



Article Title: Detection and Differentiation of blood cancer cells using Edge Detection method

Detection and Differentiation of blood cancer cells using Edge Detection method

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ABSTRACT

Medical imaging is an essential data source that has been leveraged worldwide in health-care systems. In pathology, histopathology images are used for cancer diagnosis, whereas these images are very complex and their analyses by pathologists require large amounts of time and effort. On the other hand, although convolutional neural networks (CNNs) have produced near-human results in image processing tasks, their processing time is becoming longer and they need higher computational power. In this paper, we implement a quantized ResNet model on two histopathology image datasets to optimize the inference power consumption

1 Introduction

Medical imaging is an essential data source is used worldwide for disease analysis, diagnosis, and prognosis. Many types of medical images span the wide field of medicine. Radiology is the branch of medicine the uses radian based images such as bone X-ray, brain MRI, cardiac ultrasound, and liver CT to diagnose diseases and guide treat-ment. pathology, . Pathology, on the other hand, focuses on studying the causes and effects of diseases using different kinds of images, such as histopathology, cytopathology, and dermatopathology images. Histopathology is the study of diseases using tissue changes from histopathology images. Medical imaging is characterized by a variety of shapes and sizes. On the one hand, in the medical field, machine learning (ML) and deep learning (DL) have led to significant advancements in image processing. One of the main machine learning methods in image processing is convolutional neural networks (CNNs), which have produced near-human results in image processing. However, most state-of-the-art CNNs are very deep and complex and require numerous parameters to be trained properly. Thus, training these CNNs takes quite some time, such as weeks or months. Many well-known CNN models have been used extensively in computational pathology, such as ResNet [1]. On the other hand, power-limited devices are widely used in medical applications, but they cannot handle deep and complex CNNs. Hence, there is a need for software and hardware optimization techniques to deploy CNNs on low-powered devices. One powerful form of optimization is quantization.



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2 Procedure for Paper Submission

2.1 Related works in Medical Imaging

Considerable medical disciplines utilize imaging for the diagnosis of various diseases, such as radiology, pathology, and dermatology. A number of recent review papers have surveyed the use of deep learning (DL) in medical image classification object detection, segmentation, and registration [4–10]. Another review of commonly used CNNs in medical imaging, such as ResNet and GoogleNet, is presented by [11]. Varoquaux and Cheplygina 2022 discuss the challenges and pitfalls that impede the progress of ML applications in medical images, such as data limitations. They also present some recommendations, for enhancing ML application research, such as using higher standard benchmarking for evaluation [12]. A brief and practical tutorial for writing the first DL application in medical imaging is provided by [13].

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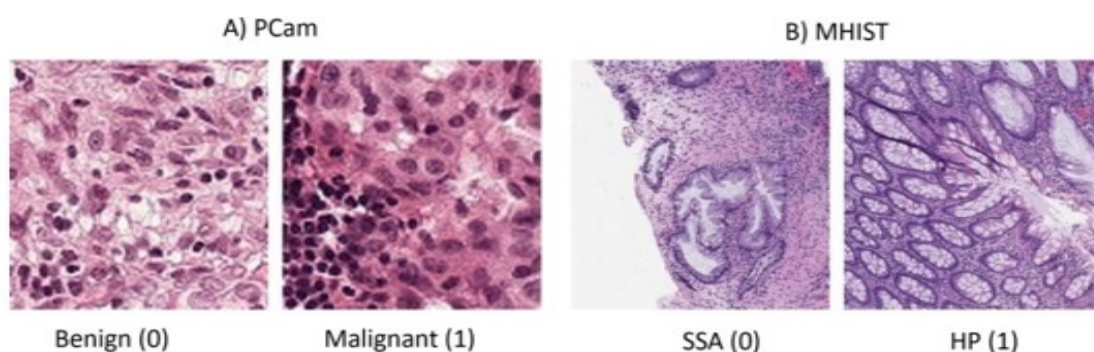


Figure 1: A) Images from PCam, B) MHIST

Computational pathology is the study of pathology images using computational tools, and, herein, we specifically focus on histopathology images, which are histology images that pathologists use to diagnose diseases or cases. The research area of computational pathology recently developed primarily due to advances in image processing, especially by using CNNs.



