Evaluating Neural Networks for Energy Expenditure Estimation with Wearable Data: Challenges and Limitations

Tyler Anderton

Abstract—**Obesity and weight gain remain unyielding public health concerns, driving a great demand for wearable devices that can accurately and conveniently monitor physical activity and energy expenditure. Recent advancements in neural networks, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, have shown promising abilities to extract complex features from raw data signals and yield high accuracies in energy expenditure estimation. However, these studies have either relied on additional data that modern wearable devices cannot provide, or have been limited in the types of physical activities performed during data collection. This research builds upon the work of these authors by evaluating their methods of CNN feature extraction, with and without the assistance of an LSTM, on a dataset that reflects the capabilities of modern wearable devices and a broader range of activities. After testing a total of 192 hyperparameter combinations to rule out model architecture issues, the best RMSE that could be achieved was 5.08 kcal/min, yielding a 146%CV, which is far beyond any acceptable limit for real-world accuracy. These findings highlight the continuing challenges posed by implementing these devices and algorithms on the consumer market.**

Introduction

Measuring Energy Expenditure

For decades obesity has been a massive and growing problem in nearly all developed and developing countries [1], with obesity rates tightly linked to an increased risk for many deadly diseases including cardiovascular disease and Alzheimer's disease [2, 3]. We have known for a long time that weight gain and obesity can be largely held at bay by moderate adjustments to caloric intake and physical activity, with some authors proposing that as little as an additional 100 kcal/day in energy expenditure could be enough to prevent much of the weight gain that causes obesity [4]. We have also known for many decades that physical activity is essential to maintaining general health and well being throughout adulthood independent of weight gain and obesity [5].

Given the crucial importance of physical activity for the purposes of health and well being, the pursuit of an accurate, non-intrusive method of measuring free-living physical activity has captured much attention in the literature for many decades. The gold standard method for estimating energy expenditure (EE) from physical activity is and has been indirect calorimetry, which is usually performed in one of two ways, each with their own advantages and disadvantages.

The ultimate goal when estimating energy expenditure is often to acquire some understanding of how normal every-day behaviors affect the total energy expended. The first method of indirect calorimetry, the use of doubly-labeled water (DLW), is the most accurate choice for measuring energy expenditure in free-living scenarios [6]. Unfortunately this method requires a great deal of technical expertise and advanced equipment and is therefore prohibitively expensive for large-scale repeatable studies [7, 8].

An alternative method of indirect calorimetry that has demonstrated high accuracy involves the measurement of oxygen and carbon dioxide exchange through a ventilated mask or within a small chamber. The ratio of these gases can then be used to estimate the energy expended by the subject using a validated formula [9, 10]. Earlier methods involved whole-body calorimetry chambers, which were quite restrictive physically and also suffered from the restrictive costs associated with utilizing these chambers on a large scale [11–14]. Contemporary indirect calorimetry devices have gotten rather compact and convenient for use in the lab, usually consisting of little more than a respiratory mask that connects to a small measurement device that either straps onto the subject's body, in the case of the COSMED K4b2 [15–19] or the Oxycon Mobile [20–22], or is even self-contained within the mask itself, as in the VO_2 Master Analyzer [23, 24]. While these calorimeters provide an excellent solution for measuring energy expenditure in a laboratory, anything that requires subjects to wear a respiratory mask is still too intrusive to implement in free-living conditions due to the potential for the Hawthorne effect and compliance issues [25].

Wearable Devices

Algorithms and methods to estimate energy expenditure need to be "accurate, fast, and comfortable" [22]. These are requirements that current indirect calorimetry procedures cannot fulfill. The ideal physical activity monitor should be in such a small and inconspicuous form-factor that users would willingly wear their device 24/7. Companies such as Apple, Whoop, and Fitbit have seen great success in selling wearable devices to consumers for the marketed purposes of activity tracking and health monitoring [26]. Such widespread adoption of these monitoring devices presents incredible opportunities, both for researchers to collect massive amounts of data on subjects engaging in free living activities, and for consumers to improve their own health and well being with empowering analytics of their own physical activity. These devices most commonly include accelerometer units and heart rate monitors at least, with some of the newest models also including temperature and blood oxygen saturation measurement capabilities [27].

