ATHLETE READINESS FORECASTING USING TRANSFORMER NETWORKS

OVERVIEW

This project creates a model that looks to predict an athlete's 'readiness' for next-day activity (e.g. competition, training) by analysing their past physiology, sleep, training, and recovery metrics. 'Readiness' can be defined as an athlete's ability to perform at their physical optimum, and takes 3 label values: Continuous Readiness Index (CRI), Binary Readiness, and Ordinal Readiness.

METHODOLOGY

Feature and label data were synthetically created and took inspiration from real-life datasets (PPG-Dalia, Sleep-EDF) to ensure realistic inter- and intraindividual variation. Data was generated via ChatGPT, in which the formulas used for feature and label generation can be viewed in `DATA_GENERATION.md`.

Feature data (and their corresponding labels) were divided into folds to fulfil the Leave-One-Athlete-Out (LOAO) approach. Each fold was divided into train, validation, and test sets where 99 athletes were split between train and validation (80/20), and the 1 athlete as the test subject. Days 1-33 and 150 did not comply with certain features and labels respectively, so were removed for each athlete. Features were normalized to capture relative deviations from baselines.

The model uses a Transformer Encoder, which analyses each day's features in relation to both earlier and later days within the window to learn overall patterns and forecast readiness for the next day (t+1).

MODEL DETAILS

The model will take a 14-day window as input, with each day comprising 17 features used to forecast readiness for the next day (15th day). Given that windows have a slide of 1 and days 47-149 have valid labels, this means that there are 103 windows per athlete for train, validation, and testing.

The Transformer Encoder consists of 3 layers, each with 4 self-attention heads and a feed-forward network. The self-attention heads learn which days within the 14-day window are most influential for forecasting next-day readiness, while the feed-forward network refines these relationships to capture complex interactions between features.

Loss calculated for CRI

- Mean Squared Error (average difference between predicted CRI and true CRI).

Loss calculated for ReadyBin
- Binary Cross Entropy (average difference between predicted probability of 0/1 and the true bin).

Loss calculated for ReadyOrd
- Ordinal (CORAL) Loss (how far predicted cumulative probabilities deviate from the true ordinal thresholds).

EVALUATION

Below are the performance metrics used to calculate the efficacy of the model during validation and testing.

CRI	ReadyBin	ReadyOrd
Root Mean Squared Error	Area Under ROC Curve - Compares true positives to false positives	Quadratic Weighted Kappa - Measures how well predicted classes match true ones
Mean Absolute Error	F1 Score - Model's precision and recall when predicting	Mean Absolute Error
		Macro-F1 - Model's precision and recall when predicting

RESULTS

Below are the results from testing. All metrics were averaged across 100 folds to ensure robust cross-athlete generalization.

CRI	ReadyBin	ReadyOrd
CRI_RMSE: 0.1203	BIN_AUROC: 0.9761	ORD_QWK: 0.9173
CRI_MAE: 0.0903	BIN_F1: 0.9054	ORD_MAE 0.3344
		ORD_MACROF1: 0.6229