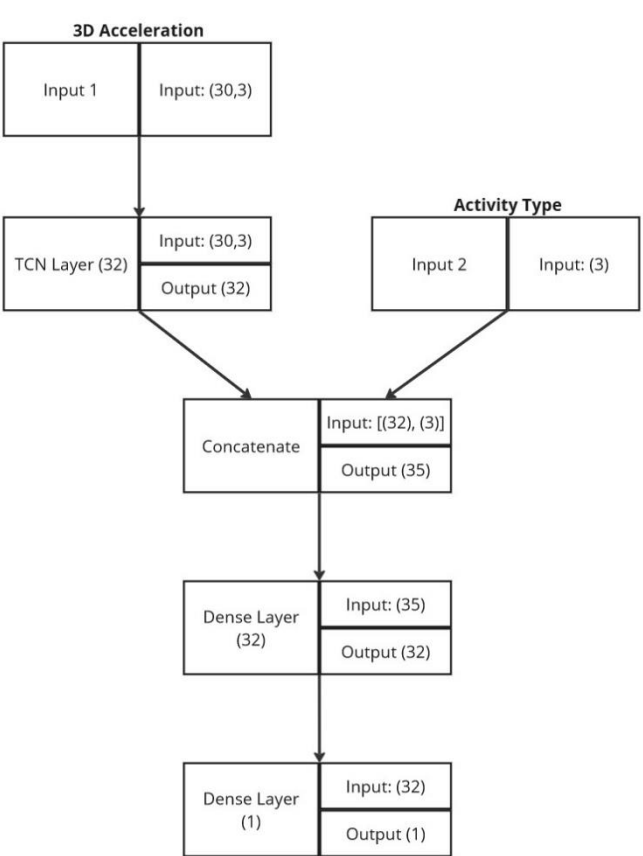


1 **Training of the stride-specific energy expenditure model**

2 For the purpose of training and optimising the model, the training sample data was
3 initially split into a training set (n = 39; 208,825 strides) and a validation set (n = 10; 47,086
4 strides) using a random 4:1 split. The data included stride level accelerations for all
5 walking, running, and cycling activities. Each sample (i.e. stride) contained 30 time points
6 of 3D acceleration data (x, y, z) and the corresponding one-hot encoded activity class as
7 features (93 features). The corresponding target values were the steady-state energy
8 expenditure normalised by the participant's body weight.

9 The hybrid model architecture was based on a non-causal TCN layer including batch
10 normalisation (Figure S3). The dilations for the TCN layer were set to [1, 2, 4, 8, 16].



11
12 **Figure S3** Hybrid TCN model architecture.

Hyperparameter optimisation was performed on the validation set to identify the optimal number of filters and kernel size for the TCN layer, as well as the number of units for the Dense layer, using a grid search with KerasTuner [23]. The model architecture with the best performing set of hyperparameters (Table S3) was then trained on the combined training and validation set. The mean absolute percentage error was used as the loss function and gradient descent-based optimization algorithm (Adam) was used to learn the model weights.

Table S3 Hyperparameter search space used for the grid search to define optimal parameters for the hybrid-TCN energy expenditure estimation model.

Hyperparameter	Values	Best set of values
Number of filters (TCN layer)	16, 32, 64	32
Kernel size (TCN layer)	2, 3, 4	3
Number of units (Dense layer)	16, 32, 64	32