Efficient segmentation method using quantised and non-linear CeNN for breast tumour classification

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A new segmentation method for mammography imaging system is proposed. Segmentation of masses is always a difficult problem in radiological image interpretation. Conventional methods such as region growing suffer from their computational complexity and hence can hardly be used for segmentation of high-resolution images. In order to achieve efficiency in both computational complexity and accuracy, a novel digital cellular neural network (CeNN) based approach is presented for segmentation. The approach is featured with quantisation to significantly reduce the computational complexity and non-linear template for robustness. After segmentation, a multilayer perceptron classifier is used for feature extraction and classification. Compared with other prior works, the proposed work is able to save resource overhead up to 63% and energy consumption up to 41% on FPGA while maintaining only up to 1.5 and 0.6% accuracy deviations for mediolateral-oblique and cranial-caudal views, respectively.

Introduction: Breast tumour segmentation is one of the most important stages in breast cancer detection and diagnosis. Numerous methods have been proposed to improve the efficiency of segmentation [1–4]. One commonly used method is region growing, which segments masses by grouping similar neighbouring pixels of seed points and is able to achieve promising accuracy [5]. However, it is computationally intensive and hence inefficient for high-resolution mammographic images, which receives increasing popularity in modern medical imaging.

In order to achieve both accuracy and efficiency, a cellular neural network (CeNN) based approach has been studied [6]. However, due to the large number of multiplications in CeNNs, conventional analog implementations suffer from I/O resource and noise interference [7]. A few recent works also investigate the digital implementations of CeNN, but are still computationally redundant and sensitive to input image variations without fully utilising the advantages of hardware acceleration.

This Letter proposes a novel digital CeNN-based approach to address the aforementioned issues in tumour segmentation, with the following contributions: (i) a *quantisation scheme* to realise multiplications by logic shift, thereby reducing hardware resource overheads; (ii) deployment of *non-linear templates* using a sequence of linear templates to improve accuracy; and (iii) *parallel hardware architecture* to improve overall efficiency. We conducted extensive experiments on Digital Database for Screening Mammography (DDSM) [8]. In comparison to the prior works, the proposed approach is able to achieve significant savings in hardware overhead and energy consumption.

Proposed CeNN-based approach for breast tumour classification: CeNN is a network of neuron cells with connection only to the neighbouring ones [6]. For a 2D CeNN with $M \times N$ cells, the dynamics of a cell $\{i, j\}$ with its neighbouring cell set of S_{ij} can be written as

$$\dot{x}_{ij}(t) = -x_{ij}(t) + I(t) + \sum_{S_{ij}} \left(A_{ij}\left(y_{S_{ij}}(t)\right) + B_{ij}\left(u_{S_{ij}}\right) \right) \tag{1}$$

The output function is then

$$y_{ij}(t) = f(x_{ij}(t)) = \frac{1}{2}\left(|x_{ij}(t) + 1| - |x_{ij}(t) - 1|\right) \tag{2}$$

where $1 \le i \le M$, $1 \le j \le N$; I, u, y and x denote bias, input, output and state variable of each cell, respectively; A is a feedback template and B is a feedforward template. Due to the large number of multipliers used in CeNNs, the efficiencies of prior CeNN-based works are limited by the available on-chip resources and can hardly fully utilise the potential of CeNN. The proposed approach in Fig. 1 is able to overcome such limitations using the proposed techniques of quantisation, non-linear template and parallel architecture to achieve much higher efficiency in both resource overhead and energy consumption.

As shown in Fig. 1, in order to reduce the computational complexity, we adopt the concept of quantisation and propose a quantisation scheme for CeNN. The scheme uses a pruning strategy to partition weights in pre-trained templates, which are sorted with an order of decreasing magnitude. The following demonstrates the process of quantising a 32-bit weight z to an m-bit $\hat{z}$ in the quantised template:

$$\hat{z} = \begin{cases} \mathrm{sgn}(z) \times 2^p & \text{if } 2^{p-1} \le |z| < 2^p, \quad a \le p \le b \\ \mathrm{sgn}(z) \times 2^b & \text{if } |z| \ge 2^b \\ 0 & \text{if } |z| < 2^{a-1} \end{cases} \tag{3}$$

where non-zero elements are constrained in the range of either $[2^a, 2^b]$ or $[-2^b, -2^a]$, a and b are determined by the expected bit-width of m (m is also an input parameter to the framework). Since each 32-bit floating number (in the very left matrix in Fig. 1) is represented by the power of 2 after quantisation (in the very right matrix in Fig. 1), a multiplication can be simplified to a logic shift in hardware implementation, thereby saving significant hardware resources.

