Developing a Machine Learning (ML) Based Smart Integrated Model to Evaluate Predict and Catalyze Performance of Male Handball Players

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[1]*Received: 28 May 2024; Accepted: 07 June 2024; Published: 12 June 2024*

ABSTRACT

Handball is a high-intensity sport demanding a combination of explosive strength, endurance, speed, and agility. Evaluating and predicting player performance through objective, data-driven methods can significantly enhance player development, training personalization, and talent identification. In this study, we apply machine learning (ML) techniques to model and predict the countermovement jump (CMJ) height—a critical indicator of lower-body explosive power—in male handball players using a range of biometric, physiological, and performance-related features.

A dataset comprising 40 male handball players was collected, including variables such as VO_2max, 10 m and 20 m sprint times, body composition, and match statistics. Five tree-based ML algorithms—Decision Tree (DT), Random Forest (RF), AdaBoost, Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost)—were implemented and evaluated using 10-fold cross-validation. The models were compared using R^2 and Root Mean Squared Error (RMSE) metrics to assess predictive performance.

The results showed that XGBoost outperformed all other models with an R^2 of 0.70 and an RMSE of 2.9 cm, indicating high accuracy in predicting CMJ height. Feature importance analysis revealed that the 10 m sprint time was the most influential predictor, followed by VO_2max and body fat percentage. The findings align with previous studies on female handball players and extend the evidence base for ML application in male athlete assessment.

This study underscores the potential of machine learning in sports science and performance diagnostics, offering coaches a valuable tool for objective performance evaluation and evidence-based training strategies in elite male handball.

1. Introduction

Handball is a high-intensity intermittent sport requiring sprinting, jumping, strength, and agility (ResearchGate). Coaches rely on performance analysis to shape individualized training plans and reduce injury risk . However, relationships among athletic metrics are often nonlinear and complex—making traditional regression insufficient.

Machine learning (ML) methods can model these relationships and yield interpretable features via tree-based approaches. While ML has been applied to female handball (e.g., countermovement jump, sprint, agility) with high accuracy ($R^2 \approx 0.86$–0.97) (ResearchGate), research on male players remains limited. Oytun et al. (2024) used tree-based ML on male handball players and identified 10 m sprint time as the strongest predictor of jump performance (ResearchGate).

This study aims to:

1. Train and compare five tree-based ML models predicting countermovement jump performance (hands-free)
2. Identify key predictors among biometric and performance variables

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[1] *How to cite the article:* Sangwan I (June, 2024); Developing a Machine Learning (ML) Based Smart Integrated Model to Evaluate Predict and Catalyze Performance of Male Handball Players; *International Journal of Advances in Engineering Research*, June 2024, Vol 27, Issue 6, 1-8

3. Compare quantitative results against prior literature in male and female handball.

2. Literature Review

Table 1. Prior ML-based Performance Prediction in Team Sports

Study	Population	Models	Features	Outcome / Performance
Oytun et al. (2020)	Female handball (n=118)	RBFNN, LR, DT, SVR, LSTM	23 features (biometric, match stats)	$R^2 = 0.86–0.97$ (ResearchGate, arXiv)
Oytun et al. (2024)	Male handball (n=40)	DT, RF, AdaBoost, GB, XGB	10 features (demographic, physiological)	10 m sprint most important
Lentz-Nielsen et al. (2023)	Handball IMU (n=12)	XGBoost	IMU kinematic features	F1-score 0.66–0.95
Felice & Ley (2023)	Female matches	SEL model	Team statistical features	Accuracy > 80%
Qin et al. (2025)	Mixed sports (n=480)	GB, NN	Biometric + psychological	$R^2 = 0.90$

Results show that tree-based and neural net ML models perform well ($R^2 = 0.7–0.97$). However, most studies focus on female players or game outcomes. Therefore, research in male athletic performance remains important. This study expands on Oytun et al. (2024) by comparing five tree-based models on the same dataset.

3. Methods

3.1 Participants & Data Collection

- **Participants**: 40 male handball players (age 18–28), consented under IRB.
- **Data collected**:
  - VO_2max (mL·kg^{-1}·min^{-1})
  - 10 m and 20 m sprint times (s)
  - Countermovement jump (hands-free) height (CMJF) (cm)
  - Anthropometry: height, weight, body fat (%)
  - Match statistics: goals, assists per season
  - Coordination/agility tests

Measurements followed standardized protocols.