The literature on estimating energy expenditure from the data available from these compact wearable devices is decades deep at this point. As early as 1979, authors have been experimenting with methods to predict energy from heart rate alone as compared to the two gold standards, whole-body indirect calorimetry [11–14], and doubly labeled water [28, 29]. Many authors also found better predictive power when combining measurements of motion through accelerometry with the heart rate information [30–35]. However, most of these studies involved explicit linear or non-linear regression, with many authors finding the need to implement complex branched equation modeling to handle the inherent non-linear relationships between heart rate, physical movement, and energy expenditure [36–42].

Supervised Learning and Neural Models

These explicit techniques involve a great deal of skill and domain-knowledge to develop, and often seem to fall short in one domain of activity or another. Researchers more recently have demonstrated supervised learning models to yield greater accuracies when estimating energy expenditure [15–19, 21, 24, 43–46]. Supervised approaches are preferable in general to the methods previously discussed, as they do not require the explicit definition of the parameters for the regression equation. These methods instead learn the regression parameters automatically through special learning algorithms [47]. Furthermore, many supervised learning models are inherently non-linear and have been shown to out-perform the branched linear equations and explicit non-linear regressions previously studied [15, 19, 24, 43, 44].

While many authors validated tree-based models like random forests and XGBoost [15, 24, 43], Rothney et al. 2007 was perhaps the first group to propose an artificial neural network (ANN) for energy expenditure estimation. They showed reduced estimation errors compared to the popular regression methods of their contemporaries. Artificial neural networks (often now simply called "neural networks" or "neural models") are models that take inspiration for their design from the neural structure of biological brains. Each "neuron" represents a linear combination of its inputs, with the "weights" and "biases" being learnable parameters that define each linear combination. The output of each neuron is fed through a non-linear "activation function" (ReLU, tanh, and sigmoid being popular choices) before being sent to the next neuron(s) in sequence or to the model output. This rather simple combination of linear and non-linear functions has proven extremely powerful in both classification and regression tasks when many layers of these neurons are connected in series and in parallel [48].

Since 2007 a large number of authors have built upon the work of Rothney et al. 2007 in the implementation of neural models [16–19, 21, 45, 46]. Many of these works still involve non-trivial effort and technical overhead in explicit feature engineering of the raw data signals to maximize the performance of these neural models. At the very least, the acceleration signals are often "counted" by proprietary algorithms determined by the accelerometer's manufacturer. Those counts are then aggregated over some time period, and their summary statistics, such as the mean, standard deviation, minimum, maximum, various percentile values, and interquartile range, are input as features to the neural network [18, 19, 21, 45]. For example, Staudenmayer et al. 2009 collected the second-by-second activity counts, then calculated the summary statistics for each minute of these counts. They also implemented lag one autocorrelation as a measure of temporal dynamics. An alternative method by Paraschiakos et al. 2022 simply calculated various summary statistics on the raw acceleration signals, rather than the proprietary count values. In addition to these temporal features, many authors have implemented much more complex feature engineering strategies to extract frequency-based features [15], such as calculating discrete Fast-Fourier Transform (FFT) component magnitudes [49], deriving frequency-domain entropies [49], implementing frequency filtering [50], and performing wavelet transforms [51] on the raw signals.

All of this manual effort of feature engineering clashes with the ethos of supervised learning with neural models, which should, in principle, be able to learn whatever optimal features can be extracted from the raw inputs. Indeed, recent authors have utilized Convolutional Neural Networks (CNNs) for automatic feature extraction on the raw acceleration signals with minimal to no filtering or processing [16, 17, 46]. CNNs are a specific type of neural network that have become very popular for a range of tasks including speech recognition, natural language processing (NLP), and especially computer vision. By using convolutional operations to extract features from their inputs, they have an unparalleled ability to capture spatial features and patterns, especially when implemented in a hierarchical structure [47].

Related Work

Zhu et al. 2015 were the first to validate the utilization of CNNs for temporal feature extraction for the purpose of energy expenditure estimation. In this study, raw signals from a single tri-axial accelerometer were fed into a CNN with no filtering or pre-processing applied. Data were collected while subjects performed "daily ambulatory activities", such as walking, running, and "low whole body motion" tasks like static standing, sitting, and riding an elevator. The authors found that a small Fully Connected Network (FCN) (also called a Multi-Layer Perceptron (MLP) or a Feed-Forward Neural Network (FFNN)) [48] performed better in the task of energy expenditure estimation when fed features extracted by a CNN rather than features handcrafted by explicit methods similar to those above.

Other recent authors have expanded on the work of Zhu et al. 2015 by testing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models against or in conjunction with the CNN feature extractor [17, 18, 46]. RNNs are another type of neural model that have been demonstrated to effectively extract features from temporal information, as they sequentially process the incoming datastream, effectively "remembering" previous inputs [18]. LSTMs are an improvement on RNNs, which effectively increase their "memory" capacity to enable effective processing of much longer sequences of data [48].

