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Identifying Musculoskeletal Injury from Movement Time Series using a Sinusoidal Representation Network.

Building the Analytical Foundation for Wearable Musculoskeletal Injury Biomarkers

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Disclaimer

The views expressed in this abstract are those of the authors and do not reflect the official policy or position of the U.S. Army Medical Department, Department of the Army, DoW, or the U.S. Government.

Learning Objectives

1. Outline considerations for designing human subject data collection protocols for developing classifiers.
2. Describe novel machine learning method for dimensionality reduction of movement data.
3. Broaden understanding of movement markers for clinical decision making.

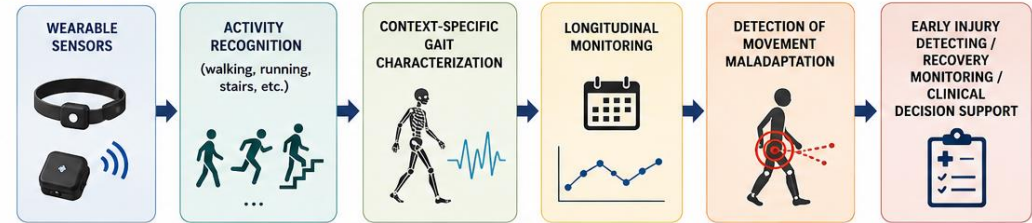
The Road Map to Wearable Derived Biomarkers of Musculoskeletal Health

- Context Matters
 - Premise
 - Collecting Data 'in the wild'
- Clinical Need
- The Challenge
- Our Strategy
- Translation

1. THE LONG-TERM VISION

Toward Wearable Biomarkers of Musculoskeletal Health

- Continuous monitoring using wearable sensors has enormous potential for musculoskeletal injury surveillance.
- Gait is highly context dependent.
- Before gait can be interpreted clinically, we must first know what activity is being performed.
- Only then can gait characteristics be compared appropriately across time.



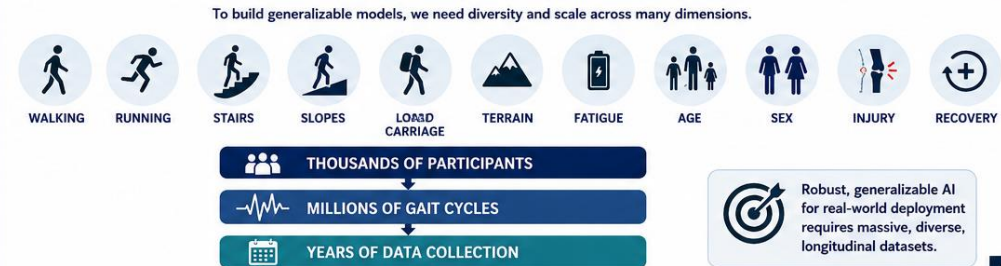
Activity recognition is the essential foundation for meaningful, longitudinal gait analysis and clinical insight.

1

2. THE DATA CHALLENGE

Developing Robust AI Requires Large, Diverse Movement Datasets

- Large human movement datasets are expensive and time-consuming to collect.
- Clinical datasets often contain relatively few participants.
- Model architecture decisions are frequently made using limited datasets.
- This increases the risk of overfitting and poor generalization.



2

3. OUR APPROACH

Leveraging Large Open Movement Datasets to Inform Model Development

RATHER THAN IMMEDIATELY COLLECTING A NEW DATASET...



WE FIRST ASKED:

- ✓ Which neural network architectures perform best?
- ✓ What temporal window is optimal?
- ✓ Which activation functions should be used?
- ✓ Which anatomical locations contribute the most information?
- ✓ How much instrumentation is actually required?
- ✓ Do findings generalize across measurement technologies (MoCap → IMUs)?

CURRENT STUDY



Use large publicly available datasets (marker-derived and IMU-derived) to answer these methodological questions before collecting our own military datasets.

**Build the analytical foundation first.
Then collect smarter.**

3



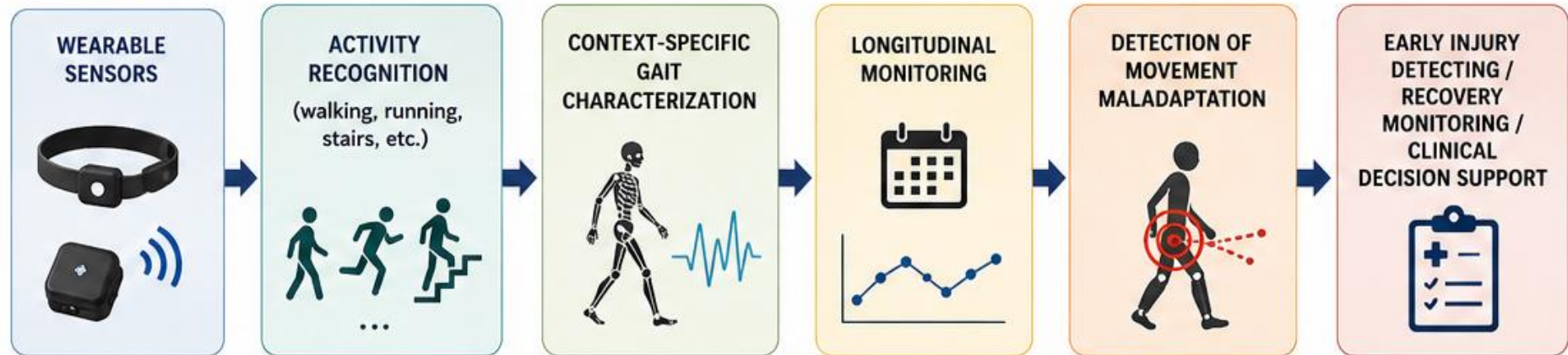
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Long Term Vision - From Wearable Sensors to Clinical Decision Support

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The Challenge - Building Robust AI Requires Large-Scale Movement Datasets

2. THE DATA CHALLENGE

Developing Robust AI Requires Large, Diverse Movement Datasets



Large human movement datasets are expensive and time-consuming to collect.



