The pre-impact Fall Detection using the quantization based on ResNet

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Purpose Fall is one of the major health risks for older people. Hip fractures are considered the most dangerous among various injuries, as they can reduce mobility and lead to many complications, and even death (Hagen, G et al., 2020). Some researchers tried to protect the user using a wearable airbag based on the threshold-based algorithm (Jung, H et al., 2021). The more accurate algorithm was developed using the deep learning methods, but it was heavy and needed GPU or PC (Yu, X et al., 2021). This study was focused on developing the lightweight deep learning algorithm to detect pre-impact falls for targeting edge devices. **Method** The KFall public dataset was used in this study. The experimental protocol consisted of 15 fall movements and 21 activities of daily living (ADLs). The 9-axis IMU sensor data with 100 Hz sampling frequency were acquired from the waists of 32 young male subjects. Data of 26 subjects were used to train the deep learning models and those of remained 6 subjects were used to test the models. We developed the fall detection algorithm based on ResNet method. It consisted of 2 convolution layers, 4 convolution blocks, 3 identity blocks, 1 average pooling layer, and 1 SoftMax layer. We removed one by one except for the factors that affect the output size. ResNet14 model was transformed to a flat buffer type and two quantization techniques were applied using TensorFlow Lite. **Results and Discussion** Table 1 showed the performance of ResNet algorithms. When continuously reducing the layers, demanded memory decreased, but there was no dramatic change in accuracy. It suggested that our model was sufficiently deep and additional identity blocks were not needed. Table 2 showed the performance of ResNet14 models according to quantization. The integer quantization showed the smallest size of memory but the worst accuracy. The float16 quantization showed the bigger size of memory than the integer quantization, but the accuracy was maintained. As a result, the float16 quantization showed 98% of accuracy with 539±278 ms of sufficient lead time and 0.104 MB of memory size.

References

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Table 1. Performance of ResNet models

Feature	ResNet24	ResNet21	ResNet18	ResNet15	ResNet14
Optimal Epoch	44	42	34	27	50
Sensitivity (%)	99.55	100	99.77	98.65	99.32
Specificity (%)	97.63	95.66	96.25	97.63	96.84
Accuracy (%)	98.53	97.69	97.9	98.11	98
lead time mean (ms)	561.72	558.31	495.3	493.54	539
lead time sd (ms)	309.12	302.86	230.88	274.58	278.07
Num. of Para. (Million)	0.055	0.052	0.048	0.045	0.032
Size of Memory (MB)	1.11	1.01	0.96	0.87	0.70

Table 2. Performance of flat buffer converting and quantization

Feature	ResNet14	Flat buffer	Float16	Integer
Sensitivity (%)	99.32	99.32	99.32	64.64
Specificity (%)	96.84	96.84	96.84	51.48
Accuracy (%)	98	98	98	57.62
lead time mean (ms)	539	539	539	247.21
lead time sd (ms)	278.07	278.07	278.07	249.01
Size of Memory (MB)	0.70	0.149	0.104	0.083