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ORIGINAL RESEARCH

Self-explaining Hierarchical Model for Fatigue Monitoring and Prediction in Basketball Self-explaining Hierarchical Model for Fatigue Monitoring and Prediction in Basketball

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Abstract
Machine learning and computer vision allow the development of sophisticated models for evaluating an athlete's readiness and fatigue. In this paper, we studied the effects of stressors faced by athletes to comprehensively evaluate their readiness and fatigue while maximizing their game performance and minimizing the risk of injury. An athlete's readiness and fatigue were quantified using a modified reactive strength index (*RSImod*), computed using countermovement vertical jumps. Our study was conducted over 26 weeks with 17 collegiate women's basketball athletes. The proposed model first learns the relationship between *RSImod* and the athletes' physical, physiological, and cognitive features. Then, it augments its learning by considering the smallest worthwhile change (SWC) of the five most significant features that correlated well with *RSImod* to account for intra-athlete variability. Finally, we used our proposed hierarchical approach employing decision tree classifiers and regressors (ensemble–boosting) to predict an athlete's *RSImod* score for the following week. Our experiments demonstrated that SWC augmentation improved *RSImod* level prediction accuracy from 92.83% (original dataset) to 95.28%. The proposed hierarchical approach performs better (MSE 0.011, R^2 0.963) than state-of-the-art prediction algorithms (multilinear and random forest regressor), generates interpretable outcomes, and helps coaches develop effective training schedules and game strategies. When tested without SWC augmentation, the hierarchical model achieved an MSE of 0.028 and an adjusted R^2 of 0.906. SWC augmentation reduced the MSE by 60.71% (from 0.028 to 0.011). It increased the adjusted R^2 by 6.29% (from 0.906 to 0.963), further highlighting the combined efficacy of SWC augmentation and the hierarchical approach. By integrating various physical, physiological, and cognitive features, the proposed model helps coaches optimize athlete performance and mitigate injury risks effectively.

Keywords Basketball · Collegiate athletes · Countermovement jumps · Fatigue monitoring · Reactive strength index · Smallest worthwhile change · XGBoost model

Introduction

Advancements in sports analytics due to recent developments in machine learning (ML) and computer vision (CV) tools and techniques have facilitated non-intrusive monitoring of athletes and the collaboration of coaches, biomechanical researchers, and data scientists in the design, development, and analysis of sophisticated models that exploit athletes' physiological, mental and cognitive data for optimizing athletes game performance while minimizing risk of injury [1]. Collegiate basketball is characterized by high-intensity activities requiring various technical and tactical abilities from the athletes to cope with game demands during a relatively short season [2]. The athletes must balance their training schedules, sleep and recovery cycles, academic

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load, social commitments, and extensive game schedules. With these multifaceted potential stressors faced during the season, it is essential to consider an athlete's physiological, mental, and cognitive state to comprehensively evaluate their readiness and fatigue for developing training schedules and game strategies [2].

Countermovement jump (CMJ) is a time-efficient, non-invasive athlete jumping performance evaluation test that measures athletes' training adaptations, a key for evaluating their neuromuscular fatigue and readiness [3]. These jumps involve the strength-shortening cycle (SSC), which is vital in sprint accelerations. The CMJ assessment is, therefore, crucial for evaluating the key performance indicators (KPIs) of basketball athletes who frequently require accelerations and decelerations [1]. Monitoring CMJs, training, emotional and mental stressors, and sleep and recovery cycles provides a comprehensive understanding of an athlete's readiness and response to physical, physiological, and cognitive stimuli.

From an athlete's CMJ, we can compute reactive strength index modified (*RSImod*). This key attribute captures an athlete's readiness. *RSImod* is an extensively used measure for assessing an athlete's ability to generate maximal vertical impulse quickly [2]. It is a composite metric computed from jump height (JH) and contact time (CT). While JH is determined using the flight time technique, CT is the time duration from initiation of the jump to take-off.

$$RSImod = \frac{JumpHeight(JH)}{ContactTime(CT)} \quad (1)$$

RSImod reflects lower extremity explosiveness, incorporating factors such as speed and force [4]. It evaluates athletes' performance and monitors their neuromuscular functional status [3]. It is preferred over conventional metrics such as JH, force, or power as it provides more relevant information about changes in the movement strategy during the jump.

A meta-analysis examining the association of *RSImod* with independent measures of sporting and neuromuscular performance was conducted. It was followed by assessing the impact of rebound test instructions on maximizing the jumping displacement and minimizing ground contact time. Results showed that *RSImod* was significantly and moderately positively associated with strength and endurance performance and negatively associated with acceleration and change of direction speed [5]. A study investigated the correlation between *RSImod* and biomechanical variables in drop jumps (DJs) performed at varying heights. Although vertical stiffness positively correlated with *RSImod*, the other parameters did not vary much at different heights [6]. Another study investigated the relationship between ground reaction force (GRF) variables and jump height, *RSImod*, and jump time in 26 male Division-I soccer players. The study concluded that countermovement characteristics are essential for time-sensitive CMJ performance measures and that researchers should include *RSImod* and jump time to improve their assessment of jump performance [7].

In studies conducted in sports with a small sample size (17 athletes here), features contributing to an athlete's performance are assessed by evaluating their impact on the key performance indicator (here, *RSImod*) based on the entire population data. These approaches are not robust due to small sample sizes. They are insensitive to intra-individual variability as different athletes progress differently during the entire season. It has motivated sports science researchers to consider the smallest worthwhile change (SWC) measures to account for intra-individual variability in athletes' performance. SWC is calculated for each feature for each athlete individually. The suggested changes in the magnitude of a feature for an athlete (based on the previous week's baseline readings and the deviation from an overall population) are augmented to the training dataset to improve prediction outcomes. Using SWC helps identify the slightest change possible in significantly contributing features that increase chances of success in competitions or personal goals [8]. It helps the coaches and practitioners to be more confident that the changes they see in athletes' *RSImod* scores are not simply due to chance [9].

The fast and dynamic nature of collegiate basketball, coupled with complex physical, psychological, and cognitive features contributing to athletes' fatigue and readiness, has necessitated qualitative studies to supplement quantitative studies to help design influential athletes training routine planning and game strategizing [10]. The existing studies have primarily presented a quantitative analysis of different internal–external loads in measuring fatigue in different team sports [11]. However, no research shows a holistic study assessing the impacts of multiple task-dependent (training, CMJs) and psycho-physiologic and intrinsic (cognitive capacity, sleep patterns, cardiac rhythm, fatigue) features in the athlete's routine on their readiness for the following days. This study presents a qualitative analysis that helps characterize the relationship between the various physical, physiological, and cognitive features and *RSImod* (inferential modeling). Quantitative analysis also validates it, which helps predict athletes' readiness regarding *RSImod* (predictive modeling). Our model predicts the *RSImod* score of athletes by considering their sleep and recovery patterns, cognitive state information, and subjective training statistics from the previous week. The model is built hierarchically, utilizing the strengths of both decision tree (DT) classifiers and decision tree regressors – with a boosting approach. The SWC analysis is conducted as a preprocessing step for augmenting the dataset with information on changes in the magnitude of significant features that could serve as valuable thresholds for interpreting the magnitude of changes in the athletes' *RSImod* score the following week.

