting, are used for classification and regression tasks related to fatigue detection and performance prediction. Scaling operations enhance model stability, and temporal sequence modelling supports trend forecasting over time. For model interpretability, SHAP (SHapley Additive Explanations) is utilized to provide feature-level insights into predictions, enabling transparent and explainable AI-driven decisions. A Streamlit-based interactive dashboard presents real-time visualizations, clustering outputs, fatigue categories, and explainability metrics, creating a comprehensive decision-support system for athlete monitoring and gait performance assessment.

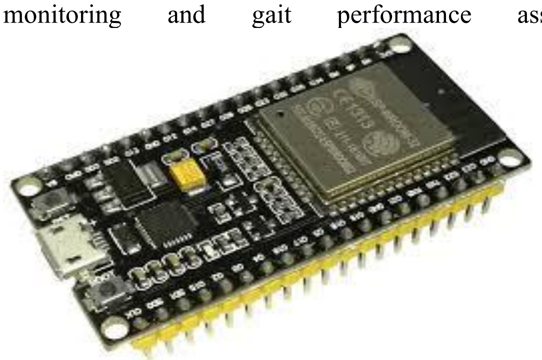

Fig. 2: ESP32

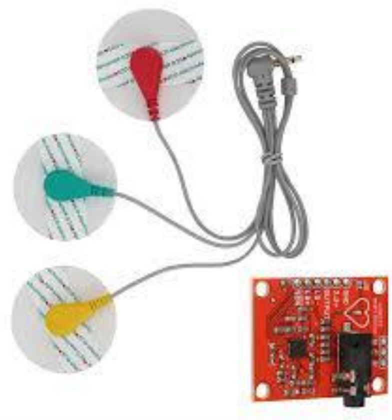

Fig. 3: ECG Sensor

Fig. 4: IMU Sensor

Fig. 5: GPS Neo 6m

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 3, March 2026)

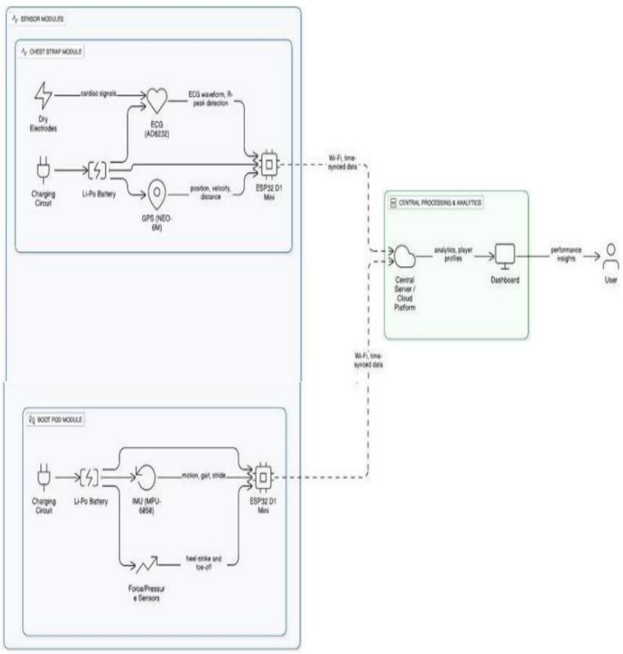

Fig. 6: Working Model Architecture

VII. RESULTS

The implemented system successfully demonstrated synchronized multi-sensor data processing and real-time fatigue prediction capability, validating the feasibility of integrating physiological and biomechanical signals within a unified wearable IoT framework. PCA analysis revealed three dominant latent components explaining the majority of performance variance, aligning closely with acceleration performance, high-intensity running intensity, and medium-intensity workload patterns. These components effectively reduced dimensional complexity while preserving critical performance information, thereby enhancing computational efficiency without compromising analytical depth. Temporal machine learning models exhibited stable and generalized predictive performance across training and testing datasets, with strong correlation observed between predicted and actual composite performance indices. The fatigue classification mechanism reliably detected sessions characterized by measurable performance decline, demonstrating robustness against data variability and noise.