Clinical datasets often contain relatively few participants.



Model architecture decisions are frequently made using limited datasets.



This increases the risk of overfitting and poor generalization.

To build generalizable models, we need diversity and scale across many dimensions.



WALKING



RUNNING



STAIRS



SLOPES



LOAD
CARRIAGE



TERRAIN



FATIGUE



AGE



SEX



INJURY



RECOVERY



THOUSANDS OF PARTICIPANTS



MILLIONS OF GAIT CYCLES



YEARS OF DATA COLLECTION



Robust, generalizable AI for real-world deployment requires massive, diverse, longitudinal datasets.



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Our Approach - Learning from Big Data Before Collecting New Data

3. OUR APPROACH

Leveraging Large Open Movement Datasets to Inform Model Development

**RATHER THAN IMMEDIATELY
COLLECTING A NEW DATASET...**



YEARS OF TIME • HIGH COST • LIMITED EARLY INSIGHT

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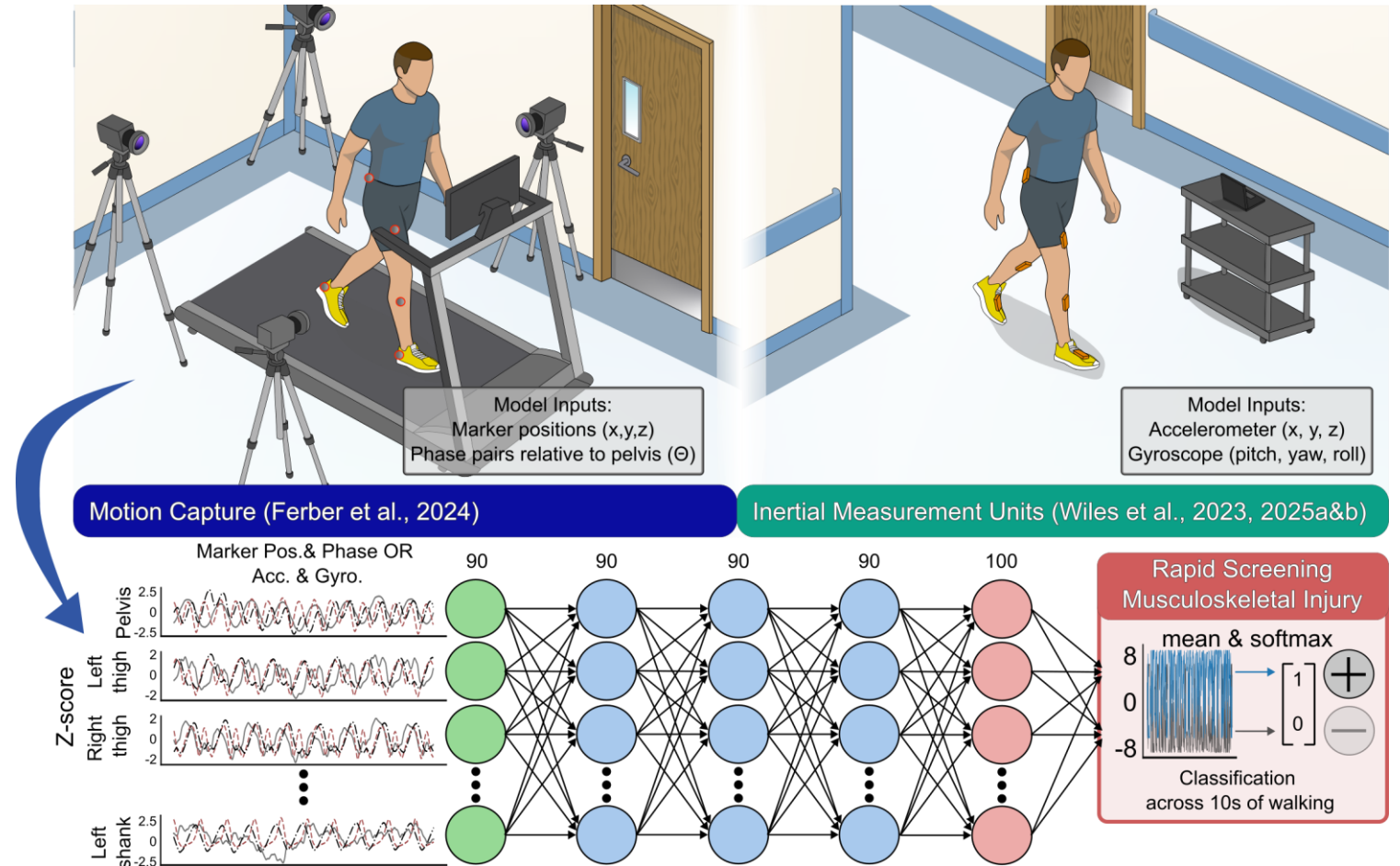
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Our Approach - Develop the Flexible Analytics First: Collect Smarter Later

- Large Public Gait Datasets Accelerate Method Development
 - Different measurement methods
 - Different contexts (treadmill vs overground walking)
 - Different musculoskeletal injuries



Optimizing Model Architecture

Our goal: Identify the analytical choices that maximize performance with the least complexity for future wearable deployment

THREE KEY QUESTIONS

1 WHAT DURATION?



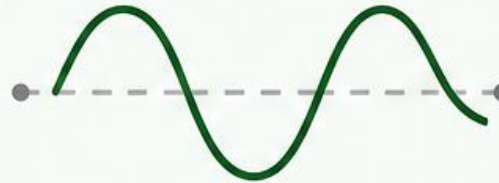
5 sec

10 sec

20 sec

How much data is enough to capture the signal?

2 WHAT ACTIVATION FUNCTION?



Sine

ReLU

Leaky ReLU

Tanh

ELU

Which function best represents the periodic nature of human movement?

3 HOW MANY SENSORS?



- Pelvis
- Thigh
- Shank
- Foot

What is the minimal sensor configuration that maintains high performance?



