MILITARY OCCUPATIONAL INJURY RISK ANALYSIS USING MACHINE LEARNING DECISION TREES

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Abstract

Purpose: Injuries are the leading cause of medical encounters among U.S. Army soldiers. A recent machine learning decision tree analysis indicated only previous injuries were predictors of future injuries among male soldiers. There may, however, be different injury risk factors for soldiers in different military occupational specialties (MOSs). This study utilized decision tree algorithms to identify injury risk factors among male soldiers from multiple MOSs. **Methods:** Enlisted male soldiers from a U.S. Army light infantry brigade of Armor (n = 426), Infantry (n = 411), and Mechanical Maintenance (n = 388) MOSs completed surveys capturing demographics, anthropometrics, previous injury occurrence within 6 and 12 months, and health-related behaviors (*e.g.,* tobacco use, physical training). Soldiers also completed physical performance assessments (functional movement screen, Army Physical Fitness Test (APFT), agility tests, *etc.*). Machine learning analysis was conducted using Classification and Regression Trees (CART) algorithms via R 3.6.3, rpart (*v* 4.1.15) package. Based on 10-fold cross-validation, the one standard error rule (1-SE rule) was used to find the optimal number of tree splits. Prospective injuries (6- or 12-month follow-up) were identified in medical records by International Classification of Diseases Ninth Revision (ICD-9) codes and included acute and overuse musculoskeletal (sprains, bone stress injuries, *etc.*) and non-musculoskeletal (blisters, heat injuries, *etc.*) injuries. Sensitivity, specificity, precision, and F1 score (harmonic mean of precision and recall) were used to assess overall model performance. **Results:** MOS-specific injury incidence at 6- and 12-months follow-up, respectively, was: Armor, 37.8% and 55.4%; Infantry, 37.5% and 56.4%; Mechanical Maintenance, 48.2% and 67.0%. CART analysis by MOS yielded different decision tree models; however, the models shared similar F1 values (range = 0.620 - 0.642). For most models, one split was optimal, with an injury 6 months prior predicting future injuries at 6- or 12-months follow-up. Only the Armor model (sensitivity = 0.658; specificity = 0.717; F1 value = 0.620) contained an additional split (APFT 2-mile run time ≥ 13 min) for soldiers injured 6 months prior. No other health behaviors or fitness factors predicted future injury within 6- or 12-months among men in these MOSs. **Conclusions:** Despite using MOS-specific injury prediction models, the most important factor predicting a future injury through 12-months follow-up was an injury within 6 months prior to the investigation. Only one additional measure (APFT 2-mile run ≥ 13 min) was a predictor of future injury in previously injured Armor soldiers. **Military Impact:** The current machine learning CART analysis provides updated information for MOS-specific injury predictions. Injury type and location may influence military decision tree models and requires further investigation.

Introduction/Background

- In 2021, injuries accounted for over 2 million medical encounters in U.S. Army Soldiers, representing the highest burdensome category of medical diagnoses.[1]
- Our recent machine learning decision tree analysis indicated only previous injuries were predictors of future injuries among a male Soldier cohort in a light infantry brigade, representing a wide-variety of military occupational specialties (MOSs).
- There may be different injury risk factors for Soldiers in different MOSs within a single brigade.

Purpose

To identify injury risk factors among male Soldiers from multiple MOSs using machine learning decision tree algorithms.

Methods

- Enlisted male Soldiers from an Army light infantry brigade (n = 2,425) completed surveys and physical performance assessments to assess modifiable and non-modifiable potential injury risk factors on prospective injuries (Table 1).
- This study was a secondary analysis from an original investigation in September 2011, with a follow-up period of 6 to 12 months.
- Used a sub-population of Soldiers from the top 3 (by population) MOSs in a single U.S. Army infantry brigade to examine the influence of MOS on future injury risk: Armor (n = 426), Infantry (n = 411), and Mechanical Maintenance (n = 388).

Table 1. Survey and Physical Performance Assessment Variables

Survey Assessments	Physical Performance Assessments
Demographics (age, sex, MOS)	Army Physical Fitness Test (Push-ups, Sit-ups, 2-mile run)
Anthropometrics (height, weight, BMI)	Field-expedient fitness tests (300-yard shuttle run, agility tests)
Injury within previous 6 and 12 months	Functional movement screen (FMS)
Health behaviors (tobacco use, physical training)	

Note: Table provides examples of each category assessed and not all potential risk factors assessed.