The prediction of *RSImod* is made at a global level (inter-athlete), taking the internal/external load quantifying feature readings of all athletes together (model trained over the entire dataset). However, the SWC calculation is made at a local level (intra-athlete) for each feature reading of each athlete individually and augmented with the dataset. It makes our method robust as general and athlete-specific patterns are considered when predicting athletes' readiness for the following week. Thus, this study's primary aim (PA) was (PAI): an examination of the impact of suggested meaningful changes in the magnitude of internal–external load quantifying features, significantly contributing to fatigue, on the CMJ-derived *RSImod* score of athletes. These changes would then be augmented to the baseline readings of the current week and used for prediction as PAII. The *RSImod* score for the following week was predicted based on the raw feature values from the previous week and the suggested meaningful changes in magnitude using ML algorithms.

Dataset

17 female collegiate competitive basketball athletes (mean [standard deviation]: $n = 17$, age = 21.00 [± 3.00] years, height = 174.21 [± 19.27] cm, body mass = 73.98 [± 11.52] kg) participated in this study. This study investigates the effects of physiological load – sleep and *recovery* cycle, training, competition, and academic load on athletic readiness. It is quantified in terms of the *athlete's RSImod score* during a CMJ. The analysis is conducted over 26 weeks of a competitive season. During this phase, the athletes wore WHOOP (Version 4.0, Boston, MA, USA) wearable devices 24/7– measuring their *resting heart rate* (*RHR*), *heart rate variability* (*HRV*), *recovery* percentage, and sleep. Their training sessions each day (stretching, core exercises, game-based training drills, technical exercises, and strength-power exercises) were assessed through a rating of perceived exertion (sRPE) calculated after each training session. The athletes also completed a short recovery short stress (SRSS) questionnaire, which assessed their cognitive state twice per week. They performed a CMJ test on dual force plates once weekly – recording jump height and contact time to calculate the *RSImod* score. The athletes were familiarized with the testing procedures and monitoring tools used.

This study has been ongoing since 2020–21 (First season). We collected the first year's sleep-recovery, training load, and stress-recovery questionnaire data. From 2022 onwards, we started collecting the countermovement jump data (dual force plate readings) that provided us with the *RSImod* scores. As this study was conducted at the end of Season 2, we had this data for 17 athletes who were a part of that season. However, after 4 years, in 2024, we have had this data for 27 athletes. Some athletes repeat in consecutive years while new ones join in. So, we have not been able to track a single athlete consistently. However, we have been able to cover athletes with different behavioral patterns tactically and physiologically. It is ongoing research, and the collection will continue in the coming years. Our proposed methodology is scalable to increasing or decreasing the number of athletes being considered. Bringing in the SWC concept helps bring respective athlete-specific variations as and when new athletes join in. However, the core model design is generalizable. It provides robust outcomes for new data, irrespective of the variability in terms of new and any number of athletes being added.

Session Rating of Perceived Exertion

Training load was assessed using the sRPE, which accounted for the workload from resistance training, sports training, metabolic conditioning, and gameplay [12]. Around 15 min after each training session, the athletes provided a rating on a 10-point scale to indicate their perceived exertion during the session. This rating was then multiplied by the duration of the training session. Various derived features were utilized for further analysis, including *total weekly load (TWLoad)*, training *strain*, *daily average*, *monotony*, and *weekly standard deviation* [13].

Sleep and Recovery

The WHOOP strap is a wearable device that tracks and analyzes biomarkers and sleep for athletes [14]. It provides sleep analysis (sleep quality, sleep duration, stages of sleep) and metrics such as *RHR*, *HRV*, *recovery*, and *respiratory rate*. Its consistency has been validated as an alternative to polysomnography for sleep analysis [12].

Short Recovery Short Stress Questionnaire

Twice each week, the athletes used an online dashboard to fill out a short *recovery* and short stress questionnaire that collected information on their emotional and mental state. There were eight questions – four related to recovery. In contrast, the rest were related to stress (overall recovery (OR), overall stress (OS), negative emotional state (NES), lack of activation (LA), muscular strength (MS), physical performance capabilities (PPC), mental performance capabilities (MPC), emotional balance (EB). They scored for each question on a scale of 0–6 (Likert scale) [12].

Fig. 1 The standardized countermovement jump task. Subjects are instructed to jump as high as possible

Countermovement Jump

The athletes perform CMJ as a component of their training regimen. Each CMJ session took place on the same day of the week (Monday or the first training day) to track the athletes' readiness profile. After a low-intensity warm-up, the athlete performed a set of three CMJs over the pressure plate. The instruction is to maximize *JH* and minimize ground CT. Figure 1 shows the standardized CMJ task performed by athletes. The athletes place their hands on their sides, take a deep squat, and jump as high as possible. The dual force plates (FDlite, Vald Performance, Brisbane, QL, AUS) sampled at 1000 Hz record several metrics for each jump, including *body weight*, *peak power*, *RSImod*, and *JH* during the CMJ. The highest *RSImod* score of the three CMJs was considered for the trial and is used for further analysis [15].

Methodology

In this study, *RSImod* is modeled as a weighted function of 40 features.

- 35 features quantifying the task-dependent (external) and the psycho-physiologic and intrinsic (internal) load an athlete undergoes during a season.
- 5 features quantifying the suggested magnitude of change in the most significant features based on a week prior readings.

Figure 2 outlines the methodology followed. The data (35 features) for each source, namely sleep and *recovery*, subjective training, questionnaire, and countermovement jumps, was collected following the techniques described in section II (***1. data collection***). During data collection, some records were found to have missing entries from the sleep and recovery data or the questionnaire data. These may have occurred due to athletes' forgetfulness in wearing the WHOOP strap, improper attachment to their wrist, negligence of charging the WHOOP strap, or keeping the application running on their mobile devices. The athletes, at times, did not complete the surveys, especially during the season. The data appeared missing at random (MAR), with thirteen missingness percentages. The multiple imputation by chained equation (MICE) technique is the most suitable for data imputation when data is MAR [16]. It is the most accurate due to its conditional modeling of the missing feature on the other features [17]. Hence, we used MICE to fill in the missing values to avoid bias in prediction outcomes (***2. data cleaning***).