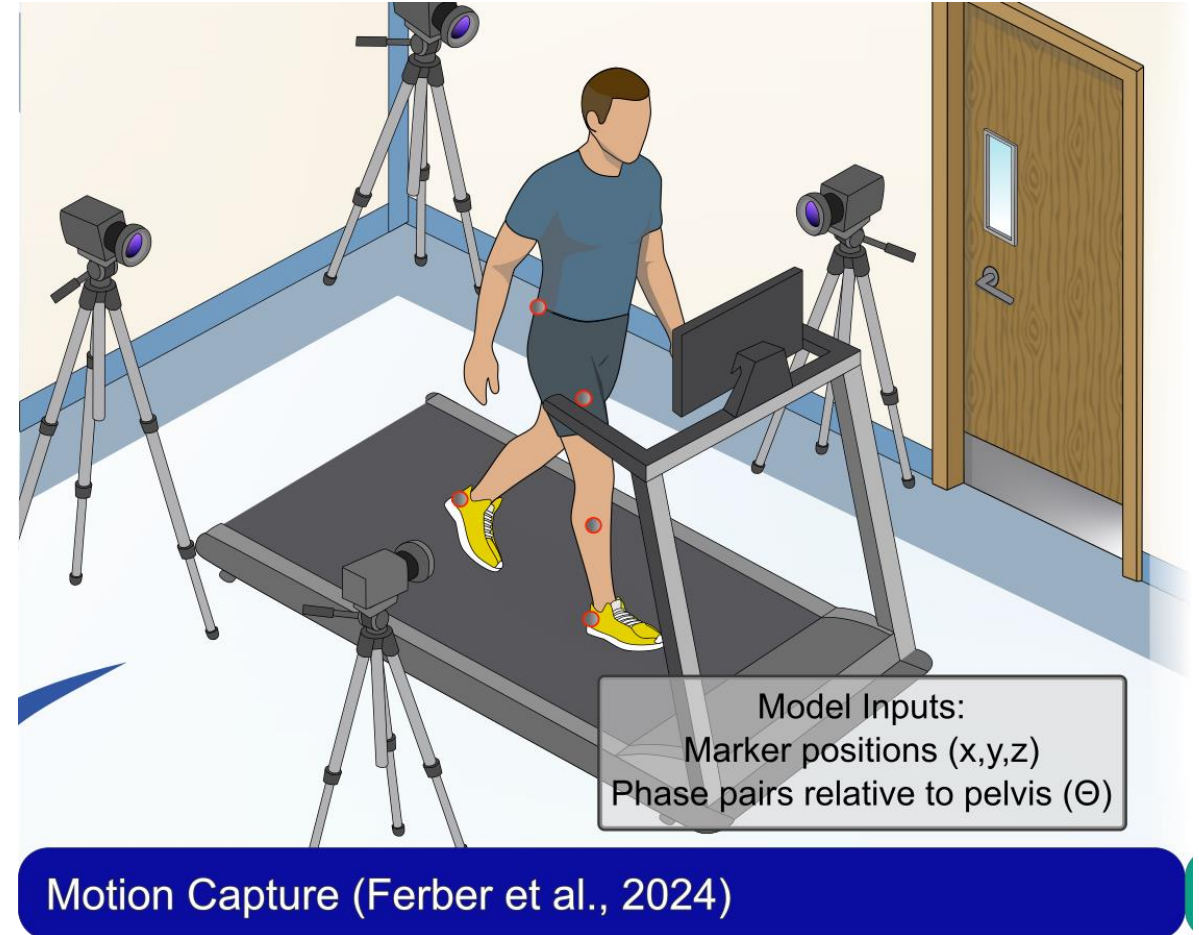
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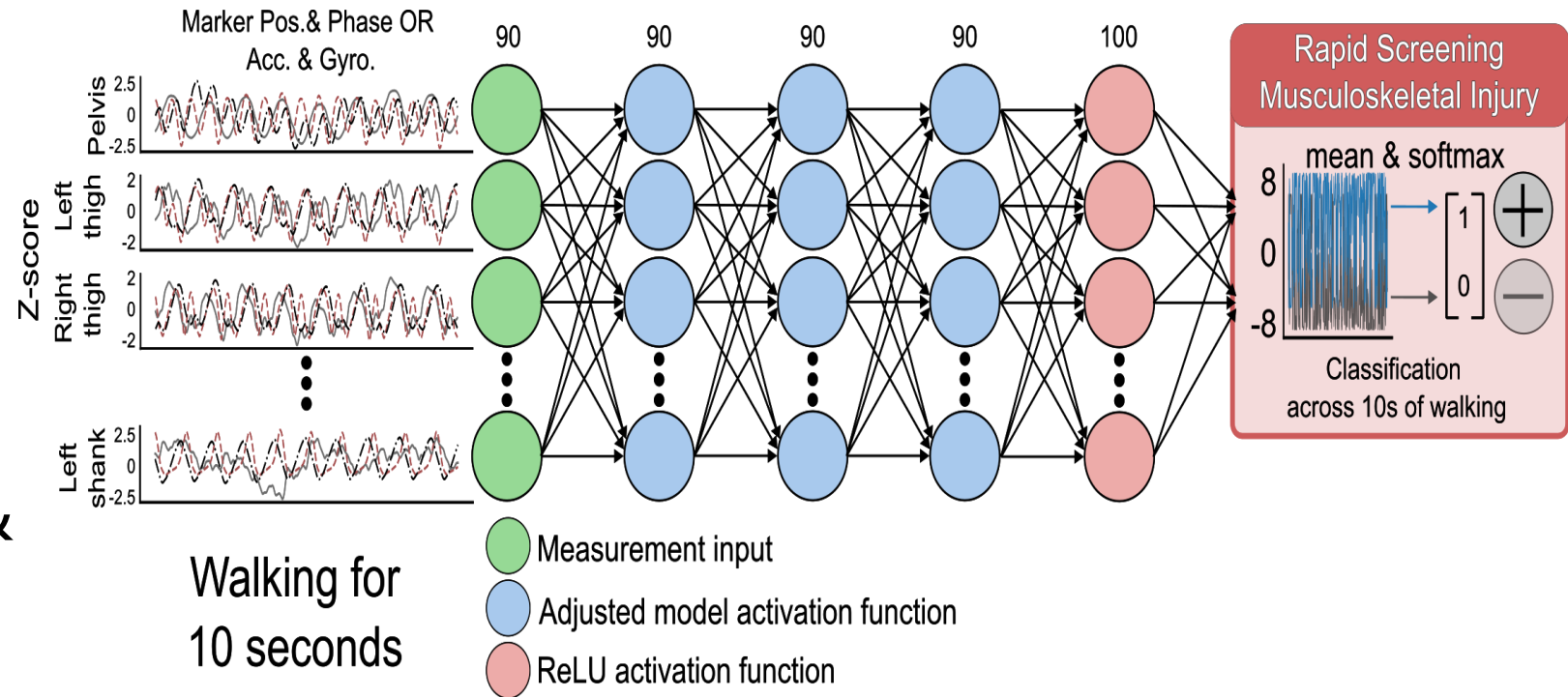
Ferber et al., 2024 Study Details

