Stress Level Prediction

Using Wearable Sensor Data

Presented By:

Nadine Safwat, Hussein Heggi, Mohamed Tarek

Introduction

Stress is a major contributor to physical and mental health problems. However, stress often goes undetected until it causes serious health issues. Traditional stress assessment relies on self-reported questionnaires or clinical evaluations, which are infrequent, subjective, and fail to capture stress as it occurs in real-time throughout daily life.

Signals that Reflect Stress Response

- **Electrodermal Activity (EDA):** Increased sweat gland activity
- **Heart Rate:** Changes in cardiac rhythm
- **Blood Volume Pulse:** Changes in circulation of blood in the extremities of the body
- **Skin Temperature:** Changes in skin temperature in the extremities of the body
- **Movement Patterns:** Activity changes captured by accelerometers

Project Objective

This project aims to build predictive models for stress detection. Our dataset provides controlled, labeled physiological data from subjects undergoing standardized stress protocols. Successful models would enable stress alerts, personalized interventions, long-term pattern analysis, and early warning systems for stress-related health risks.

Dataset Overview & Limitations

Generalization Limitations

31 subjects (18m, 13f)
Primarily young adults (19-31)
89% were physically active participants

Data Quality

Sensor disconnections and incomplete protocols
Only have around 6500 labeled windows

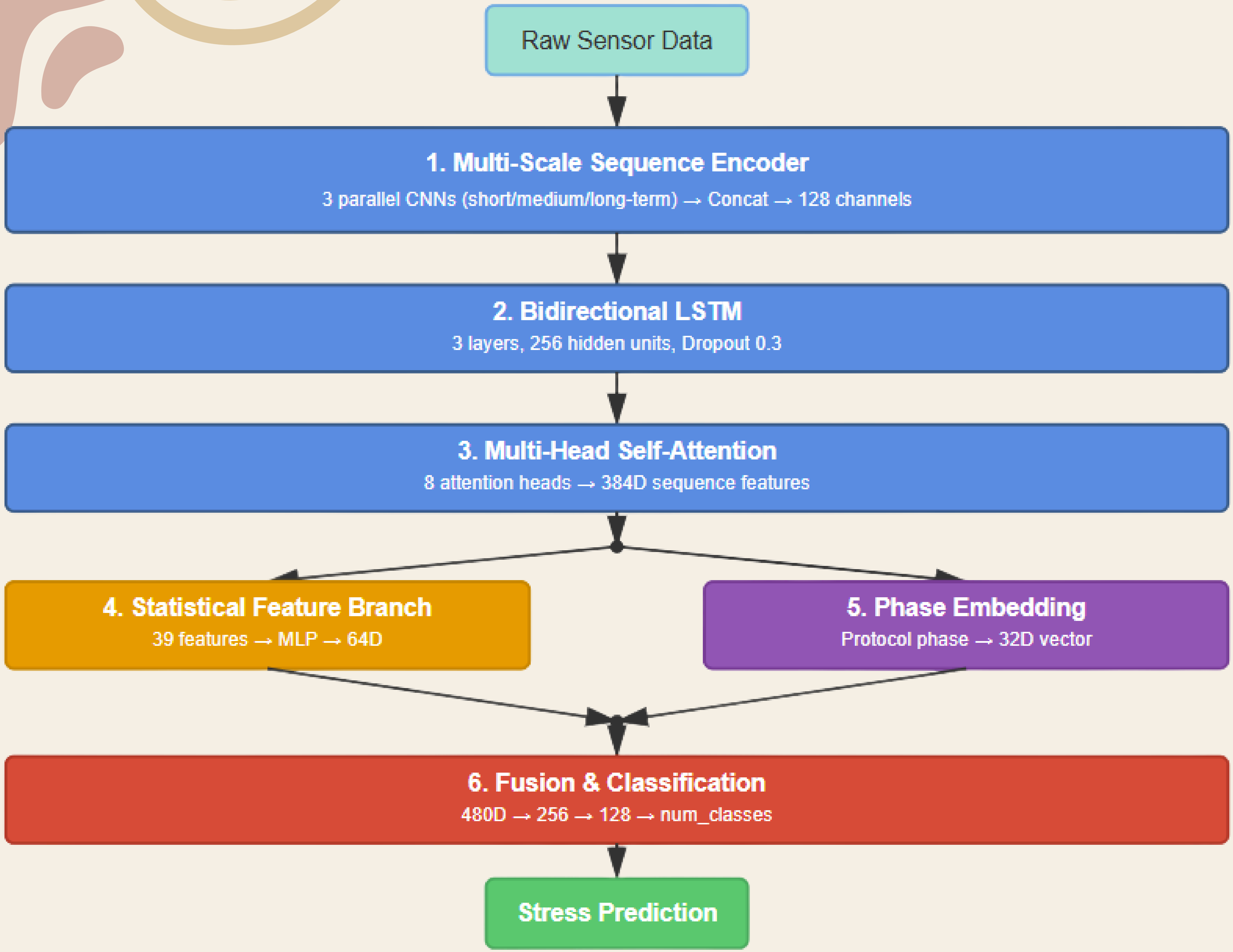
Label Reliability

Subjective nature of self-reports introduces inconsistency in ground truth labels

Class Imbalance

82% of samples represent no-stress conditions

Methodology – Model Architecture



Preprocessing & Data Enhancement

- Resampling: All sensors unified to 4 Hz
- 30 Enhanced Channels extracted from raw signals:
  - Raw signals + First derivatives
  - EDA decomposition (tonic/phasic)
  - BVP envelope, cross-signal products
  - Respiratory signal, sample entropy
  - Wavelet features
- Subject-Specific Normalization:
  - Personal baseline computed from each subject's "no-stress" windows
  - Handles individual physiological differences

Model Variants

Model 5

4-class
Augmentation: 2× low-stress
Loss: Focal (γ=2.0)
50 Epochs

Model 6

4-class
No Augmentation
Loss: Asymmetric Focal
60 Epochs

Model 7

Binary
Augmentation: 2× low-stress
Loss: Focal (γ=2.0)
50 Epochs

Model 8

Binary
No Augmentation
Loss: Asymmetric Focal
60 Epochs

Results

Model 5

Accuracy: 85.9%

Macro F1: 54.3%

Model 6

Accuracy: 80.3%

Macro F1: 41.8%

Model 7

Accuracy: 82.8%

Macro F1: 59.0%

Model 8

Accuracy: 80.7%

Macro F1: 66.4%

Conclusion

Automated stress detection from wearables is feasible and promising for consumer wellness applications, but requires larger datasets and careful validation before clinical deployment.

Thank you