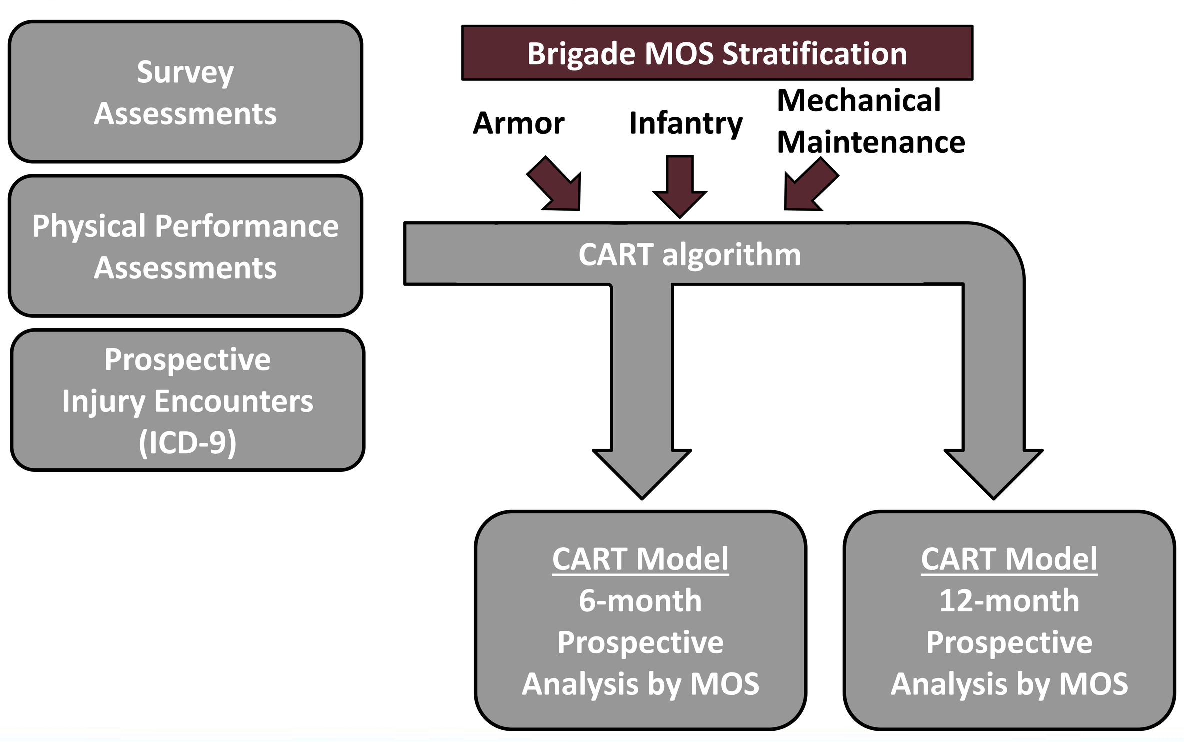
Prospective injury outcomes

- Medical records using an injury index comprised of musculoskeletal (e.g., sprains, strains, fractures, bone stress injuries, etc.) and non-musculoskeletal (blisters, heat injuries, etc.) injuries, including both acute and overuse onset.
- Prospective analysis 6 and 12 months from the time of survey and physical performance testing using International Classification of Diseases Ninth Revision (ICD-9) diagnostic codes.

Machine Learning Models

- Employed a Classification and Regression Trees (CART) algorithm using R 3.6.3, the *rpart* (*v4.1.15*) package, where decision tree models were stratified by each MOS from Soldiers within the Brigade (Figure 1).
  - CART algorithms partitioned the sample population into smaller subsets via binary splits, enabling examination of interactions between certain variables within the smaller groups. Binary splits were based on Gini impurity.[2]
- Sensitivity, specificity, precision, and F1 score (harmonic mean of precision and recall) were used to assess overall model performance (Table 3).
- Using the 10-fold cross-validation method, the One Standard Error Rule (1-SE rule) was used to find the optimal number of splits for the trees. Cross-validation error values and optimal number of splits are listed for each model (Figures 2-5).

Figure 1. CART Algorithm Processing Stratified by MOS



Results

Table 2. Injury incidence among male Infantry Brigade Soldiers

MOS	Injury incidence 6 months (n, %)	12 months (n, %)
Armor (n = 426)	161 (37.8%)	236 (55.4%)
Infantry (n = 411)	154 (37.5%)	232 (56.4%)
Mechanical Maintenance (n = 388)	187 (48.2%)	260 (67.0%)
Overall (n = 1,225)	502 (41.0%)	728 (59.4%)

Table 3. Prospective Analysis CART Model Performance Measures

Model Parameter	Armor 6 months	Armor 12 months	Infantry 6 months	Infantry 12 months	Mechanical Maintenance 6 months	Mechanical Maintenance 12 months
Sensitivity/Recall	0.658	0.585	–	0.569	0.674	–
Specificity	0.717	0.705	–	0.726	0.682	–
Precision	0.586	0.711	–	0.729	0.663	–
F1 score	0.620	0.642	–	0.639	0.668	–

F1 score = harmonic mean of precision and recall; "–" = CART algorithm indicated 0 splits for potential model; therefore, no model parameters are provided above or models presented below.