Lopes et al. 2022 compared the feature extraction ability of a CNN directly against an LSTM, each feeding their features into a small FCN regressor, like Zhu et al. 2015. The authors of this study found the CNN features to yield greater accuracy than the LSTM features. However, unlike Zhu et al. 2015, Lopes et al. 2022 utilized much more data, including heart rate data, electromyography (EMG) signals, and information from five separate 6-axis inertial measurement units (IMUs) placed in various locations on the subjects' bodies. Furthermore, the activities performed by the subjects of this study were limited to just standing and walking tasks with and without exoskeleton assistance. These additional datastreams and the studied tasks are feasible and relevant for the study's intended application of exoskeleton design, but they are not applicable to current or near future commercial wearable technology.

Lee and Lee 2024 was the first group to my knowledge to test a CNN-LSTM hybrid model for energy expenditure estimation, with the LSTM placed in series after the CNN. Their design used only IMU data with minimal filtering applied, and while in total they collected data from five separate 6-axis modules placed in various locations on the subjects' bodies, they trained and evaluated their models only on individual IMU signals. Their tasks were limited to walking and running on various inclines of a treadmill. The authors found mixed results depending on which IMU was used for training and evaluation, with the hybrid CNN-LSTM model outperforming the CNN-only and LSTM-only models on the chest, foot, and shank IMU locations, and the CNN-only model returning the lowest errors from the wrist and thigh. Overall they found the worst performance on the wrist in almost all cases, which is unfortunate, given that this is the location at which most commercial devices are designed to be worn.

Given the necessity for widely-available, comfortable, and accurate activity monitors and the limitations in data collection that current commercial devices face, we must find and validate novel techniques for solving the energy expenditure estimation problem with the data available from these devices. This study uses tri-axial accelerometer and heart rate data from a wrist-worn device to estimate energy expenditure, with ground truth EE measured by a compact indirect calorimetry mask. These devices were worn by 11 subjects while engaging in three types of physical activities including resting, stationary cycling, and running on a treadmill. This study aims to test the strategies proposed by recent authors on a dataset that more accurately represents the free living conditions under which such models might be deployed on the commercial market. Specifically I will evaluate the performance of a CNN feature extraction module combined with a FCN regression module. Then I will insert an LSTM module in series with the CNN to investigate any potential for increased accuracy with the hybrid model.

METHODS

Dataset

This study uses the publicly available Wearable Energy Expenditure Evaluation (WEEE) Dataset provided by Gashi et al. 2022. This dataset includes measurements of 17 participants performing 3 types of physical activity: resting (sitting and standing), cycling (2 speeds), and running (2 speeds). Unacceptable performance was found while evaluating 6 of these subjects' data with preliminary models. After excluding these subjects from the dataset, the rest of the study was performed on the remaining 11. The participants wore a variety of multimodal sensors on various parts of their body, but this study focuses on the data from just two of those devices. The Empatica E4 is a small, watch-like device that was worn by the subjects on their non-dominant wrist [52]. The E4 provides tri-axial accelerometer data measured at 32 Hz and photoplethysmography (PPG) data measured at 64 Hz to estimate heart rate. Photoplethysmography is an optical measurement technique that can detect blood volume changes through the skin and has become a popular method for estimating heart rate [53]. The data streams from the E4 serve as a suitable approximation to the accelerometer and PPG data that is often provided by commercially-available, wrist-worn devices [22, 24, 54]. Subjects also wore a VO_2 Master Analyzer, which measured VO_2 consumption rates at 1 Hz. This VO_2 measurement serves as a basis for the calculation of ground truth energy expenditures [55]. Demographic information about each subject – their height, weight, age, and gender – were also recorded and used as additional features in the regression models, which Paraschiakos et al. 2022 showed to reduce estimation error [16–19, 46].

Data Processing

The PPG raw signals were processed and visually inspected with the Neurokit2 package for Python [56]. This package was used to apply the default cleaning techniques and extract momentary heart rate measurements at 1 Hz. These 1 Hz measurements were merged with the 1 Hz VO_2 data by timestamp, and any times with null values or a VO_2 measurement of 0 L/min were dropped. Any small gaps (2-9 seconds) in the data for each subject were interpolated, but gaps of 10 seconds or more were left alone. The ground truth energy expenditure was then calculated as EE kcal/min = $4.934 \cdot VO_2$ L/min, which has been validated and widely used throughout the literature [10].

