Title of the work: Human Activity Recognition For Edge Fitness and Context-Aware Health Monitoring Devices using Convolutional Neural Network

Summary of the work: The vital signs can vary significantly depending on the daily physical activities, which may not be due to defects of the organs. Under remote human health monitoring applications, for reliable disease diagnosis, recorded biomedical signals such as electrocardiogram (ECG), photoplethysmogram (PPG) must be indexed with physical activity information, as it is unknown to the physicians and also to the computer aided diagnostic system. Since deep learning networks were explored for various vital signs extraction and disease classification, we present an effective convolutional neural network (CNN) based human activity recognition (HAR) method by exploring suitable hyper-parameters. CNN based methods are evaluated by using the acceleration signals taken from the standard HAR benchmark database, University of California, Irvine (UCI) with accuracy (ACC), model size (in kB) and processing time (PT), and also implemented on the Raspberry Pi 4 (R-Pi-4) to study real-time feasibility. Evaluation results showed that higher HAR accuracy can be achieved with activation function of exponential linear unit for the 2-layer CNN and segment size of 2.5 seconds (ACC of 89.05% and PT of 0.142 msec), the 4-layer CNN and segment size of 1 second (ACC of 91.66% and PT of 0.541 msec), and the 6-layer CNN with segment size of 2 seconds (ACC of 91.18% and PT of 1.672 msec). Results demonstrated that selection of an optimal number of layers, and hyper-parameters plays a major role in achieving higher accuracy with lower computational time on both PC-CPU and R-Pi computing platforms, which were not addressed in the past studies.

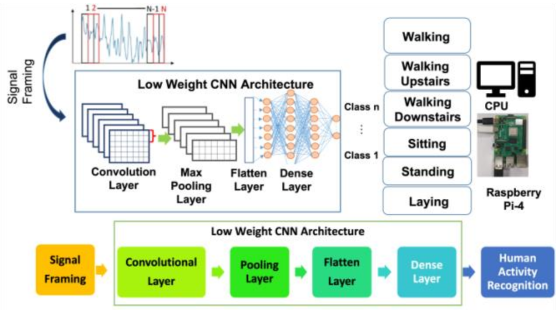

Figure 1: Block diagram of real-time human activity recognition for edge fitness and context-aware health monitoring devices using CNN.

TABLE I: Real-time performance of the HAR methods

CNN Architecture	Overall Accuracy (%)		
	ReLU	Leaky ReLU	ELU
2-layer CNN	87.83± 1.17	87.66±0.92	87.62±4.89
4-layer CNN	89.69±0.74	88.73±1.63	90.81±0.61
6-layer CNN	88.69±1.91	89.03±1.48	91.53±0.49

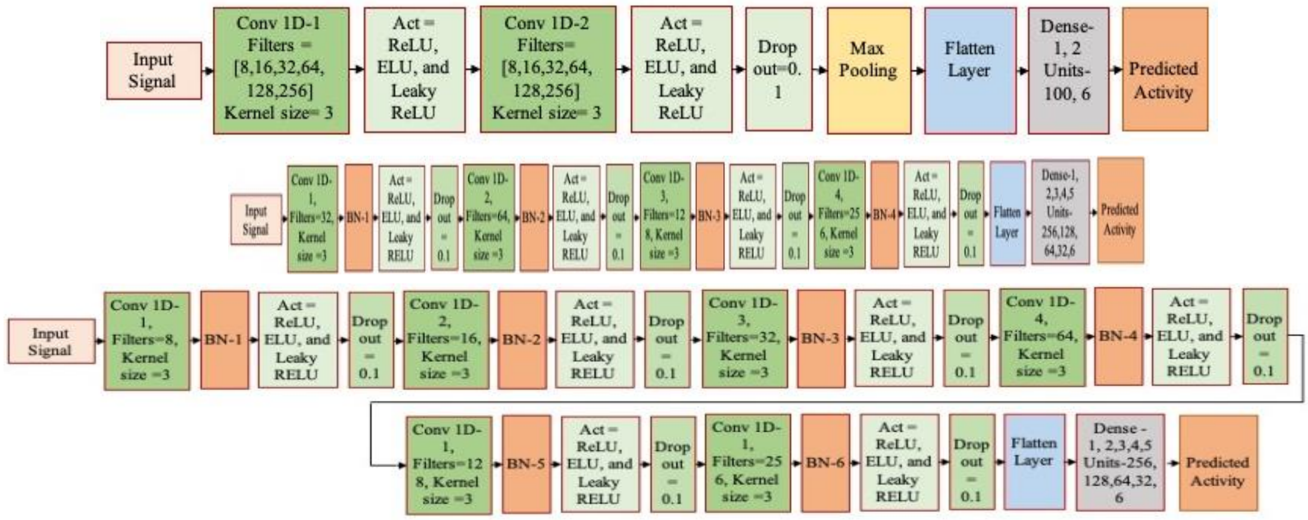

Figure 2: The 2-layer, 4-layer and 6-layer CNN architectures based HAR methods with three activation functions such as ReLU, leaky ReLU and ELU for recognition of walking, walking upstairs, walking downstairs, standing, sitting, and lying activities

TABLE II: Performance Comparison of 2-layer, 4-layer, and 6-layer CNN based methods with other relevant HAR methods

Methods	Classes	Segment Duration (sec)	Layers	Activation Function	Accuracy (%)
2 layer CNN	6	2.5	2	ELU	89.05
Xu et al.[29]	6	2.56	4	-	89.48
Cruciani et al.[33]	6	2.56	4	ReLU	90.73
Ronao et al. [34]	6	2.56	4	ReLU	95.75
4-Layer CNN	6	1.0	4	ELU	91.66
4-Layer CNN	6	0.5	4	ELU	91.27
4-Layer CNN	6	1.0	4	ReLU	91.08
Mutegeki et al.[30]	6	2.56	5	ReLU	92.00
Huang et al. [31]	6	2.56	6	ReLU	96.98
6 layer CNN	6	2	6	ELU	91.18