PREDICTING PLAYER LOAD INTENSITY WITH INTERNAL AND EXTERNAL LOAD METRICS IN MEN'S COLLEGIATE SOCCER ATHLETES

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BACKGROUND

- External load is considered the stress placed on the body during activity, and internal load is the physiological response to the imposed stress.
- Athlete self-reported wellness metrics (SRWM), session rating of perceived exertion (sRPE), and heart rate (HR) response are ways to monitor internal load.
- Monitoring external load via wearable microsensors is effective, but the cost and need for trained personnel can pose barriers.
- Machine learning has been used to create models to predict internal player load from previous internal and external load metrics with soccer athletes.
- Limited data exist examining the predictive relationship of SRWM, sRPE, HR, total distance, and player load in men's collegiate soccer athletes.

PURPOSE

- To predict player load intensity (PLI) from sRPE, SRWM, average percentage of maximal HR (%maxHR), and total distance (m) (TD) utilizing machine learning models.

METHODS

- Ten National Collegiate Athletic Association Division I men's soccer primary athletes (n=10; mean ± SD; age: 21 ± 1.55 years, body mass: 74.49 ± 5.15 kg; height: 178.41 ± 6.58 cm; body fat: 15.95 ± 1.92%) participated.
- Primary athletes were classified as those who played $\geq$45 min during 8 or more of 15 in-season games.
- Internal and external load metrics were assessed via wearable microsensors across one soccer season during practices (n=42) and games (n=15).
- Internal load metrics included: %maxHR during activity, sRPE (sRPE = RPE x session duration in minutes), daily morning SRWM (1-10 scale) of fatigue, stress, and soreness.
- External load metrics included TD and PLI.

KEY FINDINGS

Machine learning can be used to predict player load intensity in men's NCAA DI soccer athletes

