Stress level Management via Smatwatch

Introduction

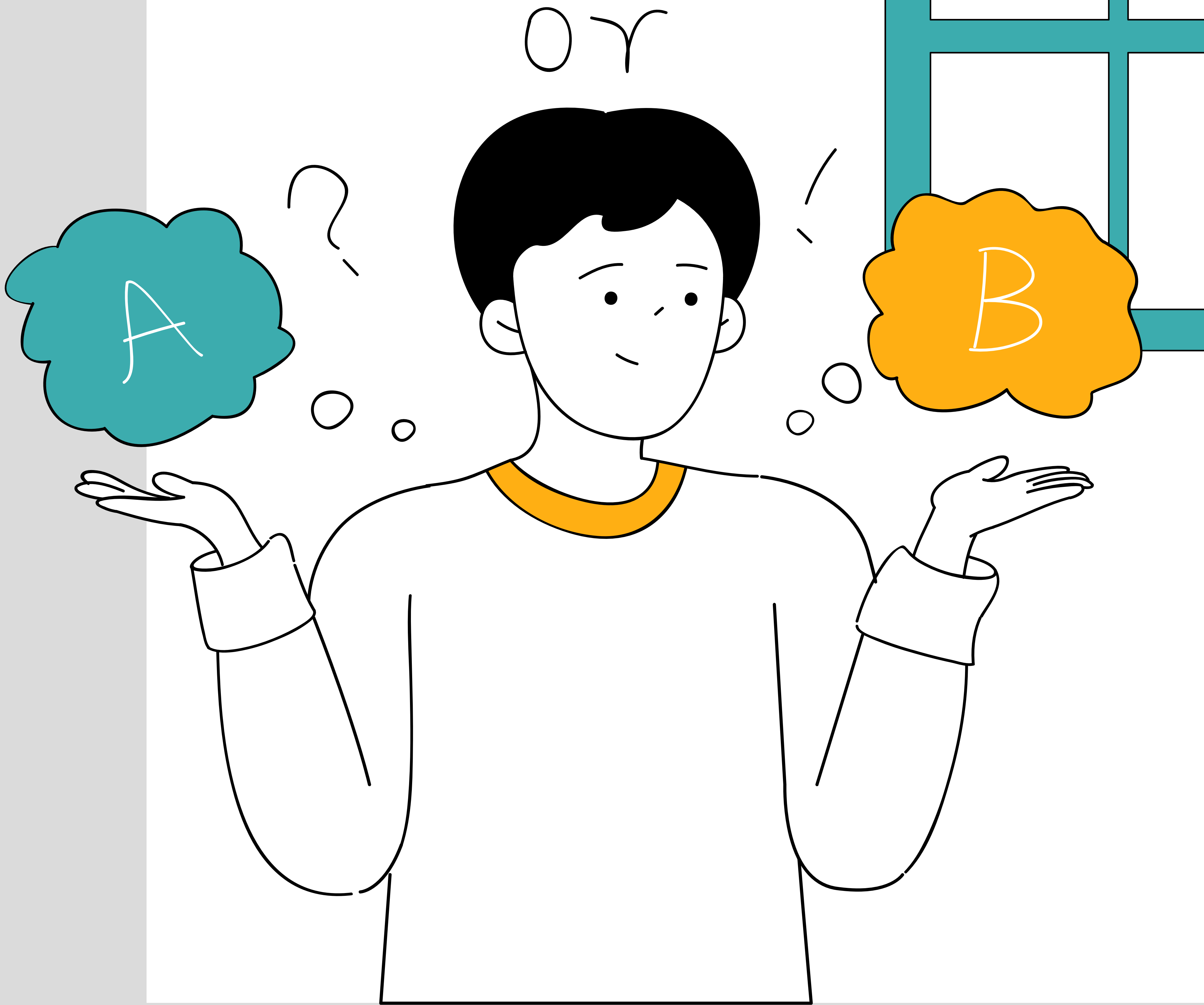
Stress is a pervasive health issue among students and professionals, reducing productivity and well-being.

Current smartwatch-based solutions lack accuracy and real-time capabilities.

This project develops a machine learning system to classify stress states using multimodal wearable sensor data:

- heart rate variability (HRV),
- blood volume pulse (BVP),
- electrodermal activity (EDA),
- skin temperature, and motion.

The goal is continuous, objective stress monitoring rather than subjective questionnaire-based approaches.



Wearable Device Dataset (PhysioNet)

Empatica E4 wristband recordings from 36 subjects (aged 18–30) undergoing structured stress induction.