The raw 32 Hz acceleration signals were maintained in frequency, but any times that did not have a matching EE label for that second were dropped. Each feature was standardized according to its mean and standard deviation across the entire dataset. The heart rate and EE values were then resampled to 32 Hz and merged to the acceleration data before applying half-sliding windows of 192 samples (6 seconds) [16]. Before feeding these temporal feature windows into the CNN, the average energy expenditure was calculated as the ground truth label for each 6 second window [16].

Using the subject IDs, 11 Leave-One-Out Cross Validation (LOOCV) splits were generated, one using each subject's data as the test set [15, 17–19, 21, 43]. The original dataset included 17 subjects, but P03, P04, P06, P11, P13, and P14 returned negative R^2 scores on preliminary models, and hence their data were entirely excluded moving forward.

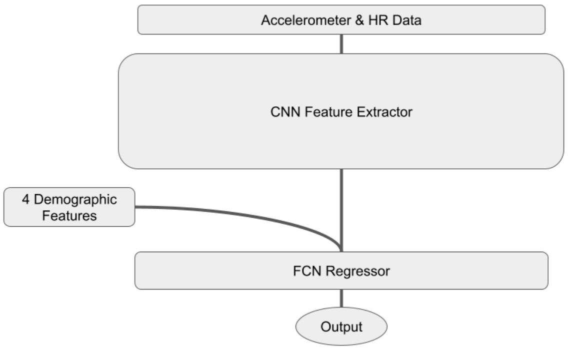

Fig. 1: CNN-FCN architecture.

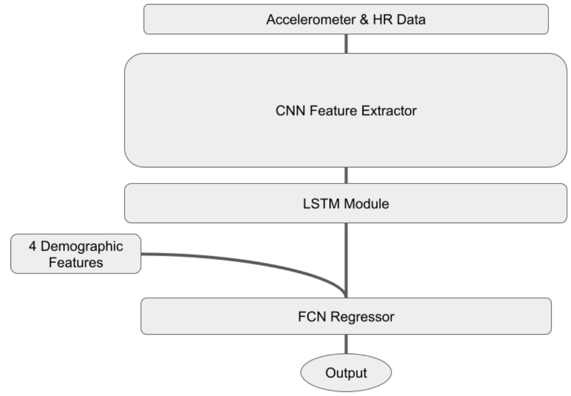

Fig. 2: CNN-LSTM-FCN architecture.

Model Designs and Training Procedures

This study evaluated two types of model architecture, each implemented with the PyTorch Python package [57]. First, the CNN-FCN (shown in Figure 1) comprised a CNN feature extractor module that fed its outputs into an FCN regression module that then output the final energy expenditure prediction. The Ray Python package [58] was implemented to perform grid search over various model hyperparameters: learning rate, batch size, number of convolution layers, number of fully connected layers, and the hidden size of the fully connected layers. In total 144 parameter combinations were evaluated for the CNN-FCN model, with the optimization goal set to minimize the average validation Mean Squared Error (MSE) over all 11 LOOCV folds. Each convolution layer in the CNN had a Conv1d layer with kernel size 3, stride 1, and padding 1, a ReLU activation layer, and MaxPool1d layer, except the very last convolution layer, which had AdaptiveAvgPool1d instead of MaxPool1d. The 4 demographic features (also standardized, except for the binary gender feature) were then concatenated to the output of the CNN before input to the FCN [16, 17, 46]. Each FCN layer had one Linear layer with the specified number of hidden units, a ReLU layer, and a 50% dropout connection between each FCN layer [17, 46]. A final Linear layer reduced the dimensionality from the hidden size to a single output to represent the energy expenditure prediction. Training was performed with the Adam optimizer with MSELoss as the criterion for a maximum of 100 epochs, but with early stopping implemented with a patience of 20 epochs.

The second model architecture, the CNN-LSTM-FCN (shown in Figure 2), took the best CNN-FCN design described above and simply inserted an LSTM module between the CNN and the FCN. Ray was used to test another 48 hyperparameter combinations for this LSTM layer, defining the number of LSTM layers and the hidden size for each. 50% dropout was implemented during training in between LSTM layers if there were more than one. The demographic features were concatenated to the LSTM output this time before feeding into the FCN, and these models were trained with the same optimizer and epoch scheme.

For each parameter combination, the training and validation MSEs, Root Mean Squared Errors (RMSEs), and R^2 scores were averaged over all 11 LOOCV folds and reported to evaluate the models' performances.