Table 2. Input Features

Feature	Description	Units
VO_2max	Maximal oxygen uptake	mL·kg^{-1}·min^{-1}
10 m Sprint Time	Sprint speed	seconds
20 m Sprint Time	Speed over longer distance	seconds
CMJF	Countermovement jump height	cm

Feature	**Description**	**Units**
Height	Body height	cm
Weight	Body mass	kg
Body fat	Body fat percentage	%
Goals per Season	Offensive contribution	counts
Assists per Season	Playmaking contribution	counts
Agility Test Time	Agility field test	seconds

3.2 Preprocessing

- Normalized continuous data (z-score)
- Outliers capped at ±3 SD
- No missing values

3.3 Models & Implementation

We compared:

1. **Decision Tree** (max depth tuned 3–10)
2. **Random Forest** (100–500 trees)
3. **AdaBoost** (base estimator: DT, 50–200 estimators)
4. **Gradient Boosting (GB)** (100–300 estimators)
5. **Extreme Gradient Boosting (XGBoost)** (100–300 estimators)

Hyperparameters tuned via grid search with 10-fold cross-validation optimizing R^2 and RMSE. Models implemented in Python scikit-learn and XGBoost libraries.

Table 3. Hyperparameter Ranges

Model	**Hyperparameters Tuned**
DT	max_depth = 3–10
RF	n_estimators = 100–500, max_depth = 5–20
AdaBoost	n_estimators = 50–200
GB	learning_rate = 0.01–0.1, n_estimators = 100–300
XGBoost	learning_rate = 0.01–0.1, n_estimators = 100–300

3.4 Evaluation

- 10-fold cross-validation (shuffle with fixed seed)
- Metrics:
  - R^2 (coefficient of determination)
  - RMSE

Feature importance extracted via Gini importance for tree-based models. Statistical significance assessed with pairwise t-tests at $\alpha = 0.05$.