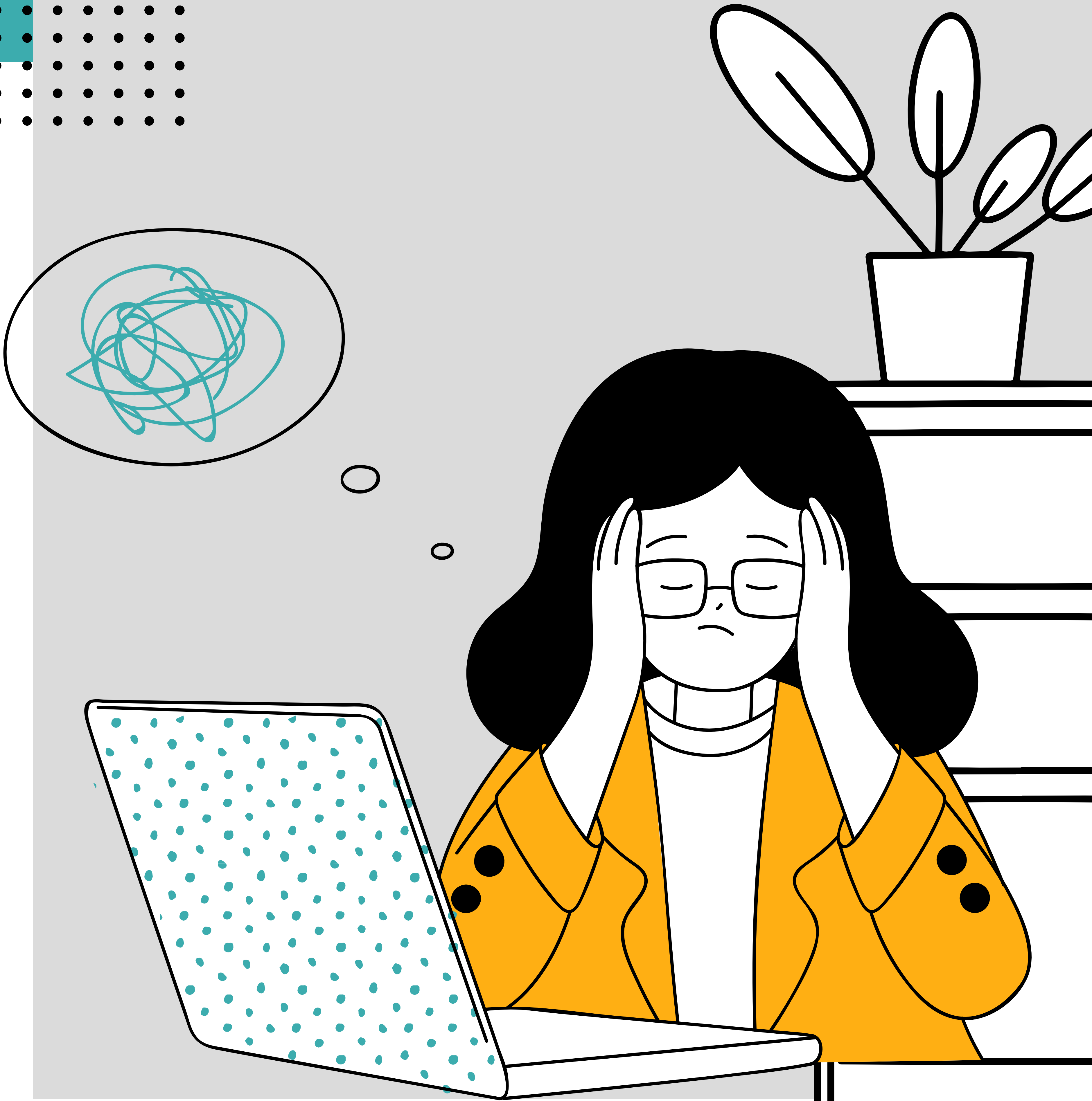
Raw multimodal signals (BVP at 64 Hz, EDA at 4 Hz, temperature at 4 Hz, 3-axis accelerometer at 32 Hz) plus self-reported stress scores and task labels.

SWELL-HRV Dataset (Kaggle)

Office-work stress from 25 subjects under three conditions:

- neutral,
- time pressure,
- interruption.

Precomputed HRV features (time- and frequency-domain) derived from ECG, plus subjective stress and task load assessments



Rationale for Using Both Datasets

Wearable dataset enables multimodal signal processing and temporal modeling;

SWELL provides real-world validation and fast prototyping.

Cross-dataset evaluation strengthens generalization claims.