After completing the hyperparameter optimization with LOOCV, the best CNN-FCN and CNN-LSTM-FCN architectures were trained and evaluated on a traditional 80/20 train/test split over the entire dataset in order to gain some insight into how each model might perform when given the opportunity to train on a larger set of data.

Results and Discussion

The best CNN-FCN model had 3 Conv1d layers and 3 FCN layers of 32 hidden units each. The best learning rate was 1e-2 and the best batch size was 16 windows, with training terminating after an average of 39 epochs across folds. Under LOOCV this model achieved a 5.42 kcal/min (74.0 cal/kg/min) average RMSE and a 0.52 average R^2 score. When trained on more data under the 80/20 split, the RMSE improved somewhat to 5.08 kcal/min (69.4 cal/kg/min) and the R^2 score improved a great deal to 0.72.

The best CNN-LSTM-FCN had a single LSTM layer with a hidden size of 32. The most effective learning rate was again 1e-2, but this model learned best with a batch size of 32. This time early stopping ended training at an average of 38 epochs. Overall I did not find that the LSTM module added any benefit to the CNN-FCN design, with the CNN-LSTM-FCN only achieving 5.49 kcal/min (75.0 cal/kg/min) average RMSE and 0.48 average R^2 under LOOCV, and 5.09 kcal/min (69.5 cal/kg/min) RMSE and also 0.72 R^2 under the 80/20 split.

The mean and standard deviation of the energy expenditures in the dataset are 3.48 kcal/min and 2.75 kcal/min, respectively. Unfortunately with coefficients of variation (CVs) on the order of 146-158%, these models cannot be said to produce results accurate enough for academic nor commercial use. Zhu et al. 2015 were able to achieve 1.12 kcal/min overall RMSE with comparable features input to their CNN model. Likewise, Lee and Lee 2024 claimed promising results from their experiment, but their results were reported in terms of the Normalized Root Mean Squared Error (NRMSE) and the Mean Absolute Percentage Error (MAPE), which are difficult to interpret without further knowledge of their data. The main difference between the data used in these studies and the WEEE Dataset of this study, is the inclusion of the stationary cycling activity in this dataset. Zhu et al. 2015 only engaged