The aggregate dataset had one reading per day for each of the 35 features, while the CMJs were performed only once a week, leading to only one *RSImod* score per week. We first mapped the seven readings for each feature into one reading (average) per week. Next, we converted the dataset to make it suitable for predicting the *RSImod* score for the following week (time-series prediction) using the XGBoost model. An instance (x, y) was formed as follows: for independent features, we used week N's average readings as $X\ (x_1, \ldots, x_{35})$, and the *RSImod* score for week $N+1$ was used as y. It helped assess the impact of the current week's (N) internal/external load on the following week ($N+1$) (***3. data preparation***).

Next, we analyzed the range of *RSImod* scores. We computed its measures of central tendency (mean, median, standard deviation, and range) and its interquartile range values (min, Q_1, Q_2, Q_3, and *max*) for understanding the distribution. Following this, we checked the Pearson's correlation coefficient score of each of the 35 independent features for the target feature *RSImod*. We selected the top five most significant features (***4. exploratory data analysis***). For each of these significant features, we conducted the SWC analysis. For each athlete Ai, where $i = 17$, and for each significant feature SFj, where $j = 5$,

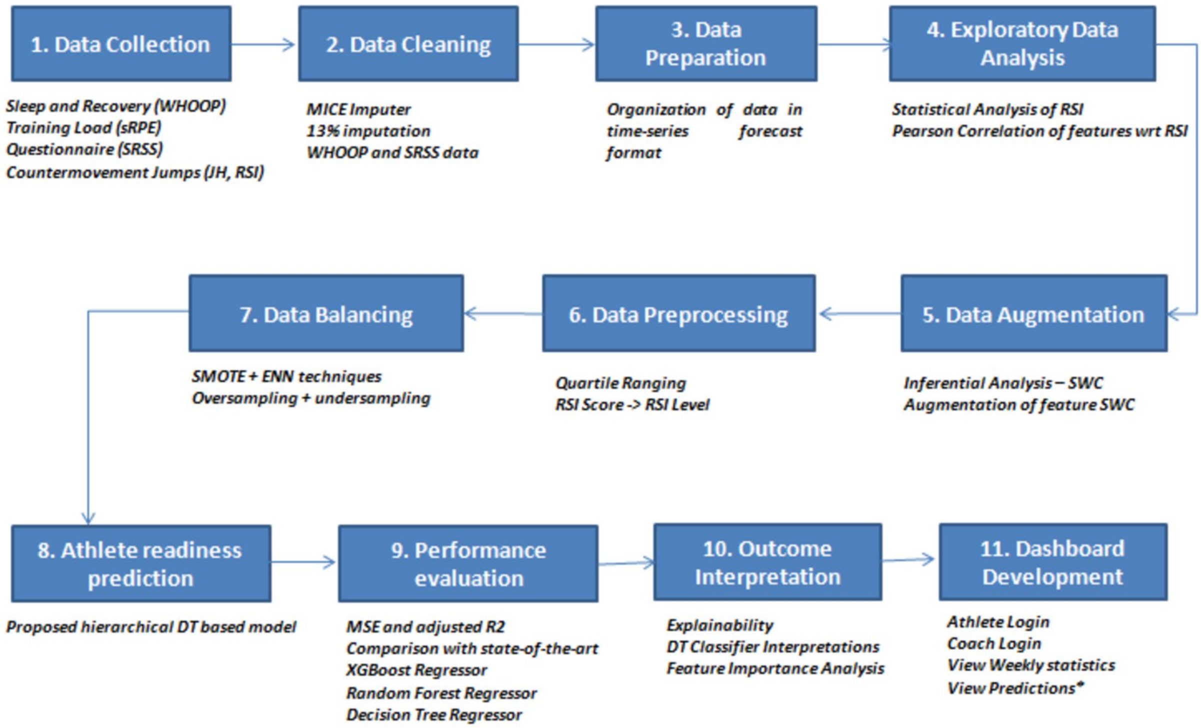

Fig. 2 Proposed methodology

SWC was calculated. Using SWC, the suggested change in magnitude of each feature for each athlete each week was computed (considering the previous week's baseline reading). These computed values were augmented to the dataset as 5 SWC features (to be used for prediction) (***5. data augmentation***).

The samples were then divided across multiple groups based on the *RSImod* score to account for heterogeneity amongst the athletes over the season. A quartile ranging approach [14, 18] was used for creating groups with *RSImod* values less than 25%, 25–50%, 50–75%, and greater than 75%, representing low (0.2 to 0.32), moderate (0.32 to 0.36), high (0.36 to 0.41), very high (0.41 to 0.67) levels of athlete readiness (6. data preprocessing). The distribution of samples across four levels revealed an imbalance, creating challenges for classification due to limited instances of the minority class [12]. To overcome this, augmenting minority class examples is essential. Balancing techniques like SMOTE [20] and ENN [21], involving data undersampling and oversampling, were applied for improved performance in decision tree-based algorithms (***7. data balancing***). Our hierarchical model first predicted the *RSImod* level with class probabilities using the ensemble of decision tree classifiers. These probabilities were then utilized by the ensemble of decision tree regressors as weights for *RSImod* score prediction (***8. athlete readiness prediction***).

The performance of the proposed approach is evaluated as follows: (i). We performed an inferential dataset analysis to validate the SWC analysis's efficacy. For each significant feature, we assessed the impact of the suggested change in magnitude on the *RSImod* score of the following week by counting and comparing the percentage records showing a positive/negative correlation. These results were mapped to the sports science literature for ground truth validation. (ii). We compared the prediction *accuracy* and *F1 score* of the XGBoost classifier (*RSImod* level as target feature) trained on the original 35-feature dataset and that trained on the 40-feature dataset (suggested change in magnitude augmented) to assess if SWC-based augmentations improved the prediction accuracy. (iii). Mean squared error (*MSE*) and adjusted R^2 value of our proposed hierarchical model were compared to the *MSE* and adjusted R^2 value of three state-of-the-art decision tree models – decision tree regressor, random forest regressor and XGBoost regressor (***9. performance evaluation***).

We visualize an ensemble's decision tree classifier to reveal internal components, aiding coaches in understanding prediction outcomes ***(10. outcome interpretation).*** Our interactive dashboard empowers coaches to assess team performance, identify areas for improvement, and make informed decisions on strategies. Athletes monitor their stats, while coaches access the same for all athletes. They plan to embed prediction algorithms for pre-game insights. Currently, two user dashboards (coach and athlete) display daily, weekly, and monthly readings of 35 load-quantifying features. ***(11. dashboard development).***

Smallest Worthwhile Change Augmentation

SWC insight empowers coaches to confidently identify causal factors or chance occurrences of *RSImod* deviations [22, 23].

$$\text{SWC} = 0.2\text{X population SD} \tag{2}$$

We use it as follows: suppose the *RSImod* score of an athlete in week 1 equals 2.7, and the SWC calculated for the athlete over the season is 0.158. In that case, the athlete needs to have an *RSImod* score > 2.858 (2.7 + 0.158) next week to improve performance. This 2.858 is the suggested meaningful change in RSI. Typical error (TE) is calculated as the difference between the suggested meaningful change in score and the actual score in the following week [23]. If the athlete's *RSImod* score next week is 2.94, the TE equals 0.082 (2.94—2.858). W.G. Hopkins et al. suggest the following interpretation for TE: < 0.2 trivial, 0.2—0.6 small, > 0.6—1.2 moderate, > 1.2—2.0 large, > 2.0—4.0 very large, > 4.0 extremely large [24]. In this case, there was a trivial improvement (TE < 0.2) in the *RSImod* score of the athlete.