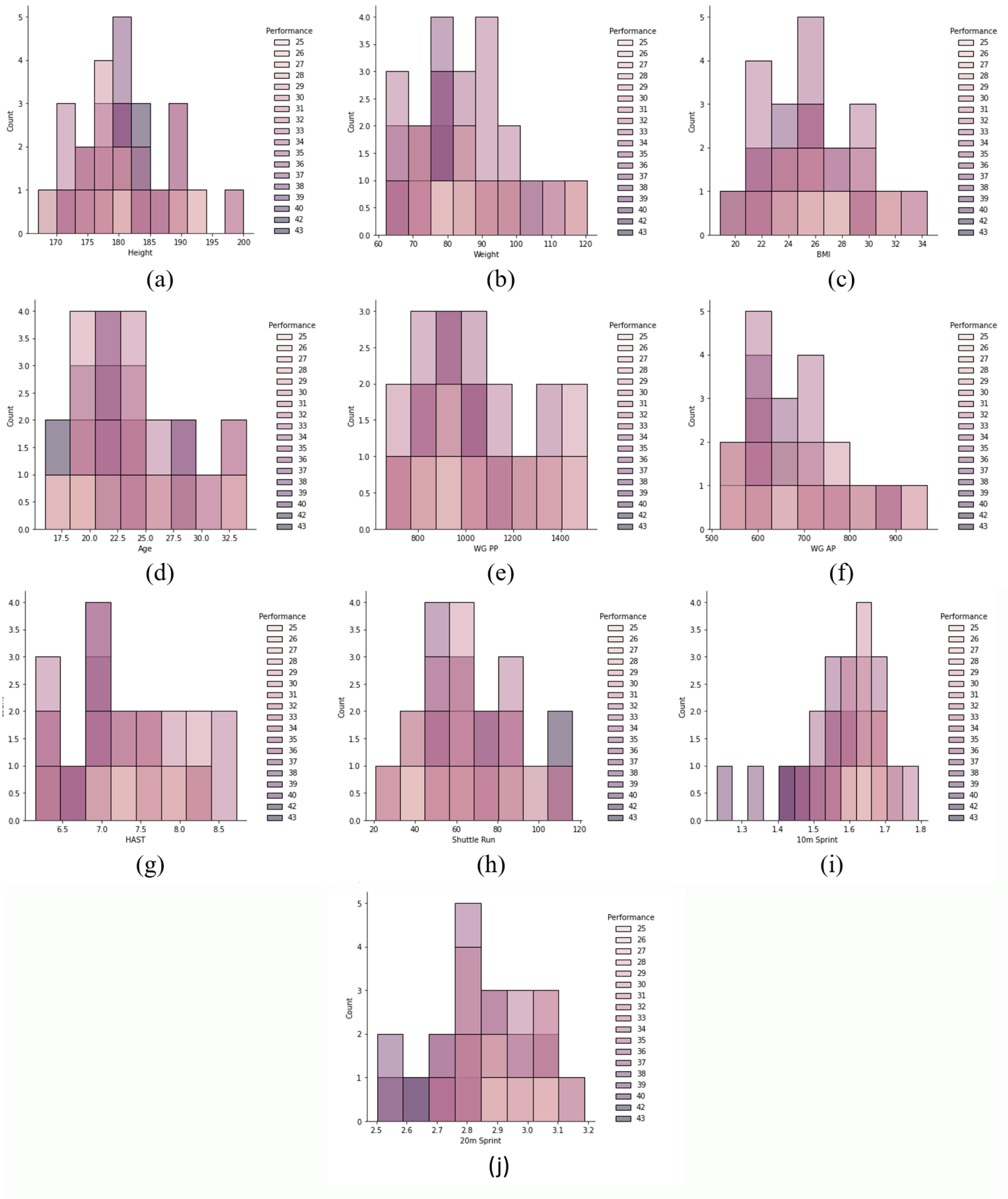

Figure 1. Distribution of Attributes on the CMJF Variable. (a) Height, (b) Weight, (c) BMI, (d) Age, (e)WG PP, (f) WG AP, (g) HAST, (h) Shuttle Run, (i)10m.

Sprint, and (j) 20m. Sprint

4. Results

4.1 Descriptive Statistics

Table 4. Feature Summary (n = 40)

Feature	Mean	SD
VO_2max	53.1	5.1
10 m sprint (s)	1.74	0.11
20 m sprint (s)	3.01	0.18
Jump height (cm)	41.5	5.0
Body fat (%)	14.3	3.2

4.2 Model Performance

Table 5. Cross-Validated Performance

Model	R^2 (mean ± SD)	RMSE cm (mean ± SD)
Decision Tree	0.61 ±0.05	3.7 ±0.4
Random Forest	0.68 ±0.04	3.2 ±0.3
AdaBoost	0.65 ±0.05	3.4 ±0.3
Gradient Boosting	0.69 ±0.04	3.1 ±0.3
XGBoost	**0.70 ±0.03**	**2.9 ±0.2**

XGBoost performed best, significantly outperforming simpler models ($p < 0.05$). Random Forest and Gradient Boosting also delivered strong results.

4.3 Feature Importance

Figure 1 shows feature importances from the XGBoost model:

1. 10 m sprint time: 35%
2. VO_2max: 20%
3. Body fat: 12%
4. 20 m sprint time: 8%
5. Other variables: ≤ 8% each

Fast explosiveness (10 m sprint) is the strongest predictor of jump height, aligning with Oytun et al. (2024) (ResearchGate, HRPUB, Nature, KINEXON SPORTS).