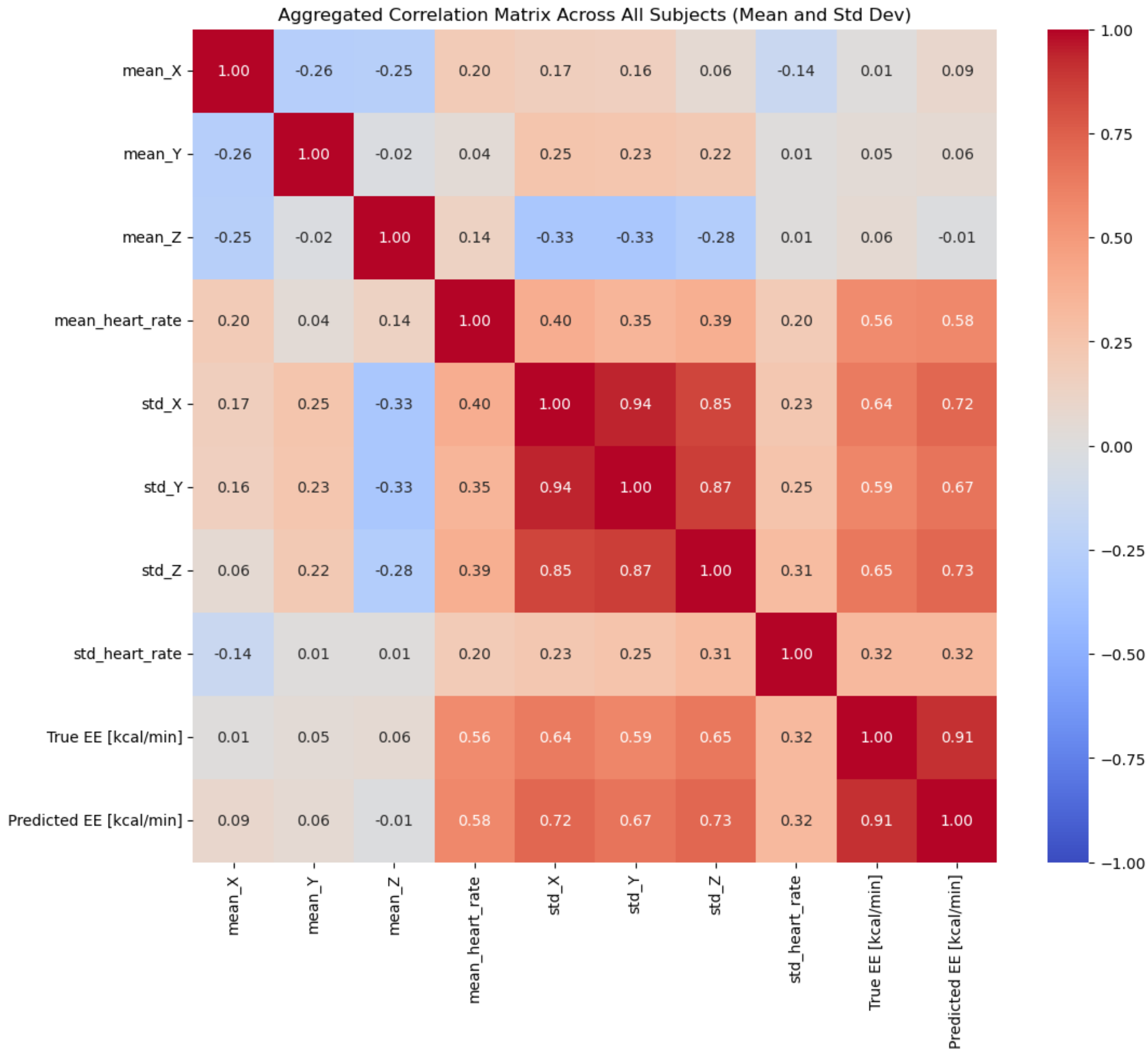

Fig. 3: Correlation matrix of the best CNN-FCN architecture, showing the correlations between the mean and standard deviations of each temporal feature and the true and predicted energy expenditures for each window.

their subjects in "daily ambulatory activities", and Lee and Lee 2024 limited their subjects' activity to walking and running on various inclines. Although these datasets presented their own challenges, the monitoring of the cycling activity through predominantly accelerometer data poses a unique obstacle. As indicated by the correlation matrices in Figures 3 and 4, the models learned to depend greatly on the variability of the accelerometer signals for their predictions. However, as shown by low accelerometer standard deviation values during the cycling phase in Figure 5 (roughly the middle third of the graph), the wrists were relatively stable during this exercise, even while heart rate and energy expenditure increased. This decoupling of the accelerometer signals from the EE ground truth likely caused significant confusion during the training of the model, leading to poor outcomes overall. This is also indicated in Figure 5, where the energy expenditure predictions for each subject during the resting phase (roughly the left third of the graph) are almost invariably over-estimations of the true energy expenditure. It is plausible that the higher true EE values during the cycling phase pulled up the walking phase EE predictions due to their very similar accelerometer variances.

Followup work could eliminate the cycling events from the dataset and repeat these training and evaluation methods to verify this hypothesis. In the event that this problem is confirmed, this highlights a major challenge for the utilization of wearable wrist devices to monitor physical activities with varying relationships to wrist motion. Most studies thus far