A comparative analysis is conducted to assess the relationship between suggested changes in the magnitude of significant features (measured in the previous week) and the *RSImod* score recorded in the following week. A SWC is calculated for these significant features with athlete-specific SD for each athlete, using the athlete's week 1 to week 26 data as population. For example, the SWC for *JH* is calculated for each athlete. The calculated SWC is added to the n^{th} week's jump height (JH_n) to compute the suggested jump height (*SJH*) for the following week. The jump height the following week (JH_{n+1}) is compared with *SJH*. The n^{th} week's *RSImod* score ($RSImod_n$) is compared with the $n+1$th week's *RSImod* score ($RSImod_{n+1}$) to assess the relationship between *JH*, *SJH,* and the *RSImod* score.

These estimates of the suggested magnitude of change using the smallest worthwhile change in the identified top five most significant features were augmented to the baseline dataset with 35 features.

Proposed Hierarchical Approach

Our model begins with the top structure consisting of an ensemble of DT classifiers (decision forest), each trained using a different subset of features, a choice of hyperparameters (max-leaf-nodes, minimum-samples, max-depth), and a random subset of training data. This pruned decision forest is divided into groups, each representing a class label, using class prediction accuracy as a threshold. Each group is used to classify data points associated with that group. This inner structure of DTs associated with each group is then analyzed to identify the most efficient operational paths for that respective class label, using operational path efficiency (respective class prediction accuracy of the operational path calculated at the leaf node) as a threshold. Next, the training dataset is divided into subsets, one for each class label, using the identified operational path traversal as a condition. A DT regressor per class is trained on these data subsets. While the pruned decision forest results in class probabilities, these DT regressors result in *RSImod* score each. The final model outcome is the *RSImod* score calculated as a weighted average over all DT regressors, with class probabilities as weights. This way, the proposed approach generates ensemble DT regressors from an initially built ensemble decision forest of classifiers. It considers the training data properties (conjunctive rules/operational paths relevant to the training instances and the class distribution) rather than solely considering the inner structure of the decision forest and the prediction outcomes.

More formally, given the training data *D* consisting of a collection of *L* data points (x_i, y_i), for $i \in [1 \ldots L]$, where xi and yi correspond to the *n*-dimensional feature vector of the i^{th} data point and its associated class label, where yi belongs to one of the *m* labels in [$class_1$, …, $class_m$]. Our decision tree (DT)-based methods essentially construct *k* DT classifiers {T_1, …, T_k} (decision forest F), where each classifier is constructed using a different subset of features, choice of hyperparameters (max-leaf-nodes, minimum-samples, max-depth), and a random subset of training data *D*. These classifiers associate a class probability vector {$h_{1(x)}$, …, $h_{k(x)}$} with each feature vector *x*.

We now describe our DT-based prediction method in five main stages: Decision Forest pruning, generation of sub-forests (DT clusters), extraction of efficient conjunctive rules, generation of class-wise sub-datasets, and outcome prediction. We first construct a minimal forest F_1 from *F* by pruning it while attempting to obtain a predictive performance close to *F.* The forest F_1 associates a class probability vector computed as an aggregate function g, a softmax applied over the sum of base trees log-odds (XGBoost). The DTs of forest F_1 are then class-wise clustered to create sub-forests {$cluster_1$, …, $cluster_m$}. Next, finite sets of conjunctive rules (operational paths) most likely to result in correct class label prediction are extracted for each sub-forest {S_1, …, S_m}. For each sub-forest, all instances (*x*, *y*) from the dataset that trace down to the correct class label using the extracted conjunctive rules form a separate subset of data—{D_1, …, D_m}. We train *m* DT regressors {R_1, …., R_m} over sub-dataset {D_1, …, D_m} respectively, considering that the data within each subset has low variability. The outcome is the weighted average of all DT regressor outcomes with the probabilistic outcome of F_1 $\{P(C_1), \ldots, P(C_m)\}$ serving as weights for each regressor, respectively.

Decision Forest Pruning

Forest pruning is a preliminary step in obtaining an ensemble with the most relevant base trees. This pruning is performed using the benefit-driven greedy approach. In this technique, the base trees are added to the ensemble iteratively. We start with an empty ensemble. The algorithm searches for a base tree with classification accuracy greater than 80% and adds it to the ensemble. In the following stage, a base tree is added, and combined with the already added base tree, it obtains an average classification accuracy greater than 80% (boosting approach). The process repeats until there is no base tree left, which would improve the classification accuracy of the ensemble.

Algorithm: Decision Forest Pruning

```
Input: F (Decision forest comprising of k DTs), D (training set)
Output: F1 (Pruned ensemble – a subset of k DTs from F)
F1 = Ø
prediction_accuracy (F1) = 0
for Tk in F do
  if prediction_accuracy (Tk) > 80% then
   add Tk to F1
   prediction_accuracy (F1) = prediction_accuracy (Tk)
   break;
  end
end
for Tk in F do
  for Tk in F1 do
   prediction_accuracy (F1) = AVG(prediction_accuracy (F1), prediction_accuracy (Tk))
  end
  if Tk not in F1 then
   if AVG (prediction_accuracy (Tk), prediction_accuracy (F1)) > 80%
   then
    add Tk to F1
   end
  end
end
```

Generation of Sub-Forests (Decision Tree Clusters)

The DTs of the ensemble forest F_1 are next divided into class-specific clusters. This clustering is performed based on class prediction accuracies. For each DT T_k, we determine the percentage data instances (x, y) from training dataset D that belong to class m and have correctly been classified as class m by the DT, for each class{class_prediction_accuracy (C_1), …, class_prediction_accuracy (C_m)}. For each class m, the DTs with class_prediction_accuracy (C_m) greater than 80% are added to class m representing sub-forest (cluster). Since each T_k in F_1 has an overall prediction accuracy greater than 80%, each DT will become a part of at least one cluster. Moreover, a DT can also be a part of more than one cluster.