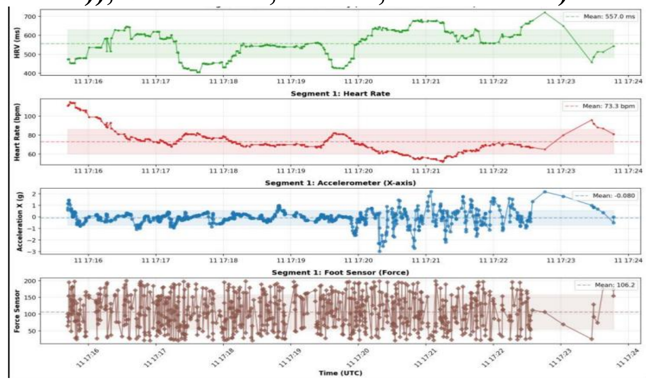

Figure 7 ECG Sensor Output Data

A	B	C	D	E
player_name	epoch_ms	time_utc_iso	latitude	longitude
PLAYER1	31207	1970-01-01T00:00:31.	13.0895	80.2739
PLAYER1	37007	1970-01-01T00:00:37.	13.0895	80.2739
PLAYER1	40127	1970-01-01T00:00:40.	13.0895	80.2739
PLAYER1	48507	1970-01-01T00:00:48.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:36.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:36.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:37.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:37.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:38.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:41.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:41.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:41.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:42.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:42.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:42.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:43.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:44.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:44.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:44.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:44.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:45.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:45.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:45.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:45.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:45.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:46.	13.0895	80.2739
PLAYER1	1.76E+12	2025-11-11T17:15:46.	13.0895	80.2739

Fig. 8: GPS Output Data

The clustering framework successfully segmented athletes into distinct performance archetypes, including high cardiovascular workload profiles, explosive-dominant performers, and balanced physiological profiles. This categorization enables tailored training prescriptions, workload optimization, and injury-risk mitigation strategies. Overall, the proposed system establishes a scalable, data-driven, and objective monitoring solution that enhances tactical insight and long-term athlete development.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 3, March 2026)

Compared to conventional observational or manually recorded methods, the integrated architecture offers higher analytical precision, automated decision support, and adaptability for future extensions such as advanced deep learning models, cloud-based analytics expansion, and longitudinal performance tracking.

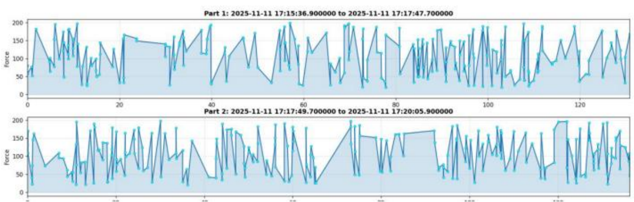

Fig. 9: IMU Sensor Output Data

Fig. 10: Dashboard View

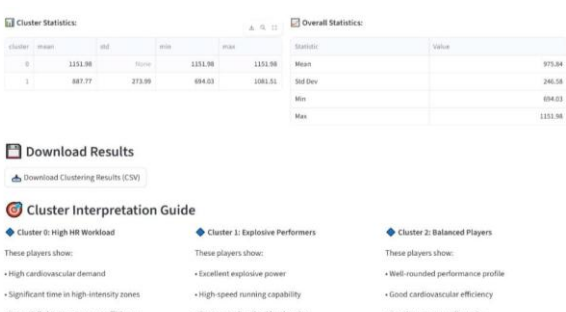

Fig.11: Dashboard View of Cluster Distribution

VIII. CONCLUSION

The Holistic Athlete Performance Analyzer is a data-driven sports analytics system that combines tri-modal sensor fusion, PCA-based modeling, temporal machine learning, and explainable AI to assess athlete performance in real time. It enables continuous fatigue detection and informed substitution decisions, overcoming the limits of single-sensor and post-session analysis. The scalable, cost-effective design suits both professional and semi-professional sports. Future work includes expanding multi-season datasets, adding more physiological biomarkers, and validating the system in live competitions.

References

[1] F. Wu, Y. Zhang and Z. Guo, "Multi-Model Gait Fatigue Detection and Feature Sensitivity Analysis Based on the DUO-GAIT Dataset," IEEE International Conference on Machine Learning and Applications (ICMLA), 2025.

[2] M. F. Igbal Prastyo, I. A. E. Zaeni, P. W. Agung Sucipto and A. Pratama, "Design of Wearable Device as a Fatigue Detector in Sports Activities Based on the Internet of Things," IEEE Tenth International Conference on Semantic Computing (ICSC), 2024.

[3] K. Gopalakrishnan, et al., "Fatigue Detection with Machine Learning Approaches Using Data from Wearable Devices," IEEE International Conference on Data Engineering (ICDE), 2024.

[4] M. F. Iqbal Prastyo, I. A. E. Zaeni, P. W. Agung Sucipto and A. Pratama, "Design of Wearable Device as a Fatigue Detector in Sports Activities Based on the Internet of Things," IEEE Conference on IoT Applications, 2024.

[5] Konefat, M., Szmigiel, B., Bochenek, B., et al., "Match Running Performance Preceding Scoring and Conceding a Goal in Men's Professional Soccer," Scientific Reports, vol. 14, 12885, 2024.

[6] J. Lee and M. Park, "Real-Time Athlete Fatigue Monitoring Using Edge-Based Wearable Sensors," IEEE Sensors Journal, vol. 23, no. 5, pp. 4567–4576, 2023.