MSSDA: Multi-Sub-Source Adaptation for Diabetic Foot Neuropathy Recognition

Anonymous submission

Abstract of This Supplement

This supplement provides a comprehensive introduction to our proposed dataset DFN-DS. First, we describe the detailed data construction process. Next, we outline the data preparation steps. Finally, we present the details of the experiments conducted in the intra-subject setting.

Dataset Construction

The approval from the Medical Aircraft Ethics Committee of the relevant department has been obtained prior to the data construction. Here are the details presented step by step:

- Step 1: Participants are informed about the experiment's content, purpose, procedures, and precautions. They must sign an informed consent form before participating.
- Step 2: A questionnaire is used to gather personal details for analysis, including gender, age, height, weight and diabetic duration. Information from the doctor regarding diabetic foot neuropathy (DFN) is also collected.
- Step 3: Participants receive new standard socks, and smart shoes are prepared based on their foot measurements to ensure full plantar surface coverage. The device is activated and connected to a mobile phone via Bluetooth for data recording.
- Step 4: Participants wear the smart shoes and engage in free gait activities to adjust to the testing environment and equipment, replicating their daily walking patterns. A doctor accompanies them, allowing approximately 2 minutes for adaptation.
- Step 5: Participants walk at a normal gait along the hospital corridor for 5 minutes. During this time, the smart shoes record real-time plantar pressure data via Bluetooth, as shown in Figure 1.

Finally, we save the data collected from participants walking normally for 5 minutes. All details are presented in Figure 2, and the characteristics of the dataset obtained are summarized in Table 1.

Figure 1: We use the smart shoes' Bluetooth signal to record real-time plantar pressure data, which connects directly to a mobile phone.

Table 1: Characteristics of patients in DFN-DS. The symbol $\pm$ denotes the mean and standard deviation.

Characteristics	DM	DFN
Number of Subjects	41	94
Sex (M/F)	19/22	47/47
Age	53.34 ± 14.73	57.85 ± 12.34
Diabetes duration (Years)	5.15 ± 5.83	7.77 ± 6.85
BMI (kg/m2)	23.73 ± 3.82	24.20 ± 4.71

Data Preparation

We first split the original 5-minute data into samples of 5 steps each, identifying gaits by analyzing the signal valleys in the summed signals from a foot. Note that we filter valid valleys by only retaining valleys spaced more than 10 points and filter out any valleys whose values fall below a set threshold to ensure their validity. Since the lengths of different individuals' steps may vary, we standardized the sample length to 147. If a sample exceeds the length of 147, it is proportionally downsampled to fit the length of 147. If a sample is shorter than 147, linear interpolation is applied to extend it to the fixed length. After these processed, we get 6983 samples and each of them has the shape $x \in \mathbb{R}^{147 \times 16}$.

Note that a typical plantar pressure sequence containing a gait exhibits an 'M'-shaped pattern in the sum of the data

Figure 2: Detailed flow of the data construction process.

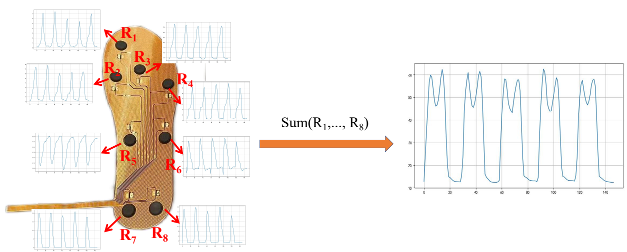

Figure 3: An example, where $R_i, i \in 1, .., 8$, denotes the i-th sensor in the right shoe. We provided a physical map along with the signals corresponding to each of these sensors in a sample. Note that, the sum signal of the signals from the right foot exhibits an 'M'-shaped pattern.

from either the left-foot or right-foot channels (Qian et al. 2006), which is as shown in Figure 3.

Experiments in Intra-Subject Setting

We conducted experiments in intra-subject setting based on these four fundamental models: Random Forest (RF) (Breiman 2001), XGBoost (Chen and Guestrin 2016), a network constructed by 4-layer 1D-CNN (1D-CNN), LSTM (Hochreiter and Schmidhuber 1997).

Parameters Setting

We firstly shuffle the dataset, then 6983 samples are divided into training set and test set in an 8: 2 ratio.

RF We set 10 as the number of trees.

XGBoost We set logarithmic loss as the evaluation metric and do not use the internal label encoder.

1D-CNN It is a 1D CNN network with four 1D-CNN layers, each followed by batch normalization and ReLU activation, with output channels of 32, 64, 128, and 256, respectively. The outputs then pass through three fully connected layers, resulting in a final output value for classification. We train the model with a learning rate of 1e-3 and a batch size of 32. The training is set for 20 epochs, using the Adam optimizer with a weight decay of 1e-3. For better performance, all samples are divided into training set, validation set and test set in an 6: 2: 2 ratio.

LSTM We set the number of hidden layers to 2 and the number of hidden units to 128. The model is trained with a learning rate of 1e-3 and a batch size of 32. The training is configured for 20 epochs and we use the Adam optimizer.

Results

We used 5 different random seeds to partition the dataset and calculated the average of their results. The results, displayed in Figure 4, show that all models achieve an accuracy exceeding 98%. These findings indicate that the dataset has high quality and usability.

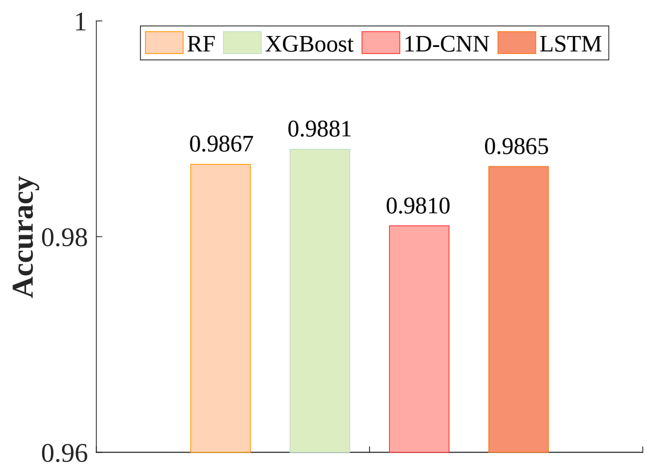

Figure 4: Results of experiments in intra-subject setting.

References

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