Smart Insoles for Detecting Fatigue through Weight Distribution and Gait Analysis

Humanist Nebija, Aurel Coza PhD

School of Biological and Health Systems Engineering, Arizona State University, Tempe, AZ, USA

Introduction

- Wearable tech revolutionizing movement monitoring (e.g., LAAF Smart Insole)
- Seven pressure sensors capture real-time gait data
- Fatigue classification using sensor features from heel-to-toe transition (fatigue-sensitive gait phase)

Fig. 1. LAAF (Live Active and Agony Free) Smart Insole.

Background

- Fatigue disrupts gait: stride length, cadence, symmetry, pressure distribution[1]
- Machine learning models (Fine Tree, Medium Tree, Fine KNN, Weighted KNN) classify fatigue from insole data
- PCA reduces data complexity, highlights key features[2]

- Hypothesis: Heel-to-toe transition parameters are key for detecting and classifying fatigue.

Methods

Experiment Setup:
- 6 participants (Men: shoe sizes 8.5-9.5, Women: 10.5-11.5)
- No pre-existing conditions affecting gait
- Gait data recorded during natural walking

Data Collection:
- Baseline gait recorded in non-fatigued state
- Fatiguing exercise performed (fatigue score ≥ 7)
- Post-fatigue gait recorded under identical conditions

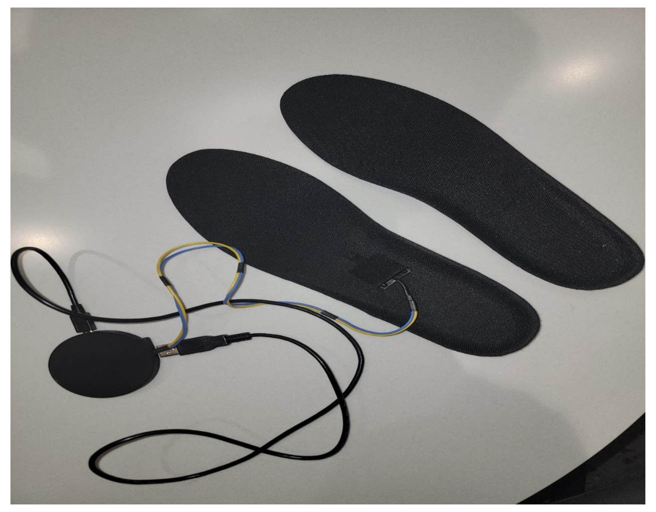

Fig. 2. LAAF Smart Insoles used to record gait data during natural walking

Methods

Sensor Data Processing:
- Steps: heel contact to toe-off
- Sensor activations grouped by global step event

- Features extracted per footstep: footstep, sensor start time, sensor end time, average pressure, peak pressure, peak time, contact duration, sensor activation delay

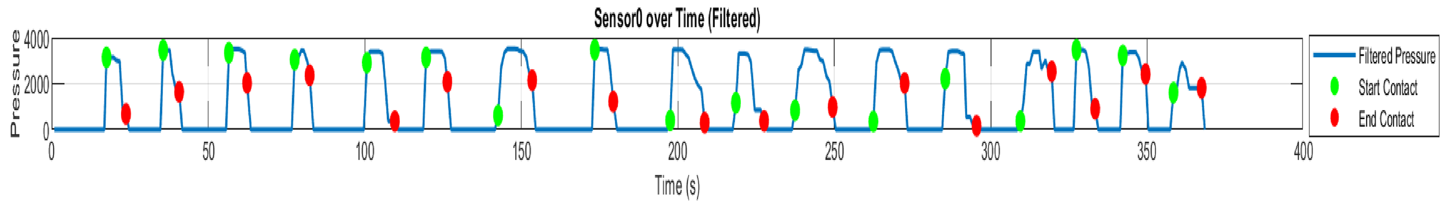

Fig. 3. Pressure data from a LAAF Smart Insole sensor over time.

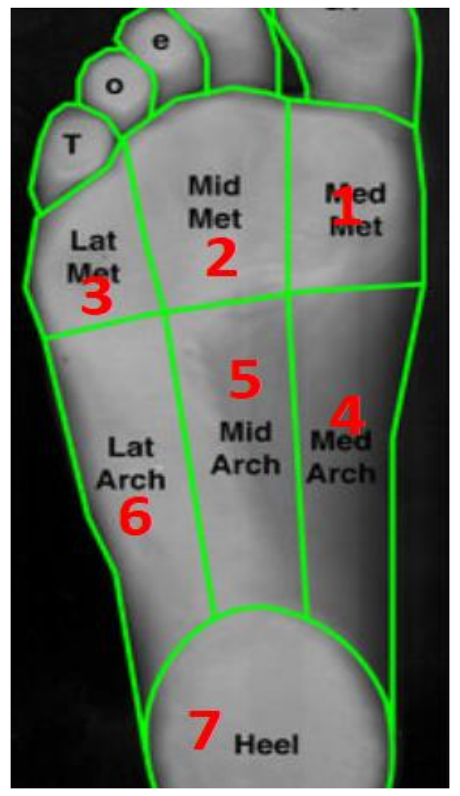

Fig. 4. Foot pressure distribution from the LAAF Smart Insole. Seven sensors placed across the heel, midfoot, and forefoot regions measure plantar pressure.