Algorithm: Generation of DT Clusters

```
Input: F1 (Pruned ensemble – a subset of k DTs from F), D (training
  set), C (class labels)
Output: cluster1, …, clusterm (class-wise sub-forests)
for m in C, do
 clusterm = Ø
end
for Tk in F1 do
 for m in C, do
  if class_prediction_accuracy (Cm) > 80% then
   add Tk to clusterm
  end
 end
end
```

Extraction of Efficient Conjunctive Rules

Following the class-wise cluster generation stage, we next apply a technique for decomposing the DTs and extracting conjunctive rules used for classification. We create a conjunction set for each class m – $\{S_1, \ldots, S_m\}$ comprising operational paths in the DT (viewed as a conjunctive rule) that are most likely to predict the correct class label m with high efficacy.

We start with empty conjunctive sets. Then, each DT T_k is broken down into a set of conjunctive rules CR $\{r_1, r_2, \ldots, r_p\}$ that map to a vector of class probabilities v $[cp_1, \ldots, cp_m]$. For each rule r_p, if the class probability of class m is greater than 80%, the rule r_p is added to the conjunctive set S_m.

Algorithm: Extraction of Efficient Conjunctive Rules

```
Input: cluster1, …, clusterm (class-wise sub-forests), D (training set),
  C (class labels)
Output: S1, …, Sm (class-wise conjunctive sets)
for m in C, do
 Sm = Ø
end
for m in C, do
 for Tk in clusterm do
  R = all operational paths of tree Tk leading to class m
  for r in R, do
   if cpm(r) > 80% then
    add r to Sm
   end
  end
 end
end
```

Generation of Class-Wise Sub-Datasets

In this stage, for each rule r in conjunctive set S_m, the instances (x, y) where $y = m$ that traversed through operational path r and got assigned the label m were added to the sub-dataset D_m—($D_1 \bigcup D_2 \bigcup \ldots \bigcup D_m = D$).

Algorithm: Generation of sub-datasets
Input: $S_1, \ldots, S_m$ (class-wise conjunctive sets), D (training set), C (class labels)
Output: $D_1, \ldots, D_m$ (class-wise sub-datasets)
for each m in C do
for each r in S_m do
for each (x, y) in D do
P = instances (x, y) that traversed through r
for each (x, y) in P do
if $y == m$ then
add (x, y) to D_m
end if
end for
end for
end for
end for

Outcome Prediction

In the final stage of the developed approach, for each class m, a DT regressor (XGBoost) is trained over sub-dataset m, resulting in m DT regressors $\{R_1, \ldots, R_m\}$. Notice that the variability in data points belonging to the training set D_m is less than dataset D. Now, for each test instance in $T = [(x_1,), \ldots., (x_p)]$, the pruned ensemble decision forest F_1 results in a class probability score vector $\{P(C_1), \ldots, P(C_m)\}$. These scores are passed as weights to the respective DT regressors $\{R_1, \ldots, R_m\}$. A weighted average of the DT regressor outcomes is presented as the outcome.

Algorithm: Outcome Prediction
Input: test instance $[(x_1,), \ldots., (x_p)]$
Output: Predicted Outcome
for $(x_t,)$ in T do
F_1 generates class probabilities $\{P(C_1), \ldots, P(C_m)\}$
DT regressors $\{R_1, \ldots, R_m\}$ generate outcome $\{y_{t1}, y_{t2}, \ldots, y_{tm}\}$
nfinal outcome = AVG $(P(C_1) \times y_{t1} + P(C_2) \times y_{t2} + \ldots + P(C_m) \times y_{tm})$
end

Table 1 Descriptive statistics for *RSImod* score

Descriptive Statistics	Values
CMJs (n)	442
Duration	Week 1–26
Athletes	17
Mean	0.37
Standard deviation (SD)	0.08
Range	0.47
Minimum	0.20
Maximum	0.67
Q1	0.32
Q2	0.36
Q3	0.41

Experimental Evaluation

The implementation was written in Python (3.13.0). Sklearn's (1.4.0) decision tree regressor, XGBoost classifier, XGBoost regressor, and random forest regressor were fitted over the dataset to evaluate the approach's efficacy. The range and values of hyperparameters were fixed: three different levels of depth of DT were defined (three, four, and five). The size of sub-samples was limited to 60%, 80%, or 100%; feature subsets were selected randomly in proportions of 60%, 80%, and 100%, and the number of classes defined was four. An exhaustive grid search was conducted with ten-fold cross-validation to find the best fitting hyper-parameters for each model.

Results

Four hundred and forty-two ($n = 442$) CMJs were analyzed. The *RSImod* was reported as mm/ms from the CMJ analysis. The duration ranged from week 1 to week 26, with one weekly CMJ session. The descriptive statistics for *RSImod* scores throughout the season (*17 athletes* × *26 weeks*) are summarized in Table 1.

To identify what internal/external load quantifying feature could have caused variability in *RSImod*, we calculated Pearson's correlation coefficient value for each feature for *RSImod*. Table 2 lists the five most significant contributing features. *RSImod* is a valuable indicator of an athlete's ability to generate force rapidly during a movement, and jump height is a direct measure of this force production, hence the high correlation. Including jump height in the analysis serves a dual purpose: validating the effectiveness of the proposed SWC augmentation to improve athlete readiness predictions while ensuring a comprehensive evaluation of factors influencing athletic performance. Interestingly, Hours of Sleep, Strain, Total Workload, and Heart Rate Variability

Table 2 Pearson's correlation coefficient for the five most significant features

Feature	Correlation Value
Jump Height (CMJs)	0.91
Hours of sleep (sleep and recovery)	0.72
Strain (training)	0.58
Total workload (training)	0.56
Heart Rate Variability (sleep and recovery)	0.52

Table 3 Percentage records depicting the relationship between JH, SJH, and *RSImod* score

%	$JH_{n+1} > SJH$	$JH_{n+1} < SJH$
$RSI_{n+1} > RSI_n$	71.66	02.35
$RSI_{n+1} < RSI_n$	04.20	18.29
$RSI_{n+1} = RSI_n$	02.10	01.40
Total	77.96	22.04

also emerged as influential factors. These features represent external and internal stressors that can impact an athlete's overall well-being and physical condition. Hours of Sleep reflect recovery and fatigue management, Strain and Total Workload quantify the external stress imposed on the body, and Heart Rate Variability provides insights into the autonomic nervous system's response.

Inferential analysis was conducted over the five most significant features and the impact of their suggested change in magnitude on the following *RSImod* score for each athlete. Table 3 presents the outcomes of the comparative analysis for features *JH* and *RSImod*.

As per the analysis, 71.66% of athletes who jumped higher than the *SJH* improved their *RSImod* score, while 18.29% of athletes who jumped lower than the *SJH* scored a lower *RSImod*. Interestingly, 4.20% of athletes scored a lower *RSImod* despite jumping higher than the *SJH* compared to 2.35% who recorded a higher *RSImod* despite jumping lower than the *SJH*. The following week, 2.10% and 1.40% of athletes recorded the same *RSImod* despite jumping higher than and lower than *SJH*, respectively. A similar analysis was conducted with features: *Hours of sleep* (HoS), *Strain*, *Total Workload* (*TWLoad*), and *Heart Rate Variability* (*HRV*). Tables 4–7 summarize comparative analysis outcomes for *HoS*, *Strain*, *TWLoad*, and *HRV*, respectively.

