Efficient Human Activity Recognition from Doppler Radar Data Using Binarized Neural Networks

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***Abstract*—Deploying deep learning models on smart, low-resource devices for human activity recognition (HAR) requires efficient approaches due to limited computational power and memory. Reducing precision during training and inference can help achieve these efficiency goals. This paper evaluates the efficiency and robustness of binarized neural networks (BNNs) compared to a baseline deep learning model of VGG16 using the University of Glasgow radar dataset for HAR. Both approaches show similar robustness and performance in terms of accuracy, precision, recall, F1 Score, and loss. However, the BNNs has a significantly smaller model size and fewer parameters, making it a more suitable choice for HAR applications where memory and energy consumption are critical. The memory usage results of the BNNs in terms of the number of parameters and model size catalyze the tradeoff between accuracy and complexity.**

***Index Terms*—activity recognition, Doppler, binarize, radar**

I. Introduction

Human activity recognition (HAR) which is a form of assistive living (AL) has grown into an instrumental tool due to the growing population of the elderly, the prevalence of non-communicable diseases, and the shortage of medical practitioners in most parts of the world [1], [2].

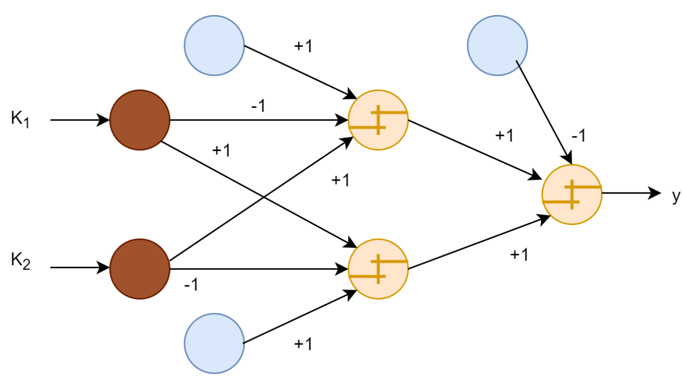

Fig. 1. The Equivalent (XNOR) gate bit wise operation used to execute computations in BNNs.

Following the ImageNet challenge of 2012 that brought the AlexNet architecture [5], several deep learning models that are robust on image data were proposed. One of them was the VGG16 [6] which we use as a baseline in this paper. It should be noted that, though the imagenet models exhibit a commendable and robust performance they are usually highly parameterized and require large memory size during both training and inference. Though recent highly parameterized models [7] perform well, it is challenging to deploy them in the low-resource devices which are the most comfortable devices to be used by the elderly, patients, and other HAR device users. In [8], the authors proposed knowledge distillation as a technique for model compression and model adaptation. Kung *et al.* [9] describes some approaches to reduce memory and power usage. Some of these are the use of a 4-bit codebook for weight parameters, data pruning, data compression, and the use of BNNs. Among these, BNNs can use binary weights and activations during training and inference [10]. BNNs have a unique advantage over conventional deep learning networks in terms of computational efficiency and memory usage which further makes them a good candidate for low-resource HAR devices. In BNNs, multiplications are replaced with bitwise operations (e.g., XNOR and bit count) shown in Fig. 1. These computations are faster than floating-point multiplications used in conventional networks [11]. This makes BNNs highly suitable for battery-powered devices and other low-power applications like the ones in which HAR is deployed. We utilize the straight-through estimator (STE) algorithm to alleviate this challenge. The STE passes the gradient without any change to the preceding layer. This implies that though the BNNs utilize binary activations and weights, the weight update is performed on real-valued floating points which are the original weights.

In this paper, we carry out experiments on radar HAR data using the VGG16 deep learning architectures as a baseline for performance comparison with the BNNs model. We report on the performance of these models in terms of accuracy, loss, number of parameters, and memory size.

II. Methods

Dataset and Feature Extraction: To evaluate the performance of the baseline and BNNs models on HAR, we used the University of Glasgow activity radar dataset which was collected using an off-the-shelf frequency modulated continuous wave (FMCW) radar.

TABLE I
COMPARATIVE RESULTS OF THE BASELINE AND THE BNNS MODELS

Model	A(%)	P(%)	R(%)	F1(%)	L	P (m)	M (KB)
Baseline	94.59	94.59	94.59	94.59	0.1482	23	277,450
BNNs	92.59	94.801	88.32	91.12	0.4420	**10**	**715**

TABLE II
THE CLASSIFICATION REPORT OF THE BNNS MODEL

Class	Precision	Recall	F1-score	Support
walking	0.97	1.00	0.99	70
sitting	0.95	0.98	0.96	54
standing	0.98	0.95	0.97	66
picking	0.85	0.85	0.85	61
drinking	0.83	0.85	0.84	65
Falling	1.00	0.91	0.96	35
accuracy			0.93	351
macro avg	0.93	0.92	0.93	351
weighted avg	0.93	0.93	0.93	351

Experiments: We used the VGG16 pre-trained model on the radar data as the baseline model. We used the TensorFlow framework and the Larq library to design a VGG16 baseline model and BNNs model. The model consists of quantized convolutional and dense layers instead of the conventional layers. The BNNs model consists of three blocks of 2 quantized convolutional layers each with 128, 256, 512 filters, and two dense layers of 1024 units before the softmax layer. We used STE to solve the backpropagation challenge of BNNs for gradient computations during training.

III. RESULTS AND DISCUSSION

We present the results of our experiments in Table I. These results show that the BNNs accuracy is slightly lower than the conventional baseline model on the HAR task due to their reduced representational capacity caused by binary weights and activations. However, the results obtained in terms of the number of parameters and memory size show that they are more suitable for deployment in HAR battery-powered low-memory resource devices compared to the baseline.

It is also shown that the size of the low-parameterized BNNs model is only 715 KB compared to 277450 KB of the baseline model. The BNNs model also exhibits a lower number of parameters compared to the baseline model. In terms of the confusion ratio of the activities that don't involve significant change in velocity like drinking and picking up items, the BNNs perform better than the baseline student model. This is evidenced in the classification report shown in Table II.

IV. CONCLUSION

In this paper, we carried out an experimental evaluation of the robustness and efficiency of the baseline and BNNs architectures on Doppler radar data for HAR in terms of accuracy, precision, recall, F1 score, and loss parameters. We found out that the BNNs model exhibits comparable performance with the baseline when subjected to the radar HAR data. However, the BNNs model exhibits a smaller number of parameters with a small model size to achieve this performance compared to the baseline. We also observe that BNNs typically suffer from reduced accuracy compared to conventional networks, especially on the complex HAR task. This is due to the reduced representational capacity caused by binary weights and activations. In the future, we hope to investigate the energy consumption of the BNNs model before actual deployment in low-resource devices.

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