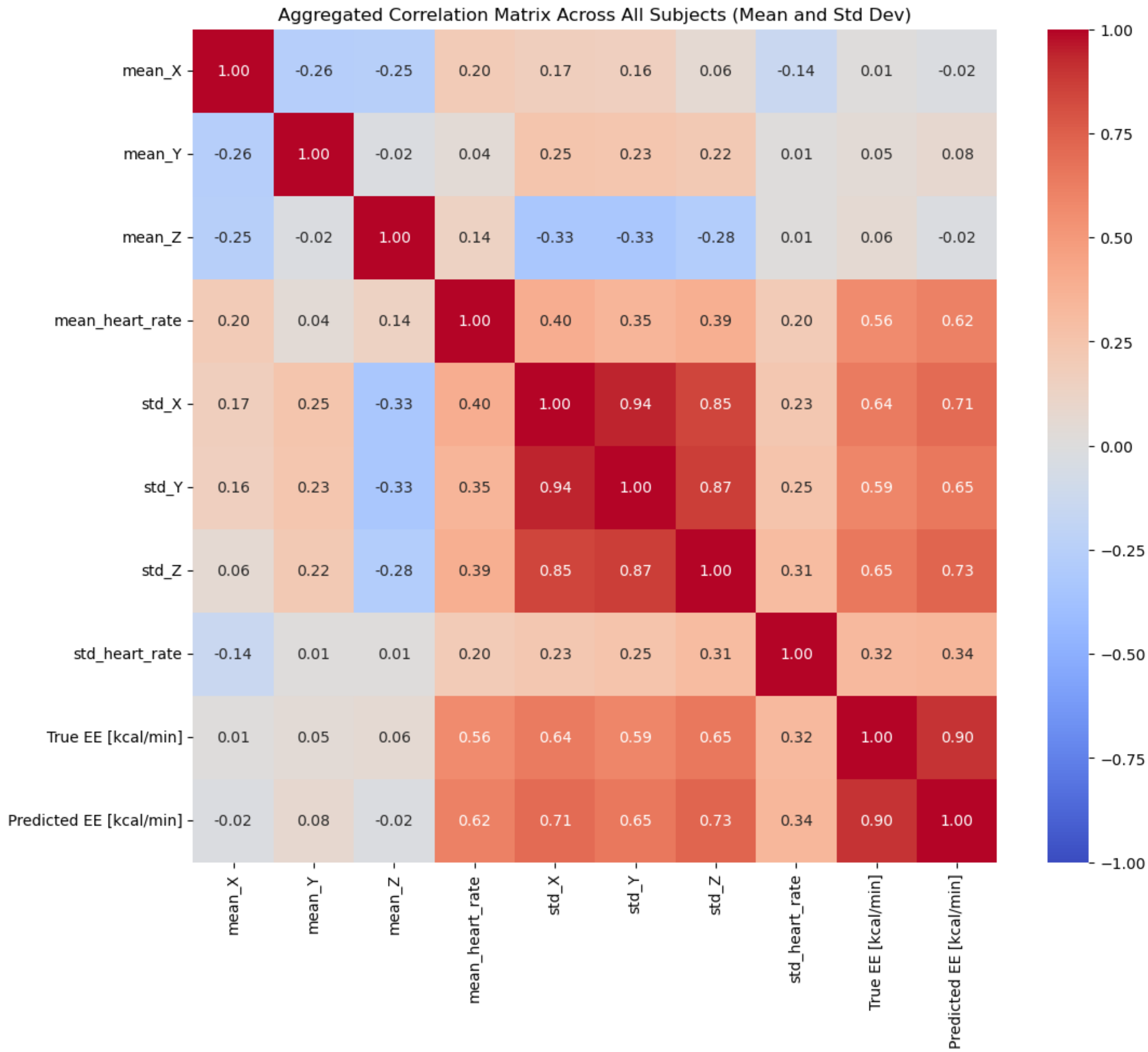

Fig. 4: Correlation matrix of the best CNN-LSTM-FCN architecture, showing the correlations between the mean and standard deviations of each temporal feature and the true and predicted energy expenditures for each window.

have focused on walking or running, which both entail a clear relationship between wrist movement and energy expenditure under normal conditions. These activities have posed a tough enough challenge for researchers, as indicated by the claim by Lee and Lee 2024 that "no studies have reliably estimated the EE while walking at various inclines with a simple sensor configuration, for example, a single IMU" prior to their study published earlier this year. Furthermore the poor accuracy values achieved in this current study indicate the complex problems that arise when just a single wrist-independent activity, cycling, is thrown into the mix. Most popular companies currently market their wearable devices' abilities to accurately measure energy expenditure during an extremely wide range of activities. Whoop for example, allows the user to log dozens of activities in their app, ranging from golf to gymnastics to video gaming [59]. However, independent studies repeatedly reveal less than ideal accuracies in commercial devices' energy expenditure estimates, illustrating a clear demand for improvement [54].

While neural models have been shown to perform well on the task of energy expenditure estimation during a limited range of activities, high accuracy on the limited data that is representative of that from commercial devices in free living situations remains elusive. Even after testing a total of 192 hyperparameter combinations (144 CNN architectures + 48 LSTM architectures) on this dataset, using both LOOCV and traditional 80/20 splits, a reasonable threshold for accurate prediction was not met. After inspecting the performance