- 1686 subjects (after close inspection)
- 53 different injury labels
- Filtered marker position (x, y, z) and “angle” calculations
- Velocity and acceleration derivatives
- Sacrum, thigh, shank, foot (not of bony landmarks often used to define joint centers).
- 90 total features/inputs



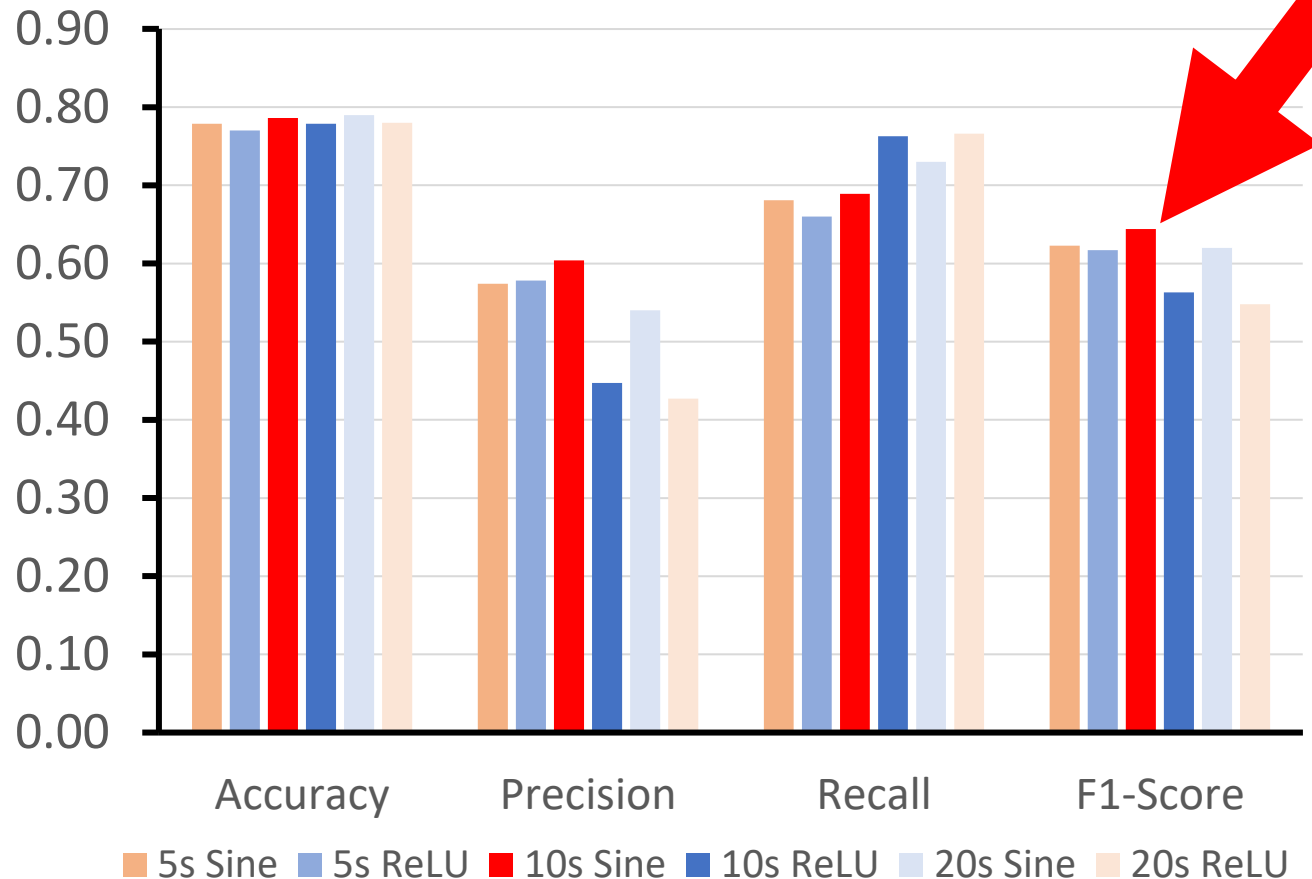
Why Use Sinusoidal Representation Networks?