Figure 1. Pearsons Correlation Matrix for PLI, SRWM, TD and %maxHR

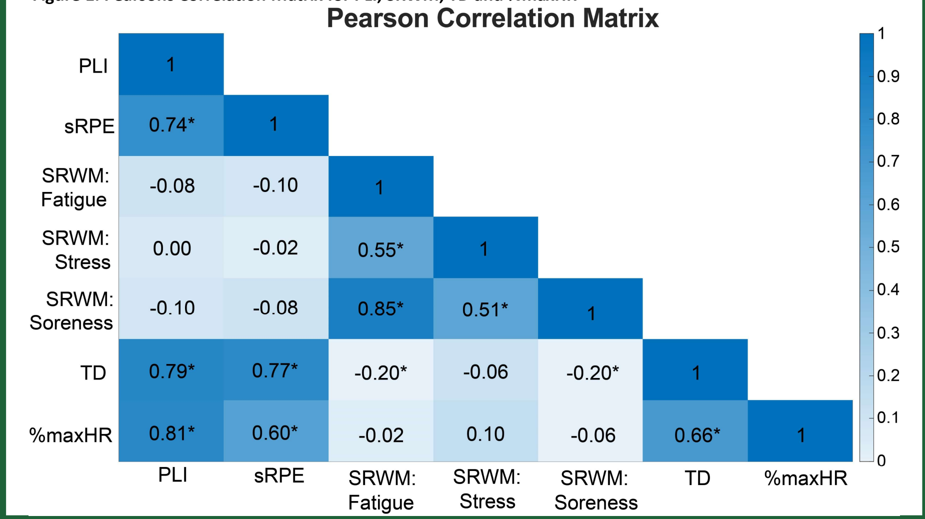
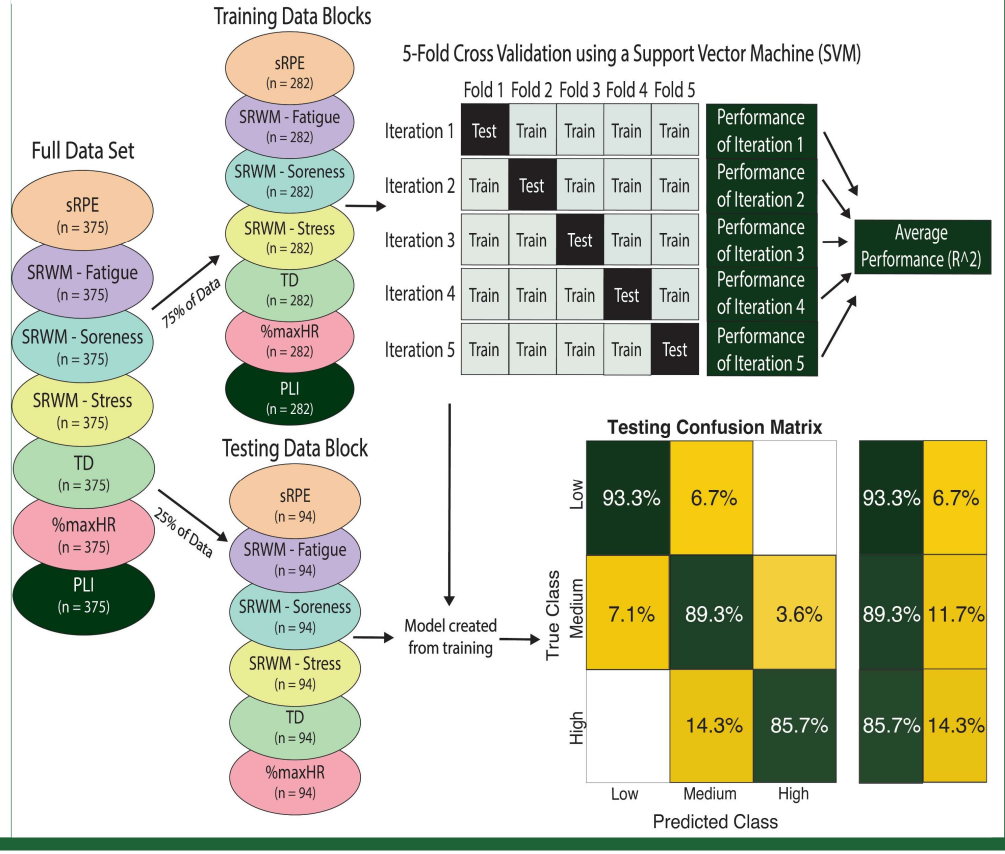


Figure 2. Validation Confusion Matrix for SVM model



STATISTICAL ANALYSIS

- MATLAB was used for statistical analysis ($p<0.05$) and machine learning analysis.
- Relationships between variables were evaluated via Pearson correlation coefficients, which were defined as very weak: <0.20; weak: 0.20–0.39; moderate: 0.40–0.59; strong: 0.60–0.79; and very strong: >0.80.
- Results from correlations informed the selection and implementation of the machine learning model.
- For this analysis, PLI was divided into three categories of low, medium, and high, which was calculated based on the mean and SD of the data distribution.
- A linear support vector (SVM) model using sRPE, SRWM, %maxHR, and TD as features and PLI as a predictor was used and evaluated by 5-fold cross-validation (CV).
- This model trained on 75% of the data and tested on the remaining 25%.

RESULTS

- Very strong correlations existed between PLI and %maxHR (0.81), and between soreness and fatigue (0.85) (figure 1).
- Strong correlations existed between PLI and sRPE (0.74), TD (0.79), between sRPE and TD (0.77), %maxHR (0.6), and between TD and %maxHR (0.66).
- The CV accuracy of the SVM model was 92.90%.
- The prospect of the model predicting each category of player intensity was 94.8% for low, 92.9% for medium, and 88.9% for high (figure 2).

CONCLUSIONS and PRACTICAL APPLICATIONS

- Results demonstrate the ability to predict PLI from a combination of sRPE, SRWM, TD, and %maxHR.
- Machine learning models can be used as a predictive tool to determine player workload intensity.
- While this model shows promise in future use for workload monitoring, caution should be exercised when utilizing metrics taken from different wearable devices.
- This can aid coaches and sport science practitioners plan in athlete workload monitoring.

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