6-month Prospective CART Models

Figure 2. Armor Soldiers 6-month model

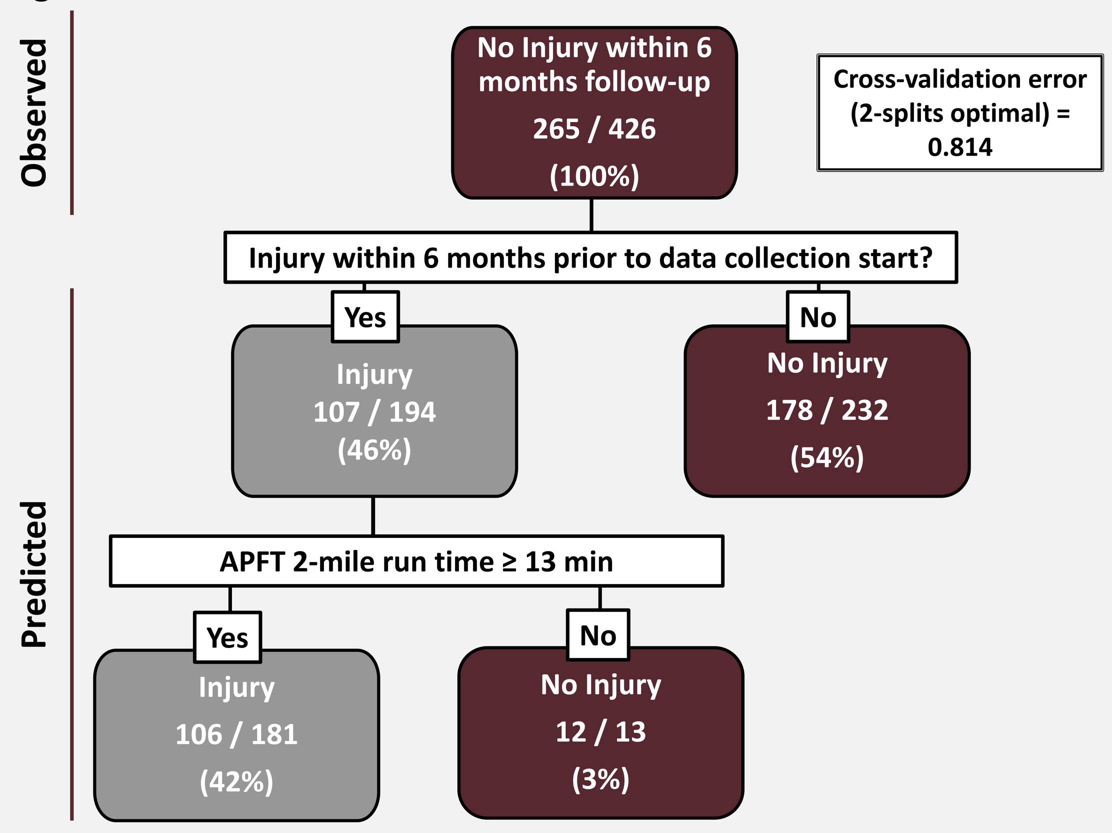


Table 4. Variable Importance for Armor Soldiers (6 months)

Variable	Variable Importance
Injury within 6 months prior	41
Injury within 12 months prior	37
APFT Two-mile run time	13

Note: Top 3 predictor variables only

<u>Armor 6-month Prospective Analysis (Figure 2)</u>

- Two splits were optimal based on cross-validation error = 0.814.
  - **Most important discriminator for a future injury was an injury occurrence within 6 months before the study.**
  - For Armor Soldiers injured within 6 months before the study, an APFT 2-mile run time ≥ 13 minutes predicted a future injury occurring within 6 months follow-up.
- No demographic, anthropometric, physical performance, or health behavior factors predicted a future injury occurring within 6 months follow-up.