- Periodic
- Prevents exploding/vanishing gradients
- Simple to implement & reasonably efficient training time



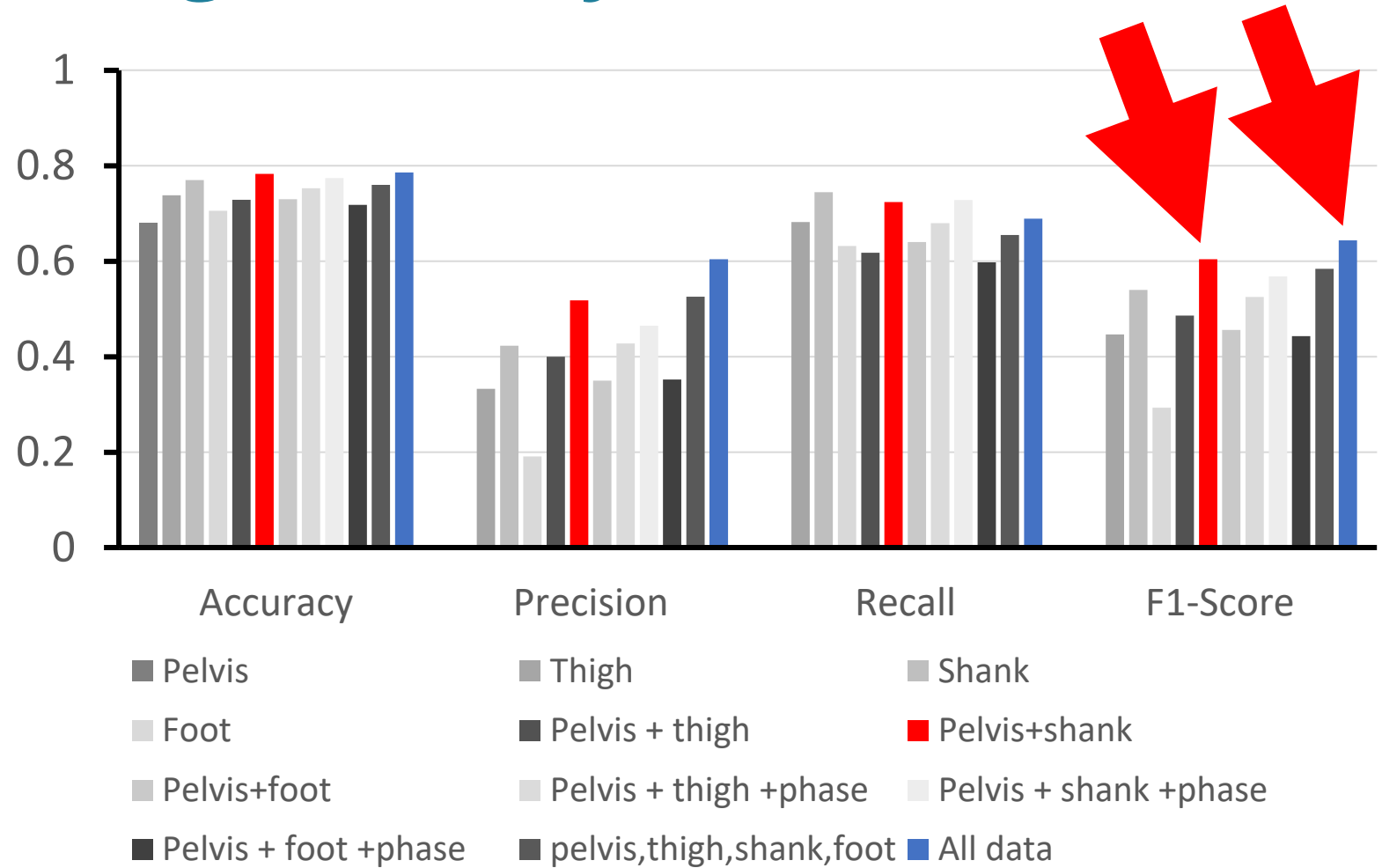
SIREN Outperformed Conventional Activation Functions

- Not much of a difference between durations
- SIREN (10s) performs better for Precision and F1-score.
- F1-Score is better for unbalanced datasets.



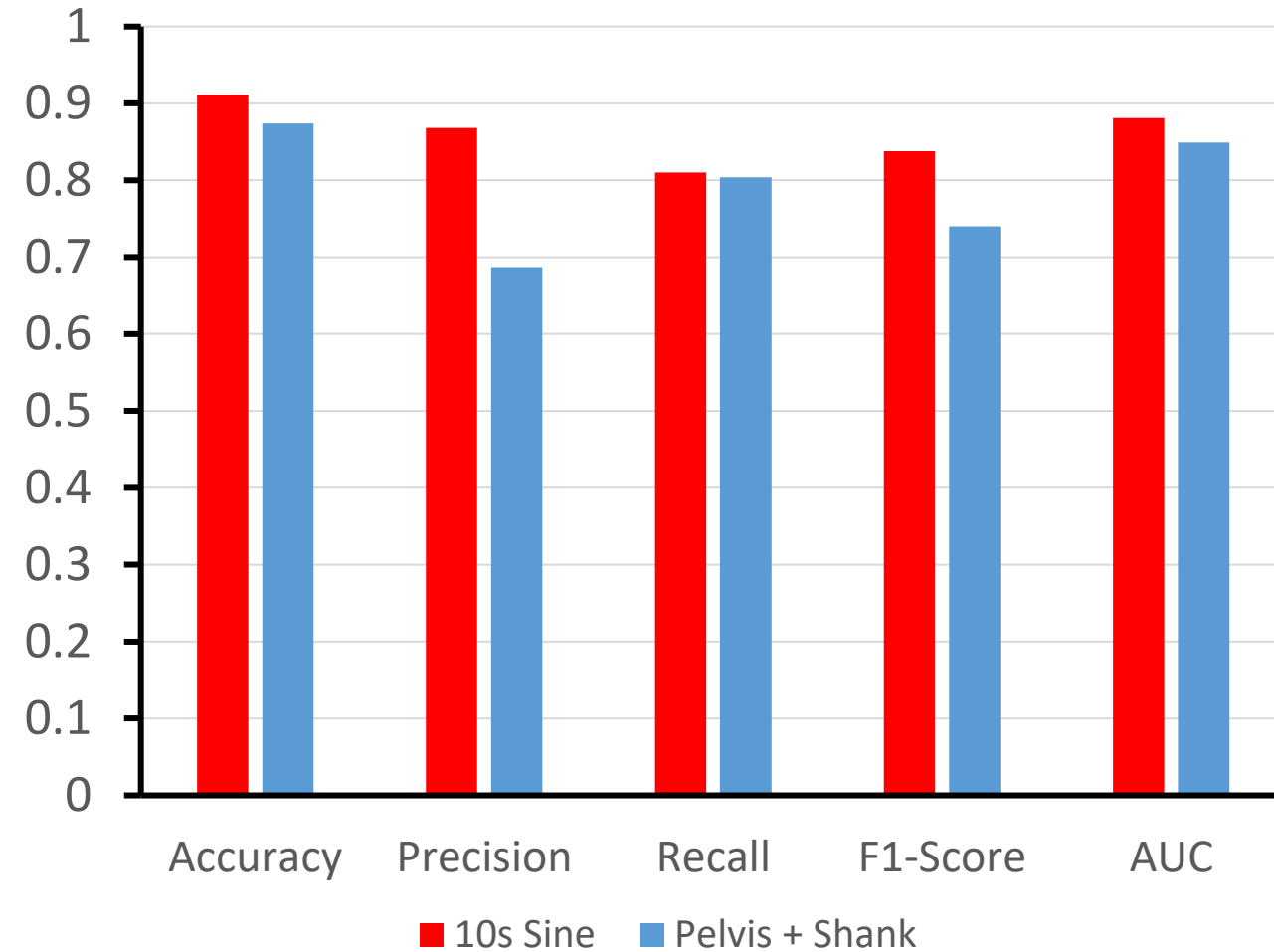
Can We Reduce Instrumentation Without Sacrificing Accuracy?

