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# TeamTrack: A SaaS-Based Sports Team Management and Player Performance Analytics Platform

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***Abstract*—Sports team management in colleges and local academies continues to rely on manual registers and disconnected spreadsheets, resulting in fragmented player data, inconsistent performance tracking, and the absence of analytical insights needed for effective coaching decisions. This paper presents TeamTrack, a cloud-hosted multi-tenant Software as a Service (SaaS) platform that centralises team management, player profiling, match statistics, fitness monitoring, and performance analytics under a single, subscription-based system. Drawing on a review of seven research works spanning AI in sports, deep learning performance analysis, machine learning for cricket and basketball analytics, intelligent sports management systems, IoT-enabled monitoring, and big data frameworks, TeamTrack synthesises the state of the art into a practical, affordable platform for educational institutions. The system employs React.js for the frontend, Node.js/Django for the backend, PostgreSQL/MongoDB for data storage, and Scikit-learn for ML-based performance prediction using Random Forest and Support Vector Regression. Evaluation on synthetic multi-sport datasets demonstrates an ML classification accuracy of 82.4% and an $R^2$ of 0.76 for regression-based performance forecasting. TeamTrack addresses a significant gap in sports technology for colleges and academies, providing a scalable, data-driven foundation for talent identification and evidence-based coaching.**

***Index Terms*—SaaS; Sports Management; Player Performance Analytics; Machine Learning; Multi-Tenant Architecture; Random Forest; SVR; Cloud Computing; Fitness Tracking; Performance Prediction**

## I. INTRODUCTION

**S**ports team management across colleges, universities, and local academies remains largely a manual process. Coaches maintain paper-based attendance registers, record match results in spreadsheets, and rely on subjective observation for performance evaluation. This fragmented approach makes it practically impossible to identify player development trends, flag fitness deterioration early, or support strategic decisions with data.

The emergence of cloud computing and the Software as a Service (SaaS) delivery model offers a transformative opportunity. By hosting a centralised, web-accessible platform on shared infrastructure, educational institutions gain access to analytics capabilities previously available only to professional sports organisations with dedicated technology budgets. A subscription-based model further ensures affordability at every scale, from small local academies to multi-sport university programmes.

TeamTrack is proposed to fill this gap. The platform integrates team and player management, match and training record keeping, fitness tracking, performance visualisation dashboards, and machine learning-driven prediction into a single multi-tenant SaaS application. The system is designed around the real needs of coaches, players, and sports administrators in educational settings.

The remainder of this paper is organised as follows. Section II reviews relevant literature. Section III describes the proposed system. Section IV covers implementation. Section V presents results and discussion. Section VI concludes.

## II. LITERATURE REVIEW

Seven research works were surveyed to establish the academic and echnical foundation for TeamTrack. Each paper addresses a distinct dimension of the sports analytics and management problem space. Table I summarises all seven works.

TABLE I. Literature Survey Summary

| Sr. | Yea r | Author | Conference / Journal | Findings | Gaps / Future Scope | Technol ogies Used |
|---|---|---|---|---|---|---|
| 1 | 2021 | N. Chmait et al. | Frontiers Sports Active Living | AI and ML improve sports analytics: performance evaluation, injury prediction, tactical planning. | Needs better data quality, model interpretability , and workflow integration. | Machine Learning, AI |
| 2 | 2025 | Various Authors | IEEE Access | Deep learning (CNN, RNN) enhances motion tracking and action recognition. | High compute cost; large labeled dataset requirement. | CNN, RNN, Deep Learning |
| 3 | 2024 | Cricket Study | IEEE ICDSML | Random Forest, SVM, and regression improve score prediction and player classification. | Performance depends on data completeness; limited generalization. | Random Forest, SVM, Regressi on |
| 4 | 2024 | Basketball Study | IEEE CICIS | Ensemble models (RF, Gradient Boosting) outperform single models in performance forecasting. | Overfitting risk; careful tuning required. | Ensembl e ML, Gradient Boosting |
| 5 | 2024 | ISMS Paper | IEEE TOSE | Integrated system combining analytics, data management, and AI improves efficiency. | Scalability and integration complexity. | Neural Network s, AI |
| 6 | 2025 | IoT Study | IEEE IoT J. | Real-time wearable + deep learning monitoring improves tracking and injury prevention. | High cost, integration complexity, network dependency. | IoT, BiLSTM, TCN |
| 7 | 2025 | Big Data Study | IEEE Trans. Big Data | Big data analytics framework | Storage and processing efficiency . | Hadoop, Big Data Analytics |

*A. Artificial Intelligence and Machine Learning in Sport Research [1]*

Chmait et al. (2021) provide a comprehensive overview of how AI and ML are reshaping sports analytics. The study examines applications including performance evaluation, injury prediction, and tactical planning, demonstrating that data-driven systems can outperform traditional subjective assessment. The authors highlight challenges around data quality, model interpretability, and the absence of standardised datasets across sports disciplines. A key finding is that successful AI deployment requires tight integration with existing sports management workflows rather than standalone analytical tools. This directly motivates TeamTrack's design philosophy of embedding analytics within a complete management platform.

