Appendix II: The Architecture of CNN and RNN Models

1. Convolutional Neural Network

CNN Model	Training Parameter	Architecture
CNN Model 1 (The best shallow CNN model we get)	Xavier Initializer Batch Size: 211 Learning rate: 0.005 AdamOptim izer Decay rate: 0.975 (after epoch > 40) Epoch: 100	Input: 2115 * 22 * 1000 * 1 Conv (stride: (1, 2), kernel: (1, 40), filter size: 40) Activation Map: 2115 * 22 * 481 * 40 Batch Normalization (momentum: 0.1) Conv (stride: (1, 1), kernel: (22, 1), filter size: 40) Activation Map: 2115 * 1 * 481 * 40 Batch Normalization (momentum: 0.1) Square Activation Average Pool (stride: (1, 15), kernel: (1, 75)) Activation Map: 2115 * 1 * 28 * 40 Dropout (p: 0.3) Fully Connect Output: 2115 * 4 Softmax
CNN Model 2 (The original shallow CNN model proposed in [1])	Xavier Initializer Batch Size: 211 Learning rate: 0.005 AdamOptim izer No decay rate Epoch: 100	Input: 2115 * 22 * 1000 * 1 Conv (stride: (1, 1), kernel: (1, 40), filter size: 40) Activation Map: 2115 * 22 * 961 * 40 Batch Normalization (momentum: 0.1) Conv (stride: (1, 1), kernel: (22, 1) filter size: 40) Activation Map: 2115 * 1 * 961 * 40 Batch Normalization (momentum: 0.1) Square Activation Average Pool (stride: (1, 15), kernel: (1, 75)) Activation Map: 2115 * 1 * 61 * 40 Dropout (p: 0.3) Fully Connect Output: 2115 * 4 Softmax
CNN Model 3 (The shallow model with extra frequency domain transferre d channel)	Xavier Initializer Batch Size: 105 Learning rate: 0.005 AdamOptim izer Decay rate: 0.975 (after epoch > 40) Epoch: 100	Input: 2115 * 44 * 1000 * 1 (for each channel, we used DFT to obtain the signal in frequency domain, and used it as extra features) Conv (stride: (1, 1), kernel: (1, 40), filter size: 40) Batch Normalization (momentum: 0.1) Activation Map: 2115 * 44 * 961 * 40 Conv (stride: (1, 1), kernel: (44, 1) filter size: 40) Batch Normalization (momentum: 0.1) Activation Map: 2115 * 1 * 961 * 40 Square Activation Average Pool (stride: (1, 15), kernel: (1, 75)) Dropout (p: 0.3) Activation Map: 2115 * 1 * 61 * 40 Fully Connect Output: 2115 * 4 Softmax
CNN Model 4 (The CNN with one more convolute layer	Xavier Initializer Batch Size: 211 Learning rate: 0.005	Input: 2115 * 22 * 1000 * 1 Conv (stride: (1, 1), kernel: (1, 25), filter size: 40) Activation Map: 2115 * 22 * 976 * 40 Batch Normalization (momentum: 0.1) Conv (stride: (1, 1), kernel: (22, 1) filter size: 40)

comparing	AdamOptim	Activation Map: 2115 * 1 * 976 * 40
to Model	izer	Batch Normalization (momentum: 0.1)
1)	Decay rate:	Max Pool (stride: (1, 6), kernel: (1, 6))
	0.975 (after	Activation Map: 2115 * 1 * 162 * 40
	epoch > 40)	Conv (stride: (1, 1), kernel: (1, 23)
	Epoch: 200	filter size: 40)
		Activation Map: 2115 * 1 * 140 * 40
		Batch Normalization (momentum: 0.1)
		Square Activation
		Max Pool (stride: (1, 5), kernel: (1, 5))
		Activation Map: 2115 * 1 * 28 * 40
		Dropout (p: 0.6)
		Fully Connect
		Output: 2115 * 4
		Softmax

- * The architectures in the table represent the best architectures and the best training parameters among each category architectures (1. The shallow convolutional net with significantly less parameters in the last fully connected layer; 2. The original shallow net proposed in the previous study; 3. The shallow net with frequency domain channels; 4. A deep convolutional net.)
- * For Model 3, we use DFT to extend from 22 channels to 44 channels, where 1-22 channels are original signals in the time domain, and 23-44 channels are the corresponding signals in the frequency domain.

2. Recurrent Neural Network

RNN Model	Hyper Parameter	Architecture
RNN Model 1 (Simple RNN)	Batch Size: 50 Learning Rate: 0.001 adamOptimizer epoch: 30	LSTM, units: 64 Dropout (p: 0.5) Fully Connected, Output dimension: 4 Softmax
RNN Model 2 (Stacked RNN)	Batch Size: 50 Learning Rate: 0.001 adamOptimizer epoch: 30	Bidirectional LSTM, units: 64 Dropout (p: 0.5) Bidirectional LSTM, units: 64 Flatten Dropout (p: 0.5) Fully Connected, Output dimension: 32 Dropout (p: 0.5) Fully Connected, Output dimension: 4 Softmax