CIS/SCM 593: Applied Project

GRIP LAB AI PROJECT

1. Executive Summary

The Grip Lab AI project addresses a gap in the current wearable technology market: the lack of external measures for athletic performance or strength in standard recovery metrics. While devices like Oura rings track physiological recovery, they do not account for physical readiness. This project aimed to design a data-driven solution integrating grip and pinch strength data with wearable health metrics to provide more accurate recovery insights.

Using datasets containing Oura Ring scores and various grip strength metrics (e.g., Squegg, Jamar), the team performed extensive Exploratory Data Analysis (EDA) and developed a Machine Learning model using XGBoost. Key findings reveal a clear positive correlation between grip strength and readiness scores, with specific performance thresholds (e.g., grip strength > 142 lbs) significantly boosting recovery prediction. The final output includes an "Adjusted Recovery Score" model that applies penalties or bonuses based on physical performance, offering a more actionable metric for athletes.

2. Business Problem Definition

Problem Statement: Wearables like smartwatches and smart rings are increasingly popular, but they lack a true external measure of athletic performance or strength. Recovery and readiness scores derived solely from biometric data (like heart rate and sleep) are not fully actionable for consumers or athletes who need to understand their physical capacity.

Business Context: By integrating grip/pinch strength data with wearable health metrics, Grip Lab AI bridges the gap between biometric tracking and real-world athletic performance. This allows for the creation of new features for wearable companies and better insights for users in grip-reliant sports like tennis, golf, and climbing.

3. Objectives, Goals, and Scope

Goal: To design a data-driven solution that integrates grip strength with wearable technology to provide more accurate recovery insights.

Measurable Objectives:

1. Conduct exploratory data analysis on smartwatch, smart-ring, and grip strength datasets.

2. Build and validate a machine learning model to enhance recovery and readiness scores.

3. Identify specific thresholds where grip strength impacts readiness scores.

4. Develop a new "Adjusted Recovery Score" metric.

Scope: The project focuses on Oura Ring data and multiple grip strength measurement devices (Squegg, Jamar, etc.).

4. Data Sources

The analysis utilized structured datasets combining wearable biometrics and physical performance logs.

- **Primary Data:** Oura Ring and Whoop data including Sleep Balance, HRV Balance, Resting Heart Rate, and Readiness Scores etc.

- **Performance Data:** Grip and pinch strength measurements collected from 7 devices such as Squegg (Lumbrical Pinch, Tripod Pinch, Grip) and Jamar etc.

5. Data Preparation

To ensure data quality and model readiness, the following steps were taken:

- **Data Cleaning:** String formatting issues (e.g., removing "%" signs) were corrected, and columns were converted to numeric types.

- **Imputation:** Missing values were handled using `IterativeImputer` to maintain dataset integrity.

- **Feature Engineering:**

    - **Asymmetry Calculation:** New features were created to measure the strength imbalance between left and right hands (e.g., `Squegg_Grip_AI`).

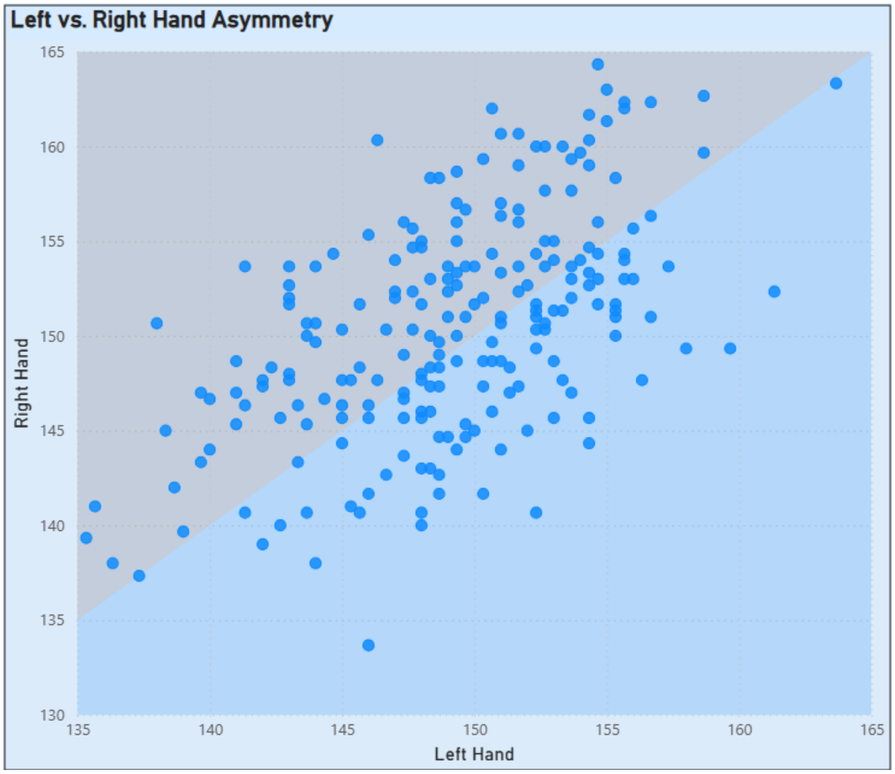
    - **Rolling Baselines:** 7-day rolling averages were calculated for recovery scores to establish a personal baseline.

    - **Penalty/Bonus Logic:** A custom logic was defined where drops in recovery below baseline triggered a penalty, while significant gains in grip strength provided a bonus to the score.

6. Exploratory Data Analysis (EDA)

Our analysis focused on visualizing the "disconnect" between physiological metrics and physical output.

- **Neuromuscular Asymmetry:** We identified a "Neural Disconnect" where significant deviations (**>10%**) between left and right-hand strength served as a clear precursor to injury. These outliers became a primary trigger for our "Fatigue Penalty".