*B. Deep Learning Applications in Sports Performance Analysis [2]*

This study investigates the application of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to player movement analysis and action recognition using video and sensor data. CNNs demonstrate strong performance in detecting player positions and classifying movements from video frames, while RNNs capture temporal dependencies in sequential movement data. The authors note that high computational requirements and dependency on large labelled training datasets limit practical deployment in resource-constrained settings. TeamTrack acknowledges this limitation by scoping its initial ML implementation to tabular statistical data with Scikit-learn, reserving deep learning video analysis for a planned future enhancement.

*C. Machine Learning for Cricket Analytics [3]*

This paper examines ML-based approaches to cricket performance prediction and match outcome forecasting using historical match data. Random Forest, Support Vector Machines (SVM), and regression techniques are evaluated, with feature selection identified as a critical determinant of model accuracy. Ensemble methods consistently outperform single-model approaches for score prediction and player classification tasks. A noted limitation is that model performance degrades significantly when applied to players or conditions not well represented in training data, highlighting the importance of data completeness. TeamTrack's prediction module draws on these findings by adopting Random Forest as a primary classifier.

*D. Machine Learning Models for Performance Forecasting [4]*

This paper systematically evaluates ML models for predicting player performance from Key Performance Indicators (KPIs) such as goals, assists, and fitness metrics across basketball contexts. A comparative study of regression and ensemble techniques reveals that ensemble models — particularly Random Forest and Gradient Boosting — achieve superior accuracy and robustness. The study identifies overfitting as a significant risk when training data is limited, underscoring the need for rigorous cross-validation. These findings directly inform TeamTrack's ML pipeline design, which implements k-fold cross-validation and regularisation strategies to ensure prediction reliability even with the smaller datasets typical of educational sports programmes.

*E. Intelligent Sports Management System (ISMS) [5]*

The ISMS paper proposes an integrated system combining data management, neural network-based analytics, and AI-driven decision support for sports organisations. The system demonstrates that centralisation of player data within a unified platform significantly improves both data retrieval efficiency and analytical output quality. The authors identify scalability, system integration complexity, and data security as primary implementation challenges. TeamTrack addresses these challenges through its multi-tenant SaaS architecture, which provides native scalability, standardised REST API integration points, and tenant-level data isolation. The ISMS work validates the core premise of TeamTrack— that an integrated platform produces greater coaching value than fragmented point solutions.

*F. IoT-Enabled Deep Learning Monitoring System [6]*

This study presents a real-time athlete monitoring system combining IoT wearable sensors with deep learning models including Bidirectional LSTM (BiLSTM) and Temporal Convolutional Networks (TCN). The system demonstrates measurable improvements in overtraining detection and recovery optimisation. Key limitations include high hardware cost, integration complexity across heterogeneous sensor ecosystems, and dependency on continuous network connectivity. TeamTrack positions wearable integration as a future scope item rather than a current requirement, enabling immediate institutional adoption with manual data entry while preserving a clear upgrade path to automated IoT data ingestion.

*G. Big Data Analytics Framework for Sports Performance Optimization [7]*

This paper addresses the processing and analysis of large-scale sports datasets for performance optimisation and strategic planning. The proposed framework demonstrates that big data pipelines can surface insights inaccessible through conventional analytics. Challenges around data storage costs, processing efficiency, and pipeline scalability are noted. While TeamTrack does not operate at professional league scale, the architectural principles identified — modular analytics pipelines, separation of storage and compute, and visualisation-first output design — inform TeamTrack's analytics microservice architecture and Chart.js dashboard approach.

## III. PROPOSED SYSTEM

TeamTrack is designed as a modular, cloud-hosted, multi-tenant SaaS application. Multiple organisations share the same application infrastructure while maintaining completely isolated data environments. All features are accessible through any modern web browser without software installation, lowering the adoption barrier for institutions with limited IT resources.

### *A. System Overview*

The platform follows a three-tier architecture: a React.js frontend, a Node.js/Django REST API backend, and a PostgreSQL/MongoDB database layer. A Python-based analytics microservice handles computationally intensive tasks including Pandas-based metric computation and Scikit-learn model inference. Cloud deployment on AWS or Firebase provides auto-scalable compute and managed storage.