Results

- Moderate accuracy across all models: Fine Tree (61.66%), Medium Tree (59.56%), Weighted KNN (66.40%), and Fine KNN (67.63%, highest)

- Using PCA, average pressure and peak pressure were identified as the strongest contributors for fatigue classification

- 77% of rested individuals correctly classified, 54.2% of fatigued individuals correctly classified

- Strong diagonal pattern, most predictions matched true labels

- Better accuracy for rested, possible sensitivity imbalance for fatigued detection

Results

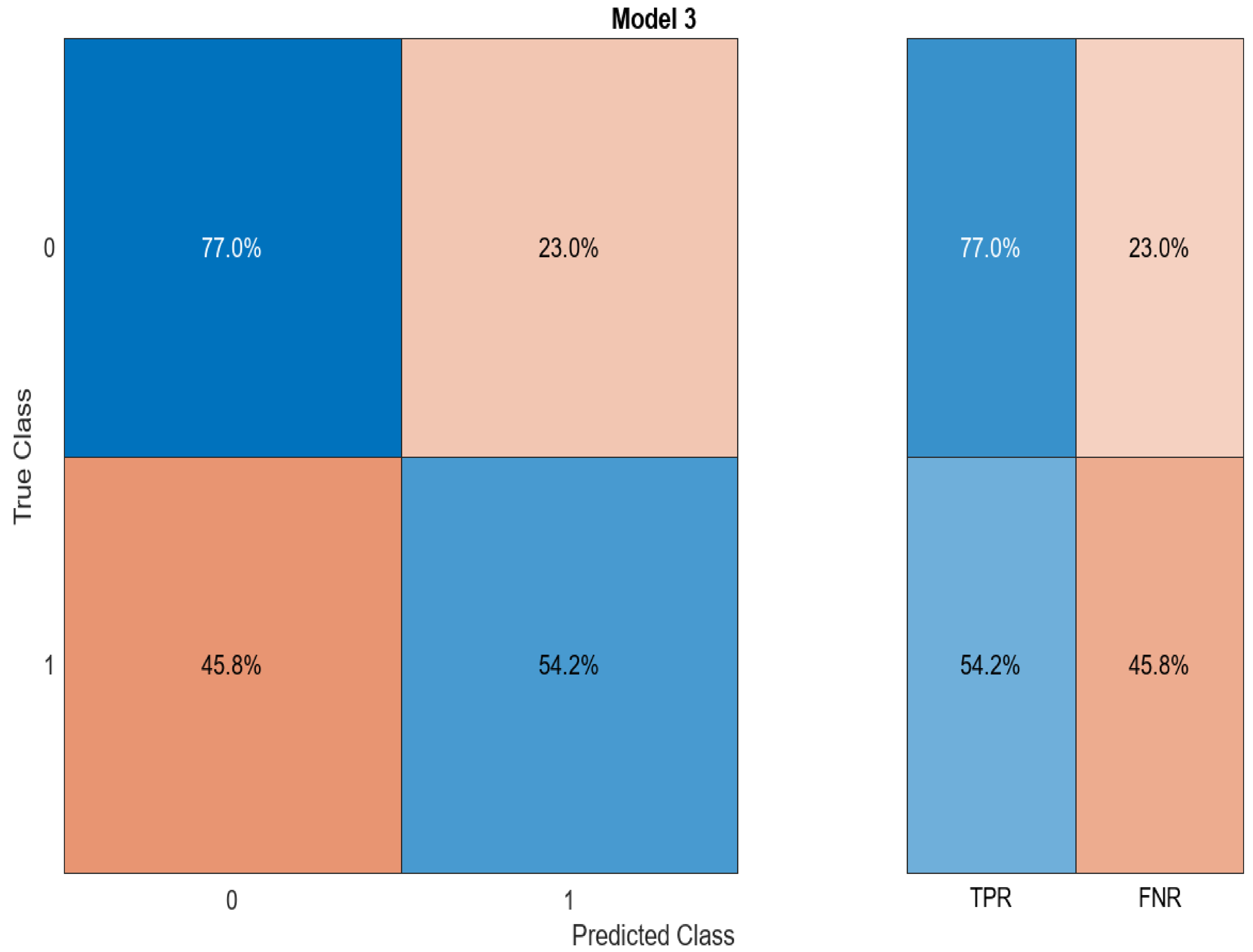

Fig. 5. Confusion matrix showing model performance in classifying rested (0) and fatigued (1) conditions using Fine KNN.

Summary, Conclusions and Future Directions

- Sensor-derived parameters can classify fatigue vs. non-fatigue states using machine learning

- KNN classifiers outperform tree-based models in fatigue classification

- Importance of pressure-related features (avg & peak pressure) in fatigue detection

- Potential for real-time fatigue monitoring in sports, rehab, and occupational health

- Expand beyond heel-to-toe transition to include more gait phases

- Increase study size and diversity for stronger generalizability

References

1. R. Mason et al., “Wearables for running gait analysis: A systematic review,” Sports Med., vol. 53, no. 1, pp. 241–268, 2023. doi: 10.1007/s40279-022-01760-6.
2. IBM, “What is Principal Component Analysis (PCA)?,” IBM, Feb. 3, 2025. [Online]. Available: https://www.ibm.com/think/topics/principal-component-analysis [Accessed: Apr. 12, 2025].

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Ira A. Fulton Schools of Engineering
Arizona State University