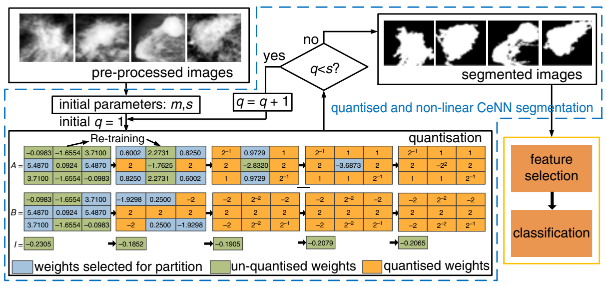

Fig. 1 *Proposed framework using a quantised and non-linear CeNN for breast tumour classification*

After quantisation the proposed approach achieves efficiency in both resource and energy consumption, but at the cost of accuracy loss. Then we utilise a non-linear template based scheme to improve the accuracy and robustness of the proposed approach as a compensation strategy [7]. However in digital implementations, it is difficult to realise non-linearity. Thus, instead of one non-linear template, we use a sequence of linear templates to approximate the non-linearity

$$\begin{aligned} y_{ij}(n) &= g(u_{ij}, y_{ij}(n-1), A_{ij;q}, B_{ij;q}, I_q) \text{ for } q = 1 \ldots s \\ &\text{s.t. } A_{ij;q} \in \hat{A}_{ij}, B_{ij;q} \in \hat{B}_{ij}, I_q \in \hat{I} \end{aligned} \tag{4}$$

where $\hat{A}_{ij}$ and $\hat{B}_{ij}$ are the two non-linear templates with a bias $\hat{I}$; $A_{ij;q}$ and $B_{ij;q}$ denote the q_{th} approximated linear templates with a bias I_q; s is the total number of linear templates; g is a piece-wise output function based on the intrinsic CeNN non-linearity as in (2). Through an iterative procedure as in Fig. 1, we can achieve higher accuracy and robustness to compensate for the loss in quantisation. Once m and s are determined, we apply a re-training algorithm of particle swarm optimisation to adapt un-quantised weights to improve overall accuracy [2], which maintains the quantised weights while optimising a subset of un-quantised weights. This method is repeatedly executed until all the required parameters are quantised. Fig. 2 presents the overall parallel hardware architecture. Stages with the same indice among different arrays are executed with pipelining, which fully utilises the potential of hardware acceleration to improve overall efficiency for segmentation.

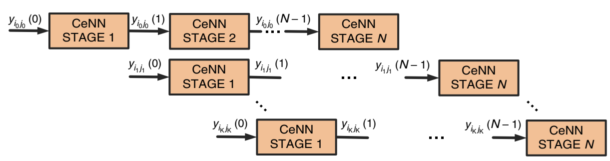

Fig. 2 *Parallel architecture of the proposed CeNN*

After segmentation, we extract the shape and texture features of masses from the segmented images. In our work, we use Zernike moments for shape features and Ripleys's K-function for texture features [2]. Then we adopt a feature selection method in [1] to differentiate benign and malignant and apply a multilayer perceptron (MLP) classifier to detect the benign and malignant masses [3]. The structure and parameters of the MLP classifier are summarised in Table 1.

Experimental results: The proposed framework is applied to the high-resolution images from DDSM. In order to evaluate its performance, we use 1000 cases of 372 benign and 628 malignant tumours as the dataset. Note that mammography views are typically based on two unique angles, MLO from oblique and CC from above [8]. The two views generate different texture and shape features in masses, and should be separated in breast tumour detection.

Table 1: Parameters of the MLP classifier

Parameters	No. of layers	Learning	Training	Input	Hidden	Output
Value	3	BP	traingdx	18/logsig	3/logsig	1/purelin