As per the analysis in Table 3, 89.95% of records suggested that a change in the jump height compared to the *SJH* positively correlates with the *RSImod* score. As per Table 4, 72.90% of records suggest that if the TE between the SHoS and the actual HoS is trivial, minor, or moderate (±), the *RSImod* either remains consistent or improves over

Table 4 Percentage records depicting the relationship between HoS, suggested HoS (SHoS), and *RSImod* score

%	$HoS_{n+1} > SHoS$	$HoS_{n+1} < SHoS$	$HoS_{n+1} \sim SHoS$
$RSI_{n+1} > RSI_n$	02.30	04.65	67.05
$RSI_{n+1} < RSI_n$	09.78	09.34	03.38
$RSI_{n+1} = RSI_n$	00.36	00.67	02.47
Total	12.44	14.66	72.90

the season, while 18% of records suggest that if the TE is large, very large or extremely large (±), the *RSImod* score decreases. It can be observed from Table 5 that 73.33% of records suggest that if the TE between the suggested *Strain* and the actual *Strain* during the weekly training is trivial, small, or moderate (±), the *RSImod* either remains consistent or improves over the season. 22% suggest that if the TE is large, very large, or extremely large (±), the *RSImod* score decreases. Similarly, Table 6 shows that 72.20% of records suggest that if the TE between the S*TWLoad* and the actual *TWLoad* athlete undergoes during the weekly training is trivial, small, or moderate (±), the *RSImod* either remains consistent or improves over the season. While 22% suggest that if the difference is significant, very large, or extremely large (±), the *RSImod* score decreases. As per Table 7, 88.60% of records suggested that an improvement in the *HRV* compared to the *SHRV* leads to an improvement in the *RSImod* score and vice versa.

The SWC in the features is highly correlated to *RSImod* and can be used to detect relevant performance effects. These estimates of the SWC in these features (previous week)—SWC_JumpHeight, SWC_HoursofSleep, SWC_*Strain*, SWC_*TWLoad,* and SWC_*HRV* would serve as valuable thresholds for interpreting the magnitude of changes in the athletes' *RSImod* score, the following week. These SWC features (five) were appended to the baseline data, including the internal/external load quantifying features (thirty-five). A total of forty independent features were used for *RSImod* prediction.

After dividing the records into four levels of *RSImod* using quartile ranging, a new column, '*RSImod* level' with labels low (0), moderate (1), high (2), and very high (3) for respective *RSImod* scores, was added to the dataset Fewer records, 38% belonging to high and very high levels of athlete readiness compared to 62% belonging to low and moderate levels, resulted in data imbalance. The combination of SMOTE and ENN for data balancing increased the sample size (*n* = *712),* with 50% of records belonging to high and very high levels of athlete readiness and low and moderate levels each.

To assess if SWC-based augmentations improved the prediction accuracy, we trained the XGBoost classifier (*RSImod* level as target feature) on the original 35 feature dataset

Table 5 Percentage records depicting the relationship between Strain, suggested Strain (SStrain), and *RSImod* score

%	$\text{Strain}_{n+1} > \text{SStrain}$	$\text{Strain}_{n+1} < \text{SStrain}$	$\text{Strain}_{n+1} \sim \text{SStrain}$
$\text{RSI}_{n+1} > \text{RSI}_n$	02.04	01.33	70.63
$\text{RSI}_{n+1} < \text{RSI}_n$	10.64	11.56	0.30
$\text{RSI}_{n+1} = \text{RSI}_n$	0.50	0.60	02.40
Total	13.18	13.49	73.33

Table 6 Percentage records depicting the relationship between TWLoad, suggested TWLoad (STWLoad), and *RSImod* score

%	$\text{TWLoad}_{n+1} > \text{STWLoad}$	$\text{TWLoad}_{n+1} < \text{STWLoad}$	$\text{TWLoad}_{n+1} \sim \text{STWLoad}$
$\text{RSI}_{n+1} > \text{RSI}_n$	02.28	01.88	69.84
$\text{RSI}_{n+1} < \text{RSI}_n$	10.66	11.60	00.24
$\text{RSI}_{n+1} = \text{RSI}_n$	00.43	00.95	02.12
Total	13.37	14.43	72.20

Table 7 Percentage records depict the relationship between HRV, suggested HRV (SHRV), and *RSImod* score

%	$\text{HRV}_{n+1} > \text{SHRV}$	$\text{HRV}_{n+1} < \text{SHRV}$
$\text{RSI}_{n+1} > \text{RSI}_n$	69.82	04.18
$\text{RSI}_{n+1} < \text{RSI}_n$	03.72	18.78
$\text{RSI}_{n+1} = \text{RSI}_n$	01.79	01.71
Total	75.33	24.67

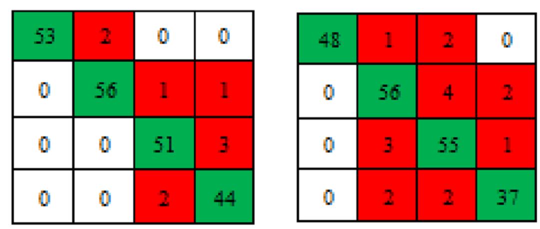

Fig. 3 Confusion matrix depicting XGBoost classifier outcomes for *RSImod* level prediction – with SWC-based augmentation (left) and without SWC-based augmentation (right)

Table 8 MSE and adjusted R^2 scores for various DT regressors

Model	*MSE*	Adjusted R^2
Classical DT regressor	0.057	0.603
Random forest regressor	0.042	0.612
XGBoost regressor	0.030	0.894
Proposed hierarchical model (original dataset)	0.028	0.906
Proposed hierarchical model (SWC augmented dataset)	0.011	0.963

(using grid search to estimate the best set of hyperparameters: colsample_bytree = 0.8, gamma = 0.5, max_depth = 3, min_child_weight = 1, n_estimators = 100) and then on the 40 feature dataset A limited number of CMJs and data scarcities could introduce significant bias in prediction accuracy. Therefore, we used the F1 score to evaluate the classifier's performance. As false positive (FP) and false negative (FN) are equally important in assessing an athlete's readiness for the week ahead, the F1 score balanced them in evaluations. We used a stratified tenfold cross-validation technique for generalizing the model. Following the traditional 70:30 training: testing ratio, 499 records were used for training and 213 for testing. The XGBoost classifier resulted in a prediction accuracy of 95.28% and an F1 score of 0.96 on the 40-feature dataset compared to a prediction accuracy of 92.83% and an F1 score of 0.92 on the 35-feature dataset. Figure 3 represents the confusion matrix depicting XGBoost classifier outcomes for RSI-level prediction. The cells in green mark the true positives and false negatives, while the cells in red mark the false positives and true negatives.