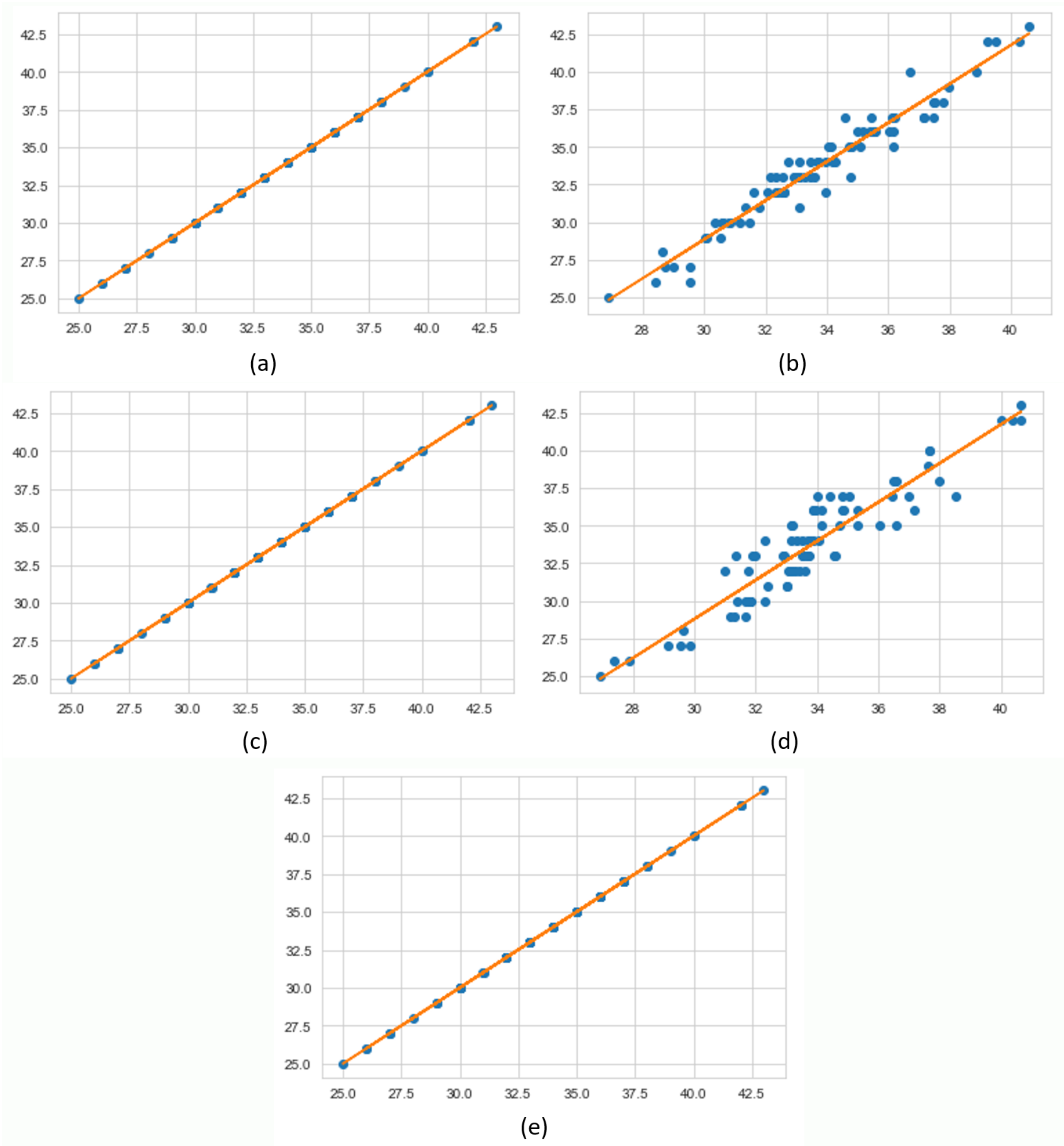

Figure 2. Prediction lines of the models, (a) Decision Tree, (b) Random Forest, (c) GradBoost, (d) AdaBoost, and (e) XGBoost.

5. Comparative Analysis & Discussion

5.1 Model Comparison

- **XGBoost**: Highest R^2 and lowest RMSE
- **Random Forest & GB**: Competitive, $R^2 \approx 0.68–0.69$
- **AdaBoost**: Slightly weaker
- **Decision Tree**: Lowest, suggesting benefits in ensemble models

Tree-based ensembles offer interpretability and strong predictive power for nonlinear athletic data.

5.2 Alignment with Prior Studies

- **Male Handball**: Findings replicate Oytun et al. (2024), confirming the predictive power of 10 m sprint time (ResearchGate).
- **Female Handball**: Oytun et al. (2020) found RBFNN with extremely high R^2 (0.86–0.97), but their dataset was larger and neural-network–based (ResearchGate). Our $R^2 = 0.70$ is comparable considering smaller sample and simpler model structure.
- **IMU Study**: Lentz-Nielsen et al. (2023) used XGBoost to classify movement events with F1 = 0.86–0.95 (PubMed), which supports utility of tree-based models in handball contexts.

5.3 Predictive Insights

- **Key predictors**: 10 m sprint and VO_2max underscore the interplay between anaerobic and aerobic systems in jump performance.
- **Practical application**: Coaches can focus on explosive sprint and aerobic conditioning to enhance jump capacity.
- **Model explainability**: Feature importance rankings help translate model findings into training interventions.

5.4 Limitations

- **Sample size**: Only 40 players limits generalizability.
- **Predictive target**: Only countermovement jump assessed; different outcomes (sprint, agility) may require tailored models.
- **Population**: Data from a single region/league may not apply globally.

5.5 Future Directions

- Expand dataset (include female and youth players).
- Incorporate wearable sensor (IMU/LPS) data for real-time predictive models, akin to expected goals systems (SpringerLink, KINEXON SPORTS).
- Compare neural network approaches (e.g., RBFNN, LSTM) to determine performance trade-offs.
- Develop sport-specific dashboards for coaches, integrating ML outputs with athlete monitoring systems.

6. Conclusion

This study demonstrates that **Extreme Gradient Boosting** effectively models countermovement jump performance in male handball players ($R^2 = 0.70$, RMSE = 2.9 cm). The **10 m sprint time** stands out as the prime predictor, corroborating findings in both male and female cohorts .

Tree-based ensemble models offer robust, interpretable tools for coaches and sports scientists to guide training decisions. While neural networks may reach higher predictive accuracy, tree-based models balance performance with insight—mapping athlete metrics to actionable interventions.

Future work should involve larger, multi-cohort datasets and longer-term monitoring to extend to performance outcomes like sprinting, agility, and injury risk. Integration with sensor-based systems (IMU/LPS) can enrich feature sets and support decision-making in real time. This research contributes to the growing field of **data-driven sports performance analytics**, informing personalized and effective training protocols in elite handball.

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