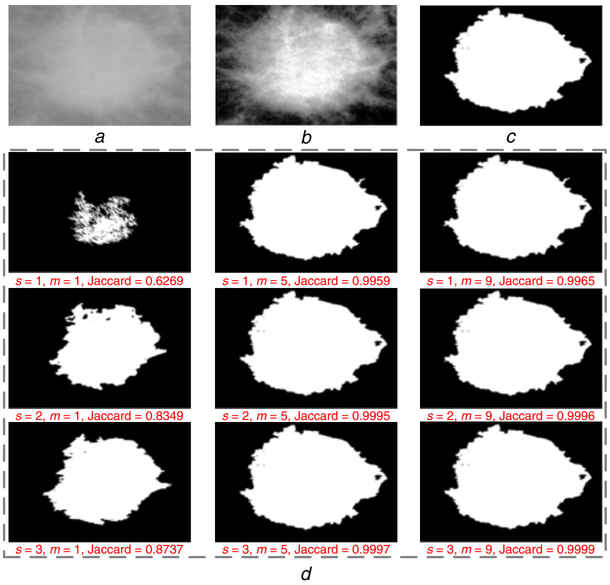

Fig. 3 *Segmentation results of the proposed CeNN-based approach*

a Original image
b Pre-processed image
c Segmented image using the original CeNN method [1]
d Segmented image using the proposed CeNN approach with quantisation and non-linear template for different parameter values of *s* and *m*

Fig. 3 depicts the segmentation results for an image randomly selected from DDSM, where 'Jaccard' is a metric denoting the similarity between the signified image in Fig. 3*c* and the segmented images using the proposed method with different parameter values ($s = 1, 2, 3$ and $m = 1, 5, 9$). It is clear that the proposed approach can match the reference pretty well while consuming significantly less resources and energy.

Experimental results in Fig. 4 and Fig. 5 demonstrate that the proposed method achieves a better performance on CC than MLO. With optimally quantised templates, it only sacrifices 0.58% and 1.51% accuracy on the two views, respectively. Table 2 summarises the comparison between the proposed approach and various prior methods on a Xilinx XC7Z020 FPGA. The last three methods [2–4] cannot be implemented on this particular FPGA platform due to insufficient resources. The optimal approach achieves a similar accuracy as [1] with only 1.51% accuracy loss and 63% lookup table (LUT) resource saving as well as 41% power saving.

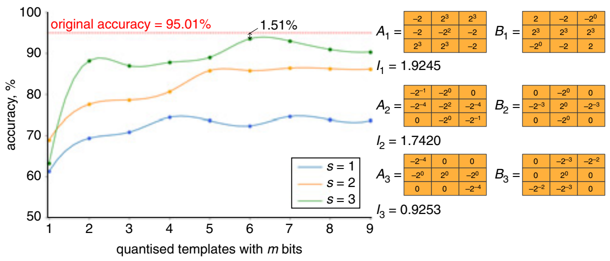

Fig. 4 *Comparisons on classification accuracy of the proposed approach for MLO views with different* m *(= 1, ..., 9) and* s *(= 1, 2, 3). The optimal template corresponds to* $m = 6$ *and* $s = 3$

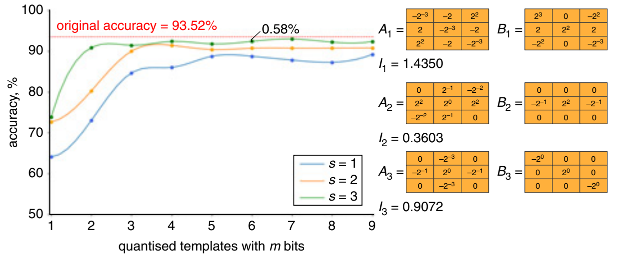

Fig. 5 *Comparisons on classification accuracy of the proposed approach for CC views with different* m *(= 1, ..., 9) and* s *(= 1, 2, 3). The optimal template corresponds to* $m = 7$ *and* $s = 3$

Table 2: Comparison between the prior works and the proposed approach on accuracy, LUT resource and energy consumption for DDSM

Method	Accuracy (%)	No. of LUTs	Energy/class. (μJ)
Original [1]	95.01	2085 (100%)	2005.4 (100%)
Proposed ($s = 3$)	93.50	772 (37.0%)	1185.3 (59.1%)
Proposed ($s = 2$)	91.39	672 (32.2%)	1132.5 (56.5%)
Proposed ($s = 1$)	88.72	541 (25.9%)	1038.1 (51.8%)
[2]	92.47	N/A	N/A
[3]	88.75	N/A	N/A
[4]	72.00	N/A	N/A

Conclusion: In this Letter, we propose a novel CeNN-based tumour segmentation method. Unlike the conventional methods that simply focus on the classification accuracy, we apply quantisation and non-linear template techniques in CeNN to reduce both computational complexity and energy consumption. Experimental results on FPGAs demonstrate a significant reduction on resource and energy consumption compared with a state-of-art CeNN method while maintaining almost the same accuracy.

Submitted: *9 April 2018* E-first: *11 May 2018*
doi: 10.1049/el.2018.1213
One or more of the Figures in this Letter are available in colour online.

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