Figure 3. Mechanical Maintenance Soldiers 6-month model

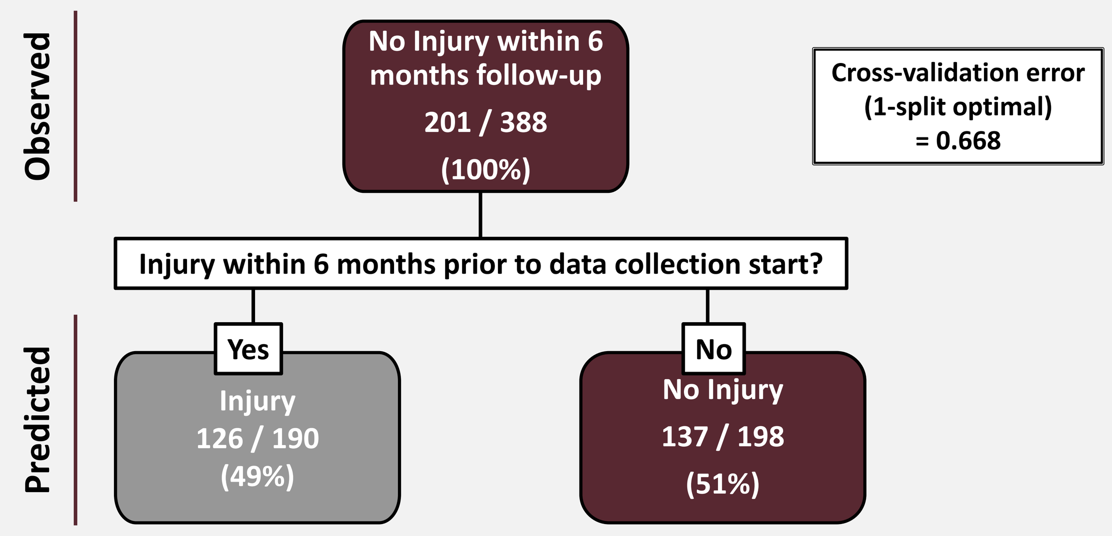


Table 6. Variable Importance for Mechanical Maintenance Soldiers (6 months)

Variable	Variable Importance
Injury within 6 months prior	41
Injury within 12 months prior	39
Age	8

Note: Top 3 predictor variables only

<u>Mechanical Maintenance 6-month Prospective Analysis (Figure 3)</u>

- One split was optimal based on cross-validation error = 0.668.
  - **Most important discriminator for a future injury was an injury occurrence within 6 months before the study.**
- No demographic, anthropometric, physical performance, or health behavior factors predicted a future injury occurring within 6 months follow-up.

12-month Prospective CART Models

Figure 4. Armor Soldiers 12-month model

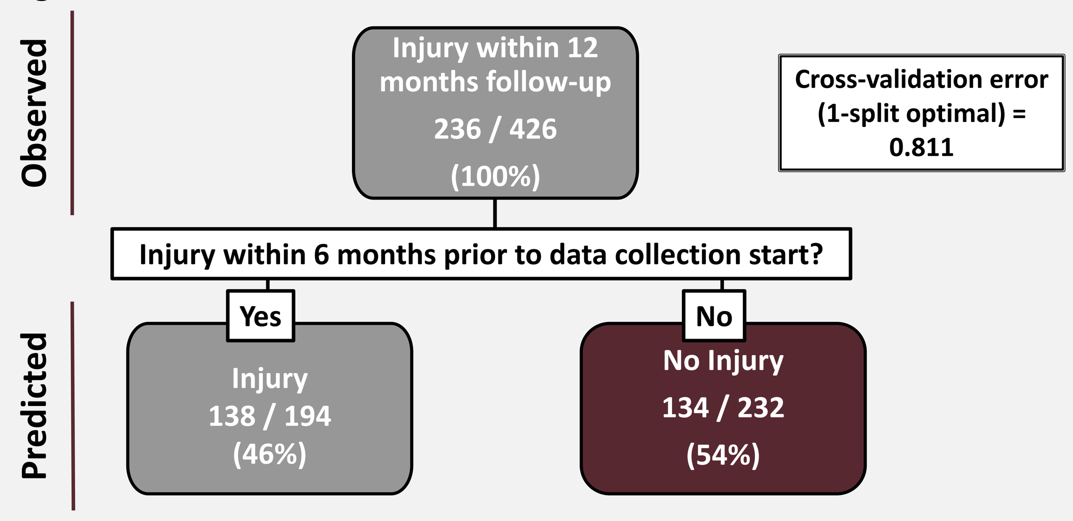


Table 5. Variable Importance for Armor Soldiers (12 months)

Variable	Variable Importance
Injury within 6 months prior	50
Injury within 12 months prior	45
FMS Rotary Stability	2

Note: Top 3 predictor variables only

<u>Armor 12-month Prospective Analysis (Figure 4)</u>

- One split was optimal based on cross-validation error = 0.811.
  - **Most important discriminator for a future injury within 12 months was an injury occurrence within 6 months before the survey.**
- No demographic, anthropometric, physical performance, or health behavior factors predicted a future injury occurring within 12 months follow-up.