We then predicted the *RSImod* score using the proposed hierarchical DT-based model. The adjusted R^2 score and Mean Square Error (*MSE*) determine how much the proposed approach improves the predictions. The predictions from the hierarchical approach have an *MSE* and R^2 score that is better than the classical DT regressor, random forest regressor, and XGBoost regressor applied over the complete dataset. Table 8 summarizes the average *MSE* and R^2 score achieved by the proposed hierarchical approach and comparable state-of-the-art models.

Figure 4 shows screenshots of the dashboard for athletes and coaches that they can currently use to view athlete weekly statistics (internal/external load quantified).

Figure 5 (Appendix I) depicts a DT classifier plotted from the ensemble. Interpreting the decision tree (DT) involved systematically analyzing the splits and thresholds at each node, starting from the root and working through the branches. First, the **root node** is examined to identify the primary factor influencing the classification—in this

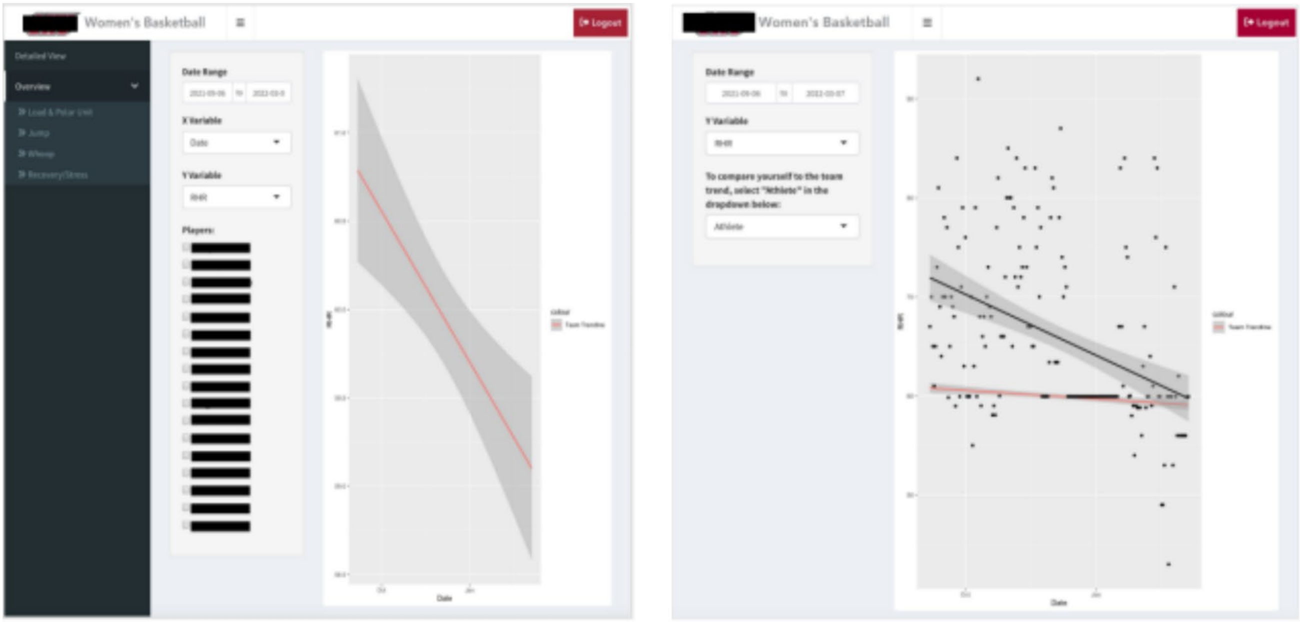

Fig. 4 Screenshots of athlete (left) and coach (right) dashboards (E. Juliano et al., 2023)

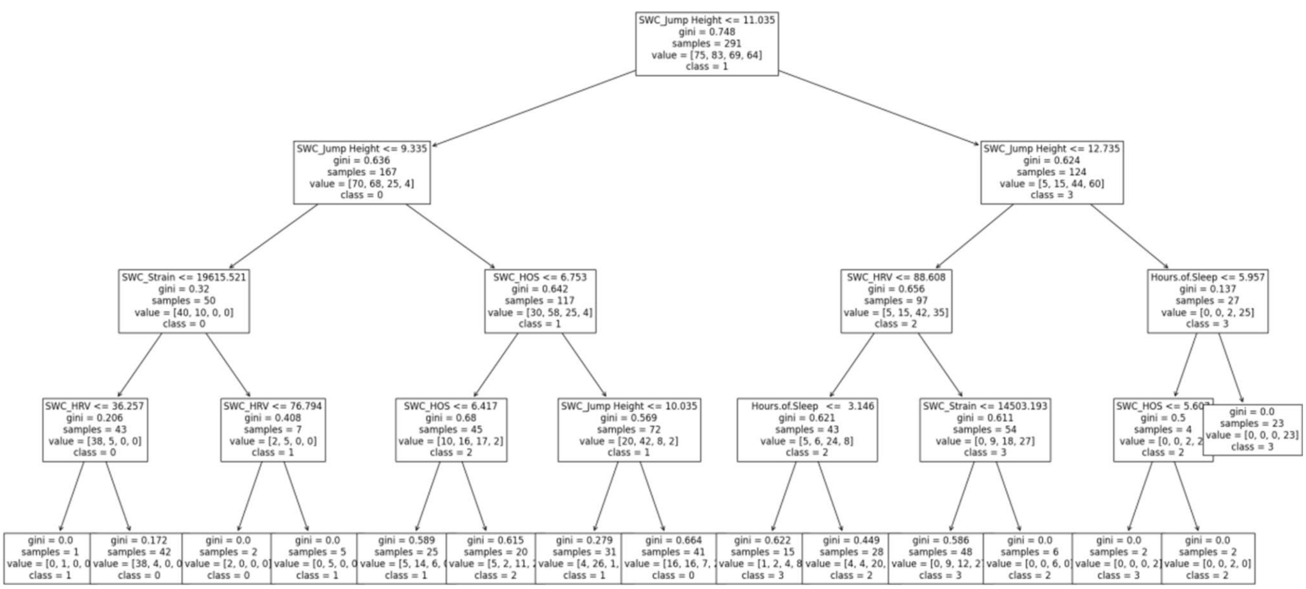

Fig. 5 DT classifier visualization

case, **SWC Jump Height**. The thresholds at this node (e.g., ≤ 9.335 and > 12.735) were used to segment athletes into readiness categories (low, moderate, and high). Next, the **branches** were evaluated to determine secondary factors affecting readiness. For example, for lower jump heights, **SWC HRV** and **SWC Strain** were identified as critical, with specific thresholds (e.g., HRV ≤ 36.257) further refining classifications and hours of sleep (HOS) emerged as the critical determinant for higher jump heights, with thresholds like HOS > 5.957 indicating sustained high readiness. Each split was interpreted by assessing the associated class values (e.g., proportions of samples per class) to understand the factor's influence on readiness levels. Finally, the entire tree was reviewed to synthesize insights, identify the relationships between metrics and readiness levels, and translate these into actionable coaching recommendations.

