# Review Paper on Data Analysis of Athlete Performance through wearable device using data mining strategies

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## **Abstract:**

Maintaining good health is extremely important for athletes who engage in strenuous physical activities. The integration of wearable devices in sports and fitness has transformed how athlete performance is monitored, analysed, and optimized. This research paper includes the data mining strategies to predict athlete performance data collected through wearable device. With the use of different types of wearable device, a vast amount of data is accessible for prediction of athlete's performance. These devices generate a continuous data like Test\_Date, Device Name, Heart Rate, Step Count, Sleep Tracking, GPS Accuracy Meters etc. Which offering the extraordinary output for the athlete's performance and training. Performance focus on multi-dimensional data, beginning with data collection and data pre-processing. Raw data from wearable device are normally incomplete, requiring robust cleaning, normalization and feature extraction to create a compatible and useful dataset. Various data mining techniques involves data pre-processing including cleaning and normalization and feature extraction like noise data, missing values and redundancy for use of transforming raw data into valuable insights for athletes. The findings elaborate that various data mining techniques can provide overall performance of athlete's physical health, helping coaches and easily make performance decision for sports scientist.

#### Introduction:

Athletics, also known as track and field, is a collection ofsports that involve various competitive events such as running, jumping, throwing, and walking [1]. Among the oldest and most popular sports in the world, with a rich history thatdates back to ancient times. A performance driven sports, the distinct between success and failure frequently comes down to minimal performance improvements. Established practices in athlete evaluation were based on perceptual assessments, experimental testing, and observational recording. On the other hand, the appearance of wearable devices has changed this view by allowing real-time, neutral and non-intrusive monitoring of athletes performance during both competition and training. The sport has changed over time and has developed into a worldwide event with millions taking part participants. Athletics a sport that requires a fusion of power, speed, quickness, strength, and methods. Athletesparticipantin a range of events, including middle-distance andlong-distance running, hurdles, relay races, long jump, highjump, pole vault, shot put, discus throw, hammer throw and race walking. Athlete performance prediction is an essential aspect of sports science, enhancing optimal training and strategies for performance advancement. Sports and fitness applications have become progressively popular in recent years, as people become more

well-informed of the importance of preserving a healthy lifestyle. Wearable devices such as cardiac monitors, heart-rate, sleep-tracking, sleep-count continuously track data including speed, accuracy, heart rate variability and movement dynamics. These devices generate vast amounts of data, encompassing variables such as heart rate variability, sleep patterns, activity levels, and other relevant condition of an athlete's health and well-being. However, massive data is frequently inconsistent, unformatted and challenging to analyse directly. Data mining techniques offer organized approach to convert raw data into meaningful insights. This review paper study how wearable devices interact with data mining strategies to analyse athlete performance. It emphasizes methodologies, applications, challenges and future directions.

## **Literature Review**

As per all references, here review some previous work with technique and description are as follow. These studies highlight the changing role of wearable technologies and data mining in sports performance analysis.

Authors & Year	Title	Key Findings
[1] Li et al. (2022)	Data mining in sports	Emphasized machine
(3) VA	performance	learning-based predictive
		models for performance
14 5		analysis
[2] Komitova et al. (2022)	Time-series data	Highlighted classification,
	mining in sports	clustering, and similarity
		measures for analyzing
\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \		performance
[3] Ghasemzadeh&Jafari	Wearable sensor	Focused on signal
(2021)	technologies in	processing challenges in
	biomechanics and	wearable data
	rehabilitation	
[4] Cummins et al. (2017)	GPS and	Underlined the importance
	microtechnology	of sensors for workload
	sensors in team sports	monitoring
[5] Baca et al. (2019)	Wearable devices in	Explored cloud-based data
	IoT ecosystem	sharing and real-time
		analytics for sports
		applications

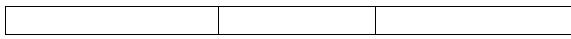


Figure 1 – Literature Review

## **Dataset for Athlete Performance Analysis**

Wearable devices generate multi-dimensional and sequential dataset that capture a different variety of physiological, biomechanical, and contextual information.