- SIREN (10s)
- Fewer Sensors May Be Enough?



Disease-Specific Models Improve Classification Performance

- Assessed classification accuracy when narrowed to most prevalent 'injury' (n=393) - OA
- Performance improved
 - F1-score all injuries = 0.64
 - F1-Score OA = 0.84
 - F1-score OA (data subset) = 0.74
- While Pelvis + Shank instrumentation performed similarly to all data for classifying all injuries, for OA only, it performed worse

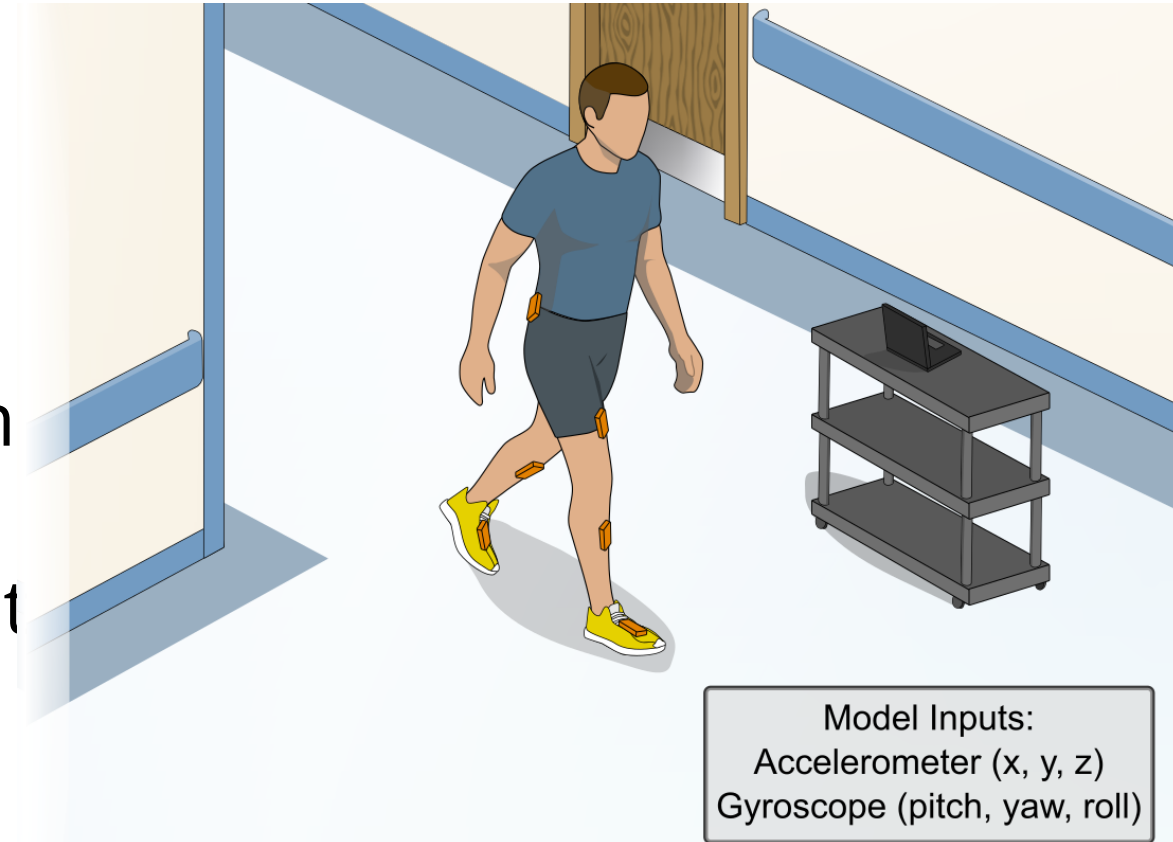


Key Findings

- Fast, easy instrumentation of markers
- Short walking period
- SIREN classification performance is similar to rapid diagnostic testing (e.g., nasal swab)
 - 62.3% for influenza
 - 80% for respiratory syncytial virus (RSV)
 - 91.84% for COVID-19
 - Each have specificities greater than 98%.
- SIREN all injuries: Sensitivity (Recall) = 0.69, Specificity = 0.87
- SIREN OA, all data: Sensitivity (Recall) = 0.87, Specificity = 0.88
- Data subsets may not generalize

Wiles et al., 2023, 2025a, 2025b: Study Details

- Three age groups
 - 'Young' 19-35 years (n= 35)
 - 'Middle aged' 36-55 years (n=50)
 - 'Older' over 56 years (n= 41)
- Self-selected overground walking on a 200-meter looping indoor track
- 18 x 4-min walking bouts evenly split between two sessions
- IMUs were placed pelvis, thighs, shanks, and feet
 - Accelerations and gyroscope for 42 features total