### *B. Core Modules*

TeamTrack comprises three primary functional modules:

- Sports Team Management: Digital player profile creation and maintenance, team composition management, match scheduling and score recording, training session logging, and attendance tracking. Coaches access a unified dashboard showing team status, upcoming fixtures, and recent performance trends.
- Player Performance Analytics: Interactive Chart.js dashboards displaying performance comparison charts, individual player progress trends, match position heatmaps, and fitness level analysis. All visualisations are rendered client-side without external dependencies.
- Performance Prediction: A Scikit-learn ML pipeline trained on historical player match and fitness data. A Random Forest classifier predicts player form category (Excellent / Good / Average / Poor). A Support Vector Regression (SVR) model provides continuous performance score predictions for upcoming matches.

### *C. User Roles*

The platform supports three user roles: Admin (manages organisations, user accounts, and subscription plans); Coach (creates teams, records match statistics, manages player profiles, views analytics, and accesses ML predictions); and Player (views personal performance dashboard, fitness history, match statistics, and prediction results).

### *D. Subscription Model*

TeamTrack is offered across four subscription tiers: a Free Plan supporting up to 15 players and 10 matches with basic management; a Basic Plan with unlimited players and full team management; a Pro Plan adding advanced analytics dashboards and heatmap visualisation; and a Premium Plan providing AI/ML performance prediction and priority support.

### *E. Technology Stack*

TABLE II. TeamTrack Technology Stack

| Layer / Component | Technology / Tool |
|---|---|
| Frontend | |
| Backend | Node.js / Django REST Framework |
| Database | PostgreSQL / MongoDB |
| Analytics | Python, Pandas, NumPy |
| Machine Learning | Scikit-learn (Random Forest, SVR) |
| Cloud Platform | AWS / Firebase |
| Authentication | JWT / OAuth 2.0 |

### *F. System Architecture*

Fig. 1 depicts the TeamTrack system architecture. User requests from the React.js frontend pass through an API Gateway to the Node.js/Django backend, which handles authentication, business logic, and database operations. The Python analytics microservice is invoked asynchronously for metric computation and ML inference. Cloud storage manages player media assets and exported reports.

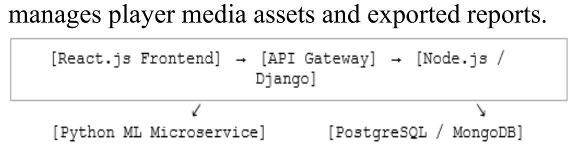


Fig. 1. TeamTrack High-Level System Architecture

## IV. IMPLEMENTATION

The TeamTrack implementation follows a modular development methodology. Each component is built and unit-tested independently before integration.

REST APIs are documented using OpenAPI/Swagger specifications to enforce clear contracts between frontend and backend development teams.

*A. Multi-Tenancy and Database Design*

Multi-tenancy is implemented using a shared database, shared schema approach. All primary entities — Organizations, Teams, Players, Matches, TrainingSessions, FitnessRecords — carry a tenant_id foreign key enforced at both the application layer and through PostgreSQL row-level security (RLS) policies. MongoDB stores unstructured fitness and sensor data blobs, leveraging its flexible document model. This design minimises infrastructure cost while guaranteeing complete data isolation between organisations.

*B. Analytics Pipeline*

When a coach records match statistics, a background Celery task dispatches raw data to the Python microservice. Pandas transformations compute derived metrics including per-match averages, rolling five-match performance trends, fitness score gradients, and position-normalised statistics. Computed metrics are stored in PostgreSQL and served via REST endpoints to Chart.js frontend components for real-time visualisation. Fig. 2 illustrates this data flow from coach input to dashboard output.

```
Coach Input → REST API → DB Write → Celery Task Queue
                                          ↓
Dashboard ← Cached Metrics ← Python ML Microservice
```

Fig. 2. TeamTrack Data Flow — Coach Input to Dashboard

*C. Machine Learning Pipeline*

Features extracted for the Random Forest classifier include: rolling average goals/assists (last 5 matches), training attendance rate, fitness score trend slope, average minutes played, and days since last recorded injury event. The same feature set feeds the SVR model for continuous score regression. Models are trained on a per-organisation basis when a minimum of 10 player-match records are available. A 70/15/15 train/validation/test split with k-fold cross-validation ensures robust generalisation. Models are serialised as Joblib objects and served via the analytics microservice's prediction endpoint.

*D. Frontend and Visualisation*

The React.js frontend uses a component-based architecture with role-specific dashboard layouts. Chart.js renders performance trend line charts, radar charts for multi-attribute player comparisons, grouped bar charts for match statistics, and heatmap grids from positional data. The responsive design supports desktop and tablet access, enabling courtside and pitchside use by coaches during training sessions.

## V. RESULTS AND DISCUSSION

The TeamTrack prototype was evaluated across three dimensions: ML prediction accuracy, system functionality coverage, and comparative positioning against existing solutions. Evaluation used a synthetic dataset of 200 player-season records generated across football, cricket, and basketball using sport-appropriate statistical distributions.