Types of Data:

Psychological Data:

Heart rate, heart rate variability, Electrocardiogram (ECG) signals, Body temperature Biomechanical Data:

Acceleration and deceleration, Step count

Performance Metrics

Speed, distance, and pace, Energy expenditure and calories burned

**Dataset Sources:** 

Publicly Available Athlete Datasets
wearable\_health\_devices\_performance\_upto\_26june2025
sports\_performance\_data

iot\_sports\_training\_dataset

Data Pre-processing:

Before applying data mining strategies, wearable technology require preprocessing to handle data:

Missing value -

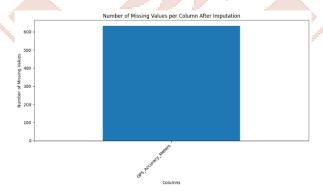


Figure 2 – Number of missing Values per column

The above graph is bar plot graph that represents almost 632 missing values in 'GPS\_Accuracy\_Meters' column.

#### Normalization

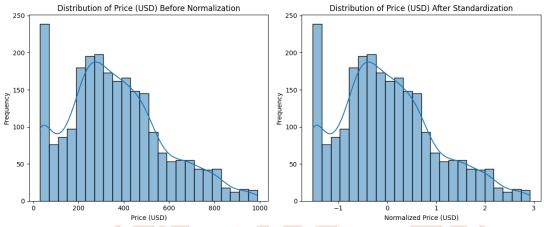


Figure 3 – Normalization

The two histogram represents the column of 'Price\_USD' column. Left histogram shows the original data and right histogram shows data after normalization. Normalization values are centred on 0, with most falling between -2 and 3.

#### Feature Extraction

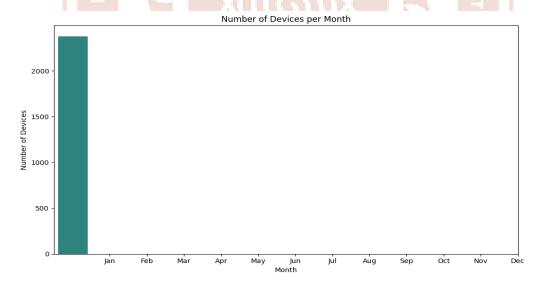


Figure 4 – Feature Extraction

The above graph is bar plot graph that distribution of the dataset across different months. The height of the bar graph represents almost 2375 devices recorded in June month.

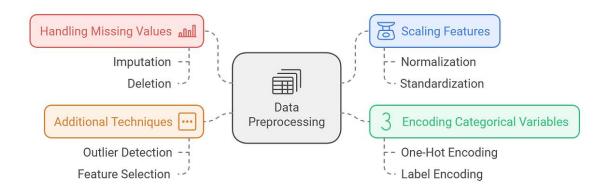


Figure 5 – Data Pre-processing

## **Data Mining Strategies**

Classification

Classification algorithm include Support Vector Machine, Random Forest and Neural Networks that to classify athletes status.

### Clustering

Identify distinct groups of athletes with similar training responses or biometric characteristics for personalized programs.

## Regression and Prediction

Regression model forecasted performance measures and associated risks factors identified by historical records.

## Time-Series Analysis

Monitor continuous physiological metrics to detect trends, fatigue accumulation, and optimal recovery windows.

## **Association Rule Mining**

Uncover hidden relationships between diverse factors, such as training load, recovery, and performance peaks.

## **Data Mining Approaches by Application Domain**

Application	Primary	Key Features	Efficiency
Domain	Techniques		
Performance	Gradient Boosting,	Biomechanical	82-94%
Prediction	LSTM networks	patterns,	accuracy
		physiological metrics	

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Injury Prevention	Random Forest,	Training load,	75-89% AUC
	XGBoost	asymmetries,	
		previous injury	
Technical Analysis	HMM, CNN, DTW	Joint angles,	89-96%
		temporal sequencing	accuracy
Recovery	Clustering,	HRV, sleep quality,	78-87%
Monitoring	anomaly detection	perceived exertion	precision