Figure 5. Infantry Soldiers 12-month model

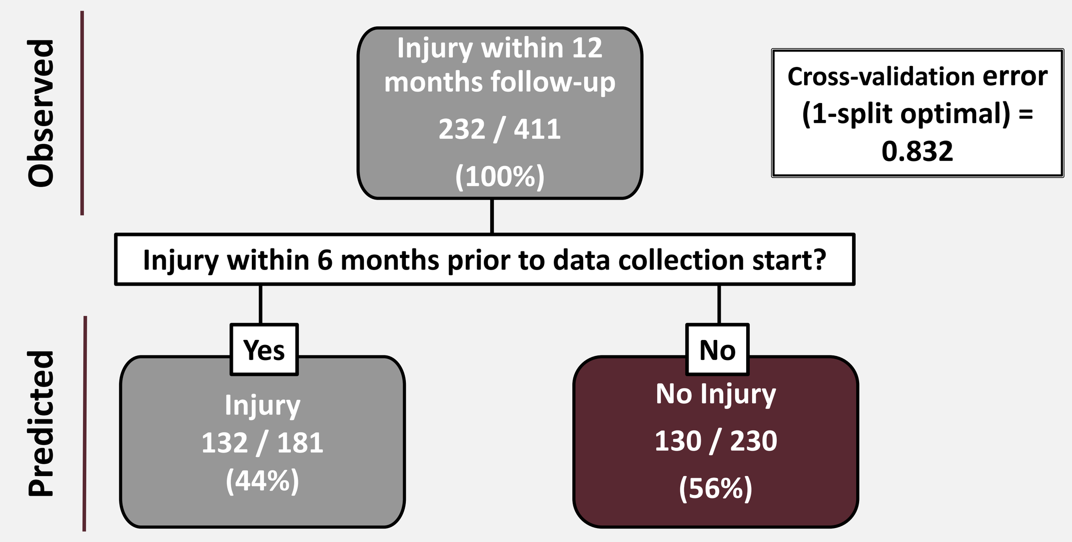


Table 7. Variable Importance for Infantry Soldiers (12 months)

Variable	Variable Importance
Injury within 6 months prior	50
Injury within 12 months prior	45
Age	2

Note: Top 3 predictor variables only

<u>Infantry 12-month Prospective Analysis (Figure 5)</u>

- One split was optimal based on cross-validation error = 0.832.
  - **Most important discriminator for a future injury within 12 months was an injury occurrence within 6 months before the survey.**
- No demographic, anthropometric, physical performance, or health behavior factors predicted a future injury occurring within 12 months follow-up.

DCPH-A photo by Graham Snodgrass

Conclusions

- Soldiers from different MOSs, even within the same brigade, appear to have slightly different injury risk prediction factors.
  - Only the Armor Soldiers had an additional measure of injury prediction (APFT 2-mile run time ≥ 13 min) beyond a previous injury within 6 months prior to the surveillance period that predicted a future injury. This may relate to consistent observations that faster run times are protective against future injuries in military populations.
- Despite using MOS-specific modeling, the most important discriminator for a future injury within 6- or 12-months follow-up was a previous injury within 6 months before the surveillance period.
  - Beyond previous injuries within either 6 or 12 months prior, the next most important future injury risk factor variables demonstrate large drop-offs in importance.
- Specific future injuries may be better predicted by previous injuries of the same type, location, and laterality.
- Further exploration of machine learning and its utility for military injury risk factor prediction is needed.

References

1) DCPH-A. "Healthcare Utilization: Information for Prevention Planning and Measuring Medical Readiness." 2022 Health of the Force Report. Aberdeen Proving Ground, MD, 2023. https://phc.amedd.army.mil/topics/campaigns/hof/Pages/default.aspx
2) Bird, M.B., K.J. Koltun, Q. Mi, et al., "*Predictive utility of commercial grade technologies for assessing musculoskeletal injury risk in US Marine Corps Officer candidates.*" Front Physiol, 2023. **14**: p. 1088813.

U.S. Army Public Health Center (APHC) recently became "Defense Centers for Public Health – Aberdeen (DCPH-A)" and is now part of Defense Health Agency (DHA).

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