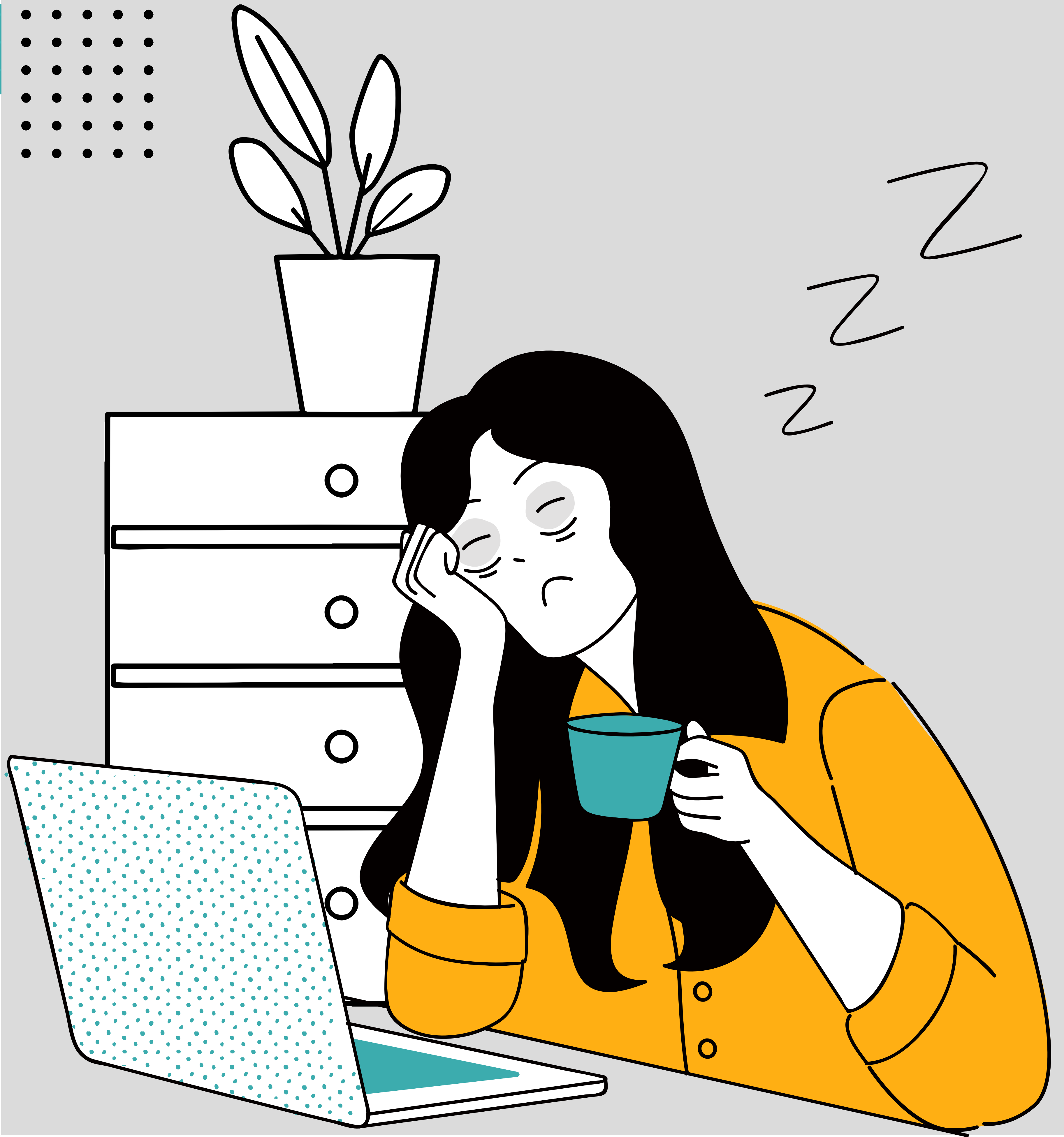
Methodology

Phase 1 — Classical Feature-Based Models

- Random Forest and Support Vector Machine using HRV and extracted multimodal features.
- Prior work reduced 67 HRV features to 8 discriminative ones with >99% accuracy.
- Feature selection via mutual information or mRMR reduces dimensionality and overfitting.

Phase 2 — Time-Series Models

- LSTM or CNN–LSTM on raw Wearable dataset signals, learning temporal dynamics of stress onset, duration, and recovery.
- Preprocessing includes alignment across modalities (different sampling rates), normalization, and sliding-window segmentation (30–120 s windows).



Challenges

Small sample sizes (36 and 25 subjects) increase overfitting risk and limit generalization.

Signal heterogeneity across datasets complicates model transfer.

Self-reported stress labels introduce subjectivity noise.

Wearable data suffers motion artefacts and missing values.

Real-world stress differs from controlled lab/office settings.

Expected Outcome

Baseline stress detection model (Random Forest or SVM) with documented accuracy, precision, recall, F1-score.

Advanced LSTM model capturing temporal stress dynamics.

Cross-subject and cross-dataset evaluation demonstrating feasibility and limitations.

Thank You