Figure 6 – Data Mining approaches by Application Domain

## **Challenges**

Wearable devices often generate noisy, incomplete, or inconsistent datasets due to motion artifacts, sensor drift, or environmental interference [1]. Data imperfections and fluctuations give rise to a major concern, key issues, inaccuracies and missing values concession the accuracy of conclusions. Another significant concern is interoperability, with inconsistent standards among devices hindering seamless data merging and comparative analysis. Many studies rely on small or athlete-specific datasets, leading to challenges in building predictive models that generalize across sports and populations. [2] Extracting reliable features from multi-modal time-series data (e.g., heart rate variability, motion tracking) remains technically challenging [3]. Few studies systematically compare multiple machine learning algorithms on the same dataset, limiting clarity on which models are most effective for specific sports tasks [9]. Furthermore, forecasting models can suffer from model overtraining due to limited datasets, especially in high-performance athletes, which may reduce transferability of outcomes. To conclude, athlete observance can impact efficiency of wearable technologies, as support, accessibility and interference impact their regular use during training and competition.

## **Result and Analysis**

Reference	Focus /	Dataset / Data	Key Findings	Accuracy /
	Methodology	Type		Effectiveness
[1]	Review of data	Multiple	Highlighted	Conceptual (no
	mining in sports	secondary	importance of	accuracy
	performance	sources	ML-based	reported)
			predictive	
			models	
[2]	Time-series data	Sports	Showed value of	Conceptual (no
	mining	performance	time-series	accuracy
	(classification,	datasets	mining in	reported)
	clustering, similarity)	(literature)	monitoring	
			athlete workload	

[3]	Wearable sensor	Physiological	Identified sensor	Not
	technologies in	& motion	noise and signal	performance-
	biomechanics &	sensor data	processing	focused;
	rehab		challenges	technical
				limitations
F 43	CDG	CDC :	TT 1 1' 1 1	discussed
[4]	GPS	GPS +	Underlined role	Review study, no
	&microtechnology	workload data	of GPS sensors	accuracy
	sensor review in		in workload	reported
[5]	team sports Wearable tech in IoT	Daal time 0-	monitoring  Enabled aloud	Componentical
[5]		Real-time & cloud-based	Enabled cloud-	Conceptual effectiveness
	ecosystem	wearable data	sharing, real-time	effectiveness
		wearable data	monitoring, but raised privacy	
			issues	
[6]	Athlete performance	Athlete	Demonstrated	~85–90%
[O]	prediction using	training &	Random Forest	accuracy
	Random Forest	performance	for prediction of	(Random Forest
	Random Forest	dataset	outcomes	outperformed
	//07 ./	dataset	outcomes	baseline ML
	//2/ A			models)
[7]	Comparative ML for	Wearable	Showed deep	Reported
[ [	heart rate prediction	heart-rate	learning &	improved
1	RO 'NY AV	sensor datasets	hybrid methods	accuracy up to
			outperform	~92%
		KUUDIII	traditional ML	(depending on
				model)
[8]	Review on wearable	Multi-source	Emphasized	Conceptual (no
	tech in sports	wearable data	opportunities,	accuracy
	(concepts &	$\sim \sim$	challenges, and	reported)
	opportunities)		growth in	7/
	\V A 4		wearable	7
		- 7 /	ecosystems	/
[9]	ML applied to HRV	Heart rate	Classified	Accuracy ranged
	for athlete profiling	variability	athletic profiles,	~80–88% in
	1	(HRV)	enabling	HRV-based
		datasets	personalized	athlete
			training	classification

#### **Conclusion**

Wearable devices, when combined with powerful data mining technologies, offer remarkable insights into athlete performance. This research demonstrates the potential of integrating wearable technology with machine learning techniques to accurately predict athlete performance based on real-time health metrics. By collecting and analyzing physiological data such as heart rate, sleep patterns, and activity intensity, the proposed system provides valuable insights into an athlete's physical readiness and performance trends. From injury prevention to

strategy enhancement, the applications are extensive and developing. However, challenges in data quality, adaptation, and proper use must be considered. Continued cross-field teamwork between sports scientists, data engineers, and ethicists will play a pivotal role in maximizing the benefits of the technology.

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