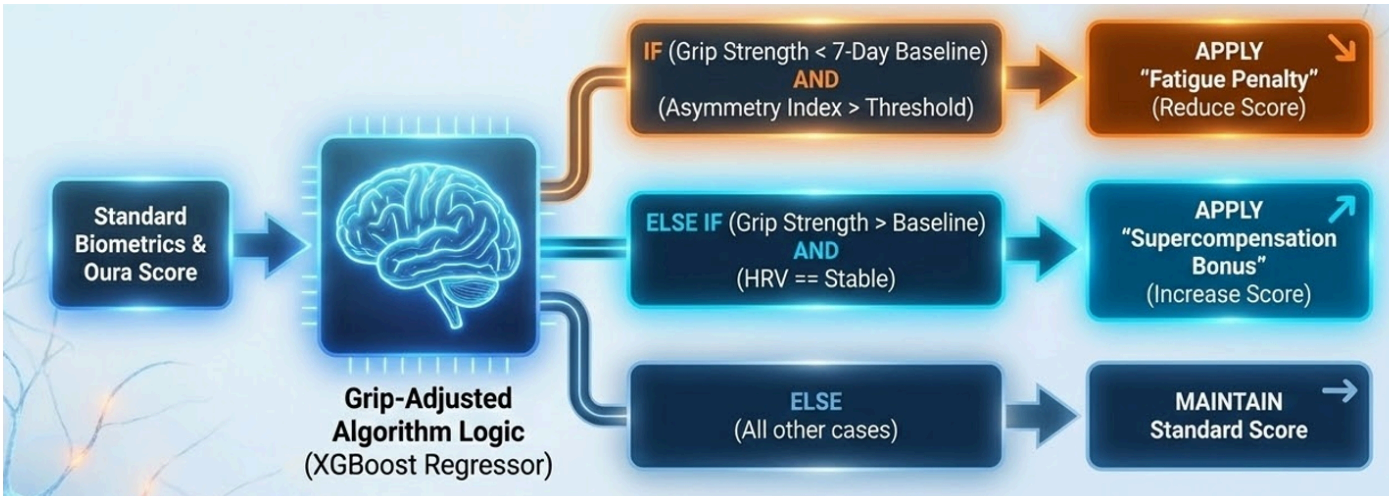
- **Performance Thresholds:** The data revealed specific "tipping points." A tripod pinch strength below **~57 lbs** correlated with consistently lower readiness, while gross grip strength showed diminishing returns after **~155 lbs**.
- **The HRV Trade-Off:** High HRV acted as a "bonus multiplier" only when grip strength was also high; high HRV with low strength (purple zone in heatmaps) did not yield peak readiness scores.

7. Modeling Approach

We selected an XGBoost Regressor to function not as a replacement, but as a "Recovery Audit" layer on top of standard biometrics.

- **The Logic:** The model compares current performance to a **7-day rolling baseline** to apply dynamic adjustments:
  - **Fatigue Penalty:** Applied if Grip < Baseline *AND* Asymmetry > 10% (flagging neural fatigue).

- ○ **Supercompensation Bonus:** Applied if Grip > Baseline *AND* HRV is stable (identifying peak capacity).



8. Model Evaluation

The model was evaluated not as a replacement for Oura scores, but as a "Recovery Audit" layer to detect blind spots.

- **The "Audit" Logic:** The XGBoost model applies a logic check: it triggers a "Fatigue Penalty" if grip strength is below baseline with high asymmetry, or a "Supercompensation Bonus" if strength is high with stable HRV.
- **Significance of Correction:** To test validity, we measured how often the new model changed the original Oura and Whoop recommendations. In **86.67% of cases**, integrating grip data resulted in a **significant correction** to the score, proving that relying solely on physiological data leaves a massive "blind spot" regarding physical readiness.

9. Key Findings and Insights

01. **Strength Thresholds Matter:**
    a. **Pinch Strength:** Below ~57 lbs, the predicted score remains low (~78.6). Once crossing ~57, the score jumps significantly.
    b. **Grip Strength:** A significant boost occurs when strength crosses ~142 lbs. Benefits plateau after ~155 lbs

02. **The HRV Trade-Off:** High HRV acts as a "bonus multiplier" only when grip strength is also high. High HRV with low grip strength does not yield the highest possible readiness scores.

03. **Actionable Insight:** Physical performance metrics can "rescue" a low recovery score, indicating that the body may be more ready to perform than biometric data alone suggests.

10. Recommendations and Action Plan

- **Feature Integration:** Wearable companies should integrate manual input or connected grip-strength testing to refine readiness algorithms.
- **Targeted Use Cases:** Marketing should focus on sports where grip is a proxy for total body readiness (e.g., climbing, tennis, weightlifting).
- **Partnerships:** Pursue partnerships with smart-equipment manufacturers (like Squegg) to automate data ingestion into health ecosystems.in

11. Conclusion

The Grip Lab AI project successfully demonstrated that integrating grip strength data with standard wearable metrics provides a more holistic view of athlete readiness. By applying the "Adjusted Recovery Model," users can see how their physical output capability influences their recovery status, specifically identifying that on days of poor physiological sleep, strength maintenance is a key indicator of readiness.

12. Appendix

Key Code Snippet (Adjustment Logic):

```python
Python
df["Penalty_target"] = (df["Baseline_Recovery"] - rec).clip(lower=0)
rel_gain = (df["Squegg_Delta"] / df["Squegg_Baseline"])
df["Bonus_Squegg"] = bonus_strength * rel_gain.clip(lower=0)
df["Adjusted_Recovery_Squegg"] = (rec - df["Penalty_XGB"] +
df["Bonus_Squegg"]).clip(lower=0, upper=100)
```