Inertial Measurement Units (Wiles et al., 2023, 2025a&b)



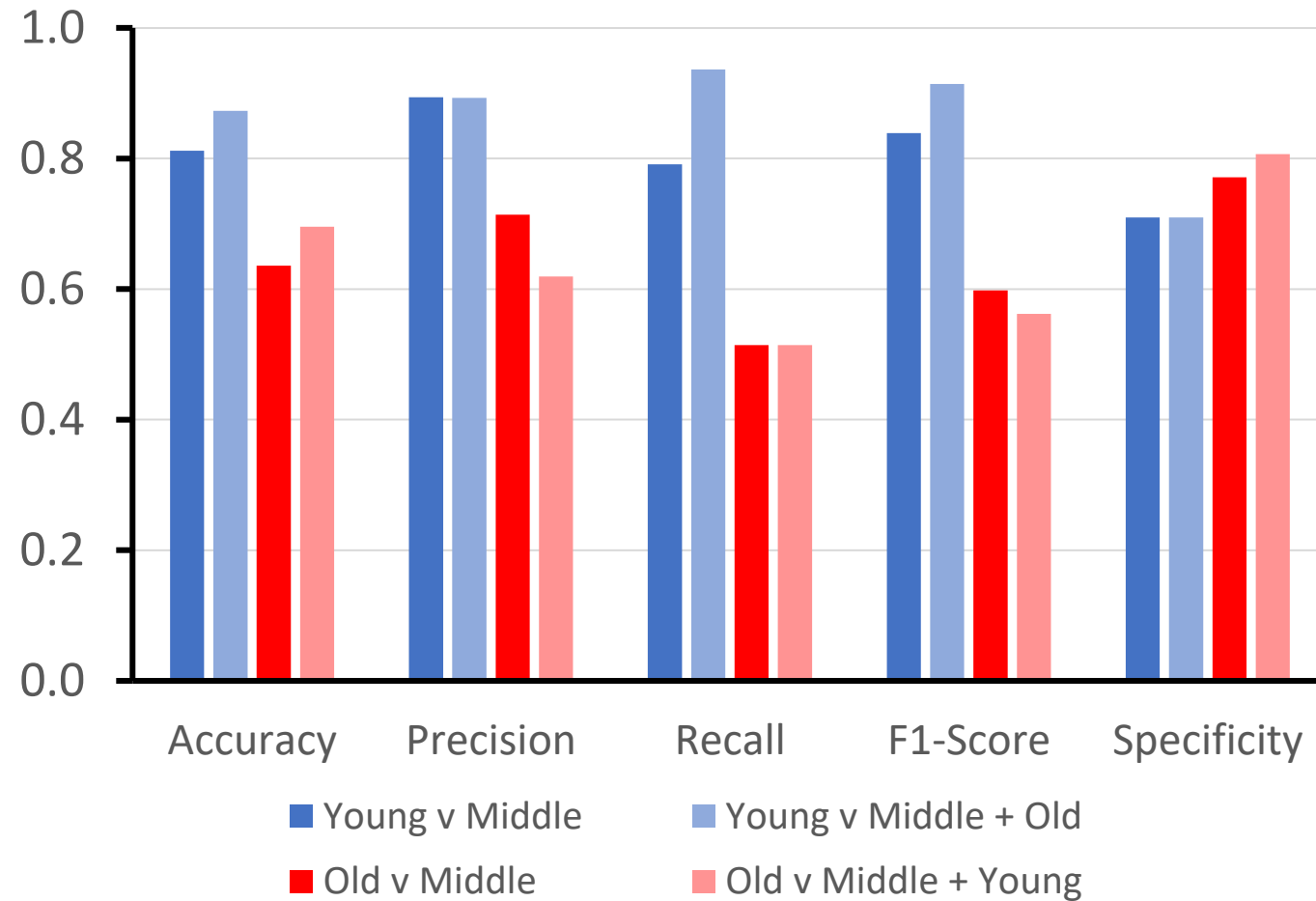
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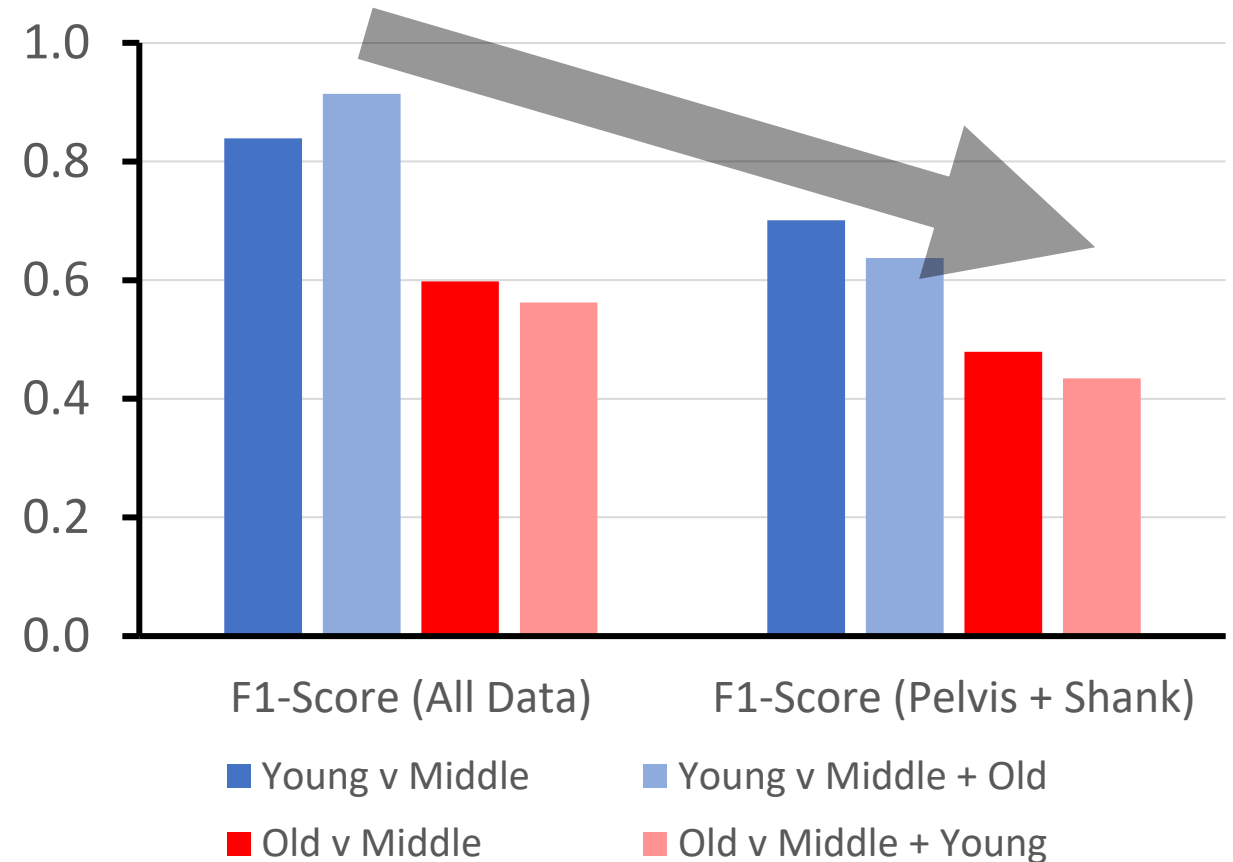
Can Models Generalize Beyond Their Training Population?