From the plotted DT (Appendix I), it can be inferred that the suggested change in magnitude of *JH* followed by the hours of sleep for an athlete is the most significantly affecting feature of the *RSImod* score prediction for the following week. Here, suppose the suggested change in magnitude of jump height for an athlete (based on intra-athlete variability) is greater than 12.73. In that case, there is an 88% chance that the athlete will have a high or very high *RSImod* score the following week. If the suggested change in magnitude of jump height is less than 9.34, there is an 81% chance of a low-moderate *RSImod* score. *A strain* greater than 19,615.52 (here, sRPE calculated) shows overtraining, resulting in a low-moderate *RSImod* score. *Hours of sleep* less than 3.14 show a lack of sleep and negatively impact athlete readiness. Such inferences help coaches estimate an athlete's fatigue in the previous week and assess their readiness for the week ahead. The coach could make informed decisions on changing athletes' training routines, suggesting rest and game strategizing.

Discussion

We have collected many of the attributes of these groups of athletes over 14 weeks during each season for 4 seasons. It, coupled with multiple attributes over multiple modes, helps get a sample of reasonable size with a sufficiently rich set of attributes. Further, the scope of this study is restricted to a few dozen athletes during each season. However, over time, we will not only have more data sets across seasons but also be able to extend this study to athletes in other teams within the conference. The study's diverse athlete profiles enhance the model's robustness and generalizability to unseen data. At the same time, SWC accounts for individual differences as athletes join.

Inferential Analysis (PA-I)

JH positively correlates with *RSImod*, which is the most significant contributing feature. *HoS* depicts the average number of hours an athlete sleeps in a day, which should be considered an essential factor to monitor and control as it directly impacts performance and the risk of injuries to an athlete [25]. The standard suggested *HoS* for athletes is 6-8 hours daily [12]. Our analysis shows that an athlete sleeping significantly more or less than the suggested HoS decreases their *RSImod* score the following week. *Strain* and *TWLoad* reflect the total workload and variability across the weekly training sessions. Our analysis suggests that athletes should avoid large spikes (both negative and positive) in training volumes as they negatively affect athletes' readiness for the following days. Less and too much training can hinder a good night's sleep, which should be considered when scheduling practices and workouts [26]. *HRV*, a measure of the autonomic nervous system, reflects physiological readiness, with higher *HRV* readings indicating better adaptability [27], thereby, a better *RSImod* score, as the analysis suggests.

Predictive Analysis (PA-II)

The predictions from the XGBoost classifier (with *RSImod* level as the target feature) trained on a dataset with SWC-based augmentation have a prediction *accuracy* and *F1 score* better compared to that trained on the baseline feature dataset (35 features). The augmentation in the significant features improved the classifier's learning of threshold and respective decision boundaries, thereby making *RSImod* score prediction the following week more accurate. The proposed hierarchical model performs better than the state-of-the-art DT-based regressors regarding the *MSE* and adjusted R^2 metrics.

Challenges and Limitations

We faced several challenges, such as forgetfulness of the athletes when wearing the WHOOP strap, filling in the questionnaire, loss of charger, or failure to charge the WHOOP strap. We overcome these challenges by applying the missing value imputation technique – the MICE imputer. We also had our graduate assistant (GA), who kept reminding the athletes to wear the straps and fill in the questionnaire on time. It helped us deal with the data collection challenges. Yet another limitation was athlete diversity. This study was conducted with a Division I women's basketball team at a specific university. While there is also a men's basketball team at the same institution, data for this group has not been collected. Collecting mental, cognitive, and questionnaires from other teams is also tricky.

Conclusion

This study attempted to quantify the internal/external load-related features causing fatigue to an athlete and the impact of suggested changes in the magnitude of these features upon the athletes' readiness (regarding *RSImod*) for the following week in a collegiate basketball setup. Using a multifaceted approach, we monitored and recorded multiple task-dependent features such as sRPE and its related features during training, *RSImod* from pressure plate during CMJs, and psycho-physiologic features such as sleep patterns, cardiac rhythm, and emotional-mental state depicting features. The inferential analysis (**PA-I**) revealed that 1) *JH*, HoS, *Strain*, *TWLoad*, and *HRV* are the five most significant features causing fatigue. 2) *JH* and *HRV* positively correlate with *RSImod,* and 3) *Strain* and *TWLoad* quantify the total workload during training. Too little training and overtraining negatively affect the *RSImod* score. 4) *HoS* is a quantity of sleep depicting feature, and an athlete sleeping too little/more than the suggested hours is expected to have a low *RSImod* in the following week.

The predictive analysis (**PA-II**) revealed: 1) suggested change in magnitude of significant feature augmentation to the baseline dataset improved the *RSImod* score prediction accuracy. The prediction *accuracy* and *F1 score* of the XGBoost classifier trained on the augmented dataset (95.28%, 0.96) were higher than that trained on the baseline dataset (92.83%, 0.92). 2) The proposed hierarchical model outperformed state-of-the-art DT regressors. The *MSE* and adjusted R^2 scores of the proposed model (0.011, 0.963) were better than the classical DT-regressor (0.057, 0.603), random forest regressor (0.042, 0.612) and XGBoost regressor (0.030, 0.894) as well as the proposed model implemented on the original dataset without SWC augmentation (0.028, 0.906).

The model presented is generalizable to a wide range of data, even with changes in the target feature. For instance, this model could be applied to publicly available NCAA data, using box or game scores as the target feature. It would involve using data from a single modality (e.g., in-game statistics) rather than incorporating physical, physiological, or cognitive data. However, athlete-specific variations in metrics, such as field goal attempts (FGA), could still be tracked for individual athletes, computing their SWC and utilizing the model's recommendations to augment data and predict performance in terms of box score or game score.

Our approach of monitoring multifaceted stressors followed by validated inferential and predictive models helps the coaches guide athletes in improving their readiness for the days ahead. Including machine learning-based predictions in the dashboard helps coaches make early decisions on game strategies, team composition, and training regimes.

Data Availability Statement Seventeen NCAA female basketball athletes took part in this study. The Institutional Review Board (IRB) approved the research, and all participants were informed and consented before participation (IRB approval number XXXXXXX on DD/MM/YYYY). Due to the personal nature of the data, it cannot be publicly released. However, an anonymized sample dataset is available on the GitHub repository (a link can be provided upon acceptance).

Declarations

Conflict of Interest No funding was received for conducting this study. The authors have no competing interests to declare that are relevant to the content of this article.

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