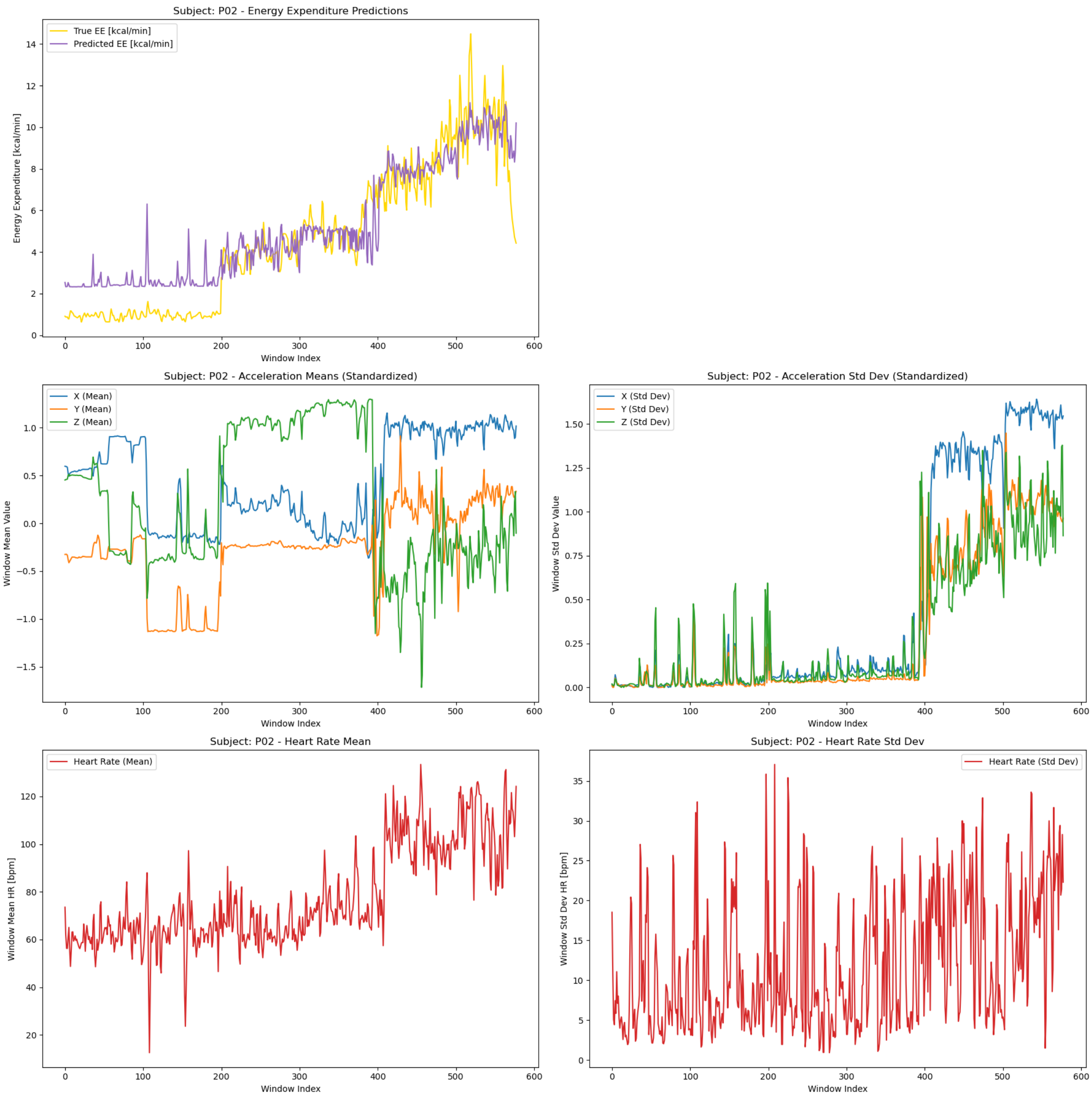

Fig. 5: Time-series graphs of the temporal features and energy expenditure labels and predictions for subject P02. Temporal features include the mean and standard deviation values for each sliding window. Energy expenditures include the ground truch mean expenditure for each window and the CNN-FCN model's prediction. The three activity phases can be seen quite clearly here, with roughly the left third of each graph representing the resting phase (which can also be seen as two distinct sitting and standing sub-phases), roughly the middle third representing the cycling phase, and roughly the right third representing the most vigorous running phase.

metrics achieved across all of these models, it is clear that the undesirable performance is not due to suboptimal model architecture, as the standard deviations in average RMSE across all LOOCV CNN-FCN models was only 0.364 kcal/min and 0.343 kcal/min across all LOOCV CNN-LSTM-FCN models, with mean RMSE values across models barely higher than those of the best-performing models (5.90 kcal/min and 5.95 kcal/min, respectively). This indicates the necessity for both further hardware engineering research toward higher resolution, multimodal data collection techniques and additional innovation in data processing and modeling strategies that are compatible with the devices that are appropriate for the consumer market.

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