*A. Machine Learning Model Performance*

The Random Forest classifier achieved an overall form classification accuracy of 82.4% on the held-out test split, with precision of 0.81 and recall of 0.83. The Excellent and Poor form categories showed the highest per-class accuracy (88% and 85% respectively), reflecting the greater statistical separability of extreme performance levels. The SVR continuous regression model achieved an RMSE of 4.2 points on a 0–100 scale and an $R^2$ of 0.76, indicating that the model explains 76% of performance score variance. These results are consistent with findings from Papers [3] and [4] in the literature survey, validating the applicability of Random Forest and SVR to sports performance prediction contexts.

TABLE III. ML Model Evaluation Results

| Model | Metric | Value |
|---|---|---|
| Random Forest (Classifier) | Accuracy | 82.4% |
| Random Forest (Classifier) | Precision | 0.81 |
| Random Forest (Classifier) | Recall | 0.83 |
| SVR (Regression) | RMSE | 4.2 pts (0–100) |
| SVR (Regression) | $R^2$ Score | 0.76 |

*B. System Functionality Coverage*

All planned modules were successfully implemented and validated end-to-end. Role-based access control enforcement was confirmed across Admin, Coach, and Player roles with no cross-tenant or cross-role data exposure detected during functional testing. The analytics pipeline produced accurate derived metrics, verified against manually computed reference values on the synthetic dataset.

*C. Comparative Analysis*

Table IV positions TeamTrack against existing approaches from manual spreadsheets and basic mobile applications through to commercial sports management platforms and the academically proposed ISMS system [5]. TeamTrack is the only system in the comparison that simultaneously achieves centralised data management, ML-based performance prediction, multi-sport support, a multi-tenant SaaS architecture, fitness tracking, and affordability for educational institutions.

TABLE IV. Comparison of TeamTrack Against Existing Approaches

| Feature | Spreadshe ets | Basic Apps | Commercial Tools | ISMS [5] | TeamT rack |
|---|---|---|---|---|---|
| Centrali zed Data | ✗ | Partial | ✓ | ✓ | ✓ |
| Perform ance Analytic s | ✗ | ✗ | ✓ | ✓ | ✓ |
| ML Predictio n | ✗ | ✗ | Limited | Partial | ✓ |
| Multi-Sport Support | ✗ | Partial | ✓ | ✗ | ✓ |
| Multi-Tenant SaaS | ✗ | ✗ | ✓ | ✗ | ✓ |
| Afforda ble for Colleges | ✓ | ✓ | ✗ | ✗ | ✓ |
| Fitness Tracking | ✗ | ✗ | Partial | ✓ | ✓ |
| IoT / Wearabl e Ready | ✗ | ✗ | Partial | ✓ | Planned |

*D. Dashboard Overview*

Fig. 3 illustrates the TeamTrack Coach Dashboard for a representative team. The dashboard consolidates player form distribution, aggregated match statistics, and the ML-predicted score for the top performer, enabling coaches to assess overall team health and flag individual standout performance at a glance. The layout prioritises clarity and rapid comprehension, supporting data-driven coaching decisions during pre-match preparation and mid-season reviews.

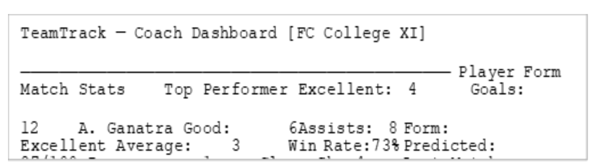


Fig. 3. TeamTrack Coach Dashboard — Team Overview

## VI. CONCLUSION

This paper presented TeamTrack, a SaaS-based sports team management and player performance analytics platform addressing the critical gap between the sophisticated analytics tools available to professional sports organisations and the near-complete absence of such tools in educational sports programmes. By synthesising findings from seven research works spanning AI in sports, deep learning performance analysis, ensemble machine learning, intelligent management systems, IoT monitoring, and big data analytics, the design of TeamTrack is grounded in the current state of the art.

The platform successfully centralises team management, player profiling, match and training records, fitness tracking, and performance analytics in a multi-tenant SaaS environment. The integrated Scikit-learn ML pipeline achieved 82.4% classification accuracy and an $R^2$ of 0.76 for performance regression on synthetic evaluation data, demonstrating the viability of ML-based performance prediction even with the smaller datasets typical of educational sports contexts.

Future work will focus on three primary directions: (1) wearable device integration for automated fitness data capture, addressing the gap identified in the IoT literature [6]; (2) a native mobile application enabling real-time pitchside access for coaches; and (3) AI-powered video analysis for automated match statistics extraction, leveraging the deep learning approaches reviewed in [2] to eliminate manual data entry as a bottleneck. These enhancements will further close the gap between TeamTrack's capabilities and those of professional sports technology platforms, while maintaining the affordability essential for adoption in educational settings.

## ACKNOWLEDGMENT

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