- Train on Young v Middle
- Train on Middle v Old
- Compare/Examine if generalized to remaining group
- Middle - Generalized to Old but not Young.
- Moreover, SIREN had weaker performance distinguishing walking between middle-aged and older adults.



Can Instrumentation Strategies Generalize Beyond Their Training Population?

- Maybe not.
- Unlike for markers, only Pelvis+Shank IMUs performed worse.

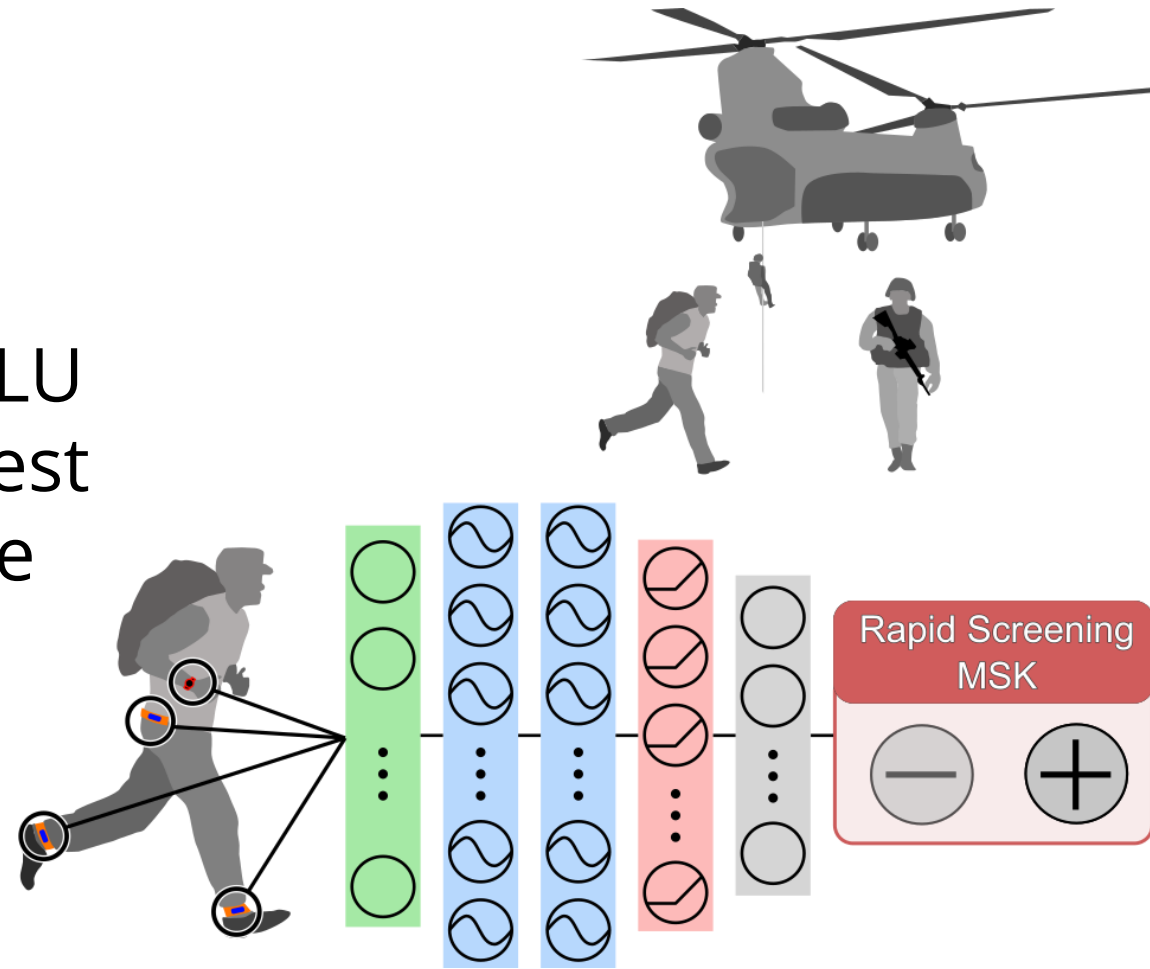


What Have We Learned?

- ✓ 10 seconds is more than enough
- ✓ SIREN consistently outperforms ReLU
- ✓ Disease-specific models perform best
- X Instrumentation may not generalize
- ✓ Model architecture generalizes

✓ This work represents an analytical foundation—not the final destination.

✓ Much more work left to do!



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