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3 Dataset

Many datasets of histopathology images are available for research use. In this work, we select datasets of smaller images that are more suitable for the application of low-power IoT devices, including the PatchCamelyon (PCam) [26] and the Minimalist Histopathology (MHIST) [27] datasets. Figure 1 shows sample images from each dataset.

The PatchCamelyon (PCam) dataset [26] that is derived from Camelyon16 is one of the datasets used in this paper. The PCam consists of 327,680 histopathologic color images of 96 96 pixels.

4 Objective

Edges are the significant local changes of intensity in an image various properties of an image can be extracted from edges of an image. Various edge detection techniques are available among these canny edge detection is most widely used because of its better performance. It computes both the research area of computational pathology recently developed primarily due to advances in image processing, especially by using CNNs. The main medium used in computational pathology is whole slide images (WSI), which are very large images that may reach 10 k 10 k pixels in size. Researchers have studied numerous computational pathology aspects, applied to various cancer type. Since directly processing is complicated and challenging, a novel and compressed representation of WSI is proposed by [19].

5 Basic Methods And Algorithm

5.1 Canny Edge Detection Algorithm

Canny edge detection is the most widely used edge detection technique due to its high performance. It compute both high and low threshold canny edge detection has the following steps:

- 1) Calculating the horizontal & vertical gradient.
- 2) Determining Gradient magnitude and Gradient direction.
- 3) Applying Non maximal suppression.
- 4) Computing high and low thresholds.
- 5) Performing hysteresis thresholding.

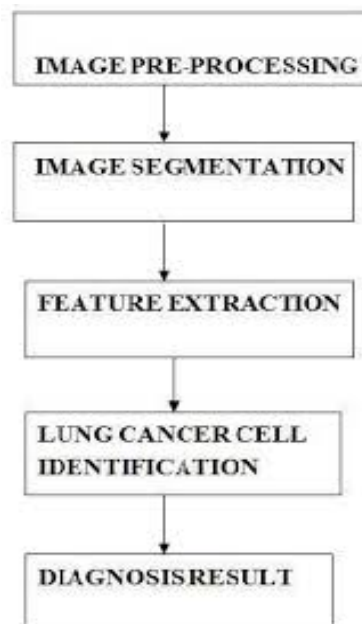
5.2 Cancer Cells Detection Algorithm

Edge detection can be used in many field such as in medical field, automated driving, on large oil and sand ore. Application of distributed canny edge detection for Ovarian Abnormality detection system is presented. Shows block diagram for abnormality detection system. The process involves six phases. Reading an image from file (conversion of 2D matrix into 1D vector), RGB to Gray conversion, Filtering, Enhancement, Segmentation, Final extraction of object (Conversion of 1D to 2D matrix, adaptive thresholding, morphological operators,



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feature extraction and classification) Ultrasound lung image is first converted from 24bit RGB format to 8 bit intensity image.



ROI (Region OF Interest) image is cropped in the next step. Then Cropped ROI image is filtered by using Speckle Reduction Filter it uses a bilateral filtering algorithm. Enhancement technology is used to provide good contrast between ROI & Background. Then ROI Image is segmented. Morphological operators like filling, closing, dilation & erosion are used to separate ROI image from complex background. In the Final stage distributed canny edge.

6 List Of Tables

Model	Method	Bit-Width (W/A)	Accuracy (%)
VGG-Small	FP	32/32	91.65
	BNN [16]	1/1	89.90
	XNOR [33]	1/1	89.80
	Ours	1/1	91.72
ResNet-20	FP	32/32	90.78
	DoReFa [43]	1/1	79.30
	Ours	1/1	84.11
	DoReFa [43]	1/32	90.00
	LQ-Net [41]	1/32	90.10
	Ours	1/32	90.24



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oint representation is used, and “-double” means testing with our double width deployment.

Method	Bit-Width (W/A/E)	Model	Accuracy	Baseline
TBP (Banner et al., 2018a)	1 1 2	ResNet-18	81.5%	90.36%
WAGE (Wu et al., 2018)	2 8 8	VGG-like	93.2%	94.1%
XNOR-Net (Rastegari et al., 2016)	1 1 32f	ConvNet	89.83%	91.8%
Ours	4 4 4	ResNet-20	91.46%	92.2%
Ours	3 3 3	ResNet-20	89.12%	92.2%
Ours-Double	3 3 3	ResNet-20	91.74%	92.2%
Ours-Double	2 2 2	ResNet-20	90.75%	92.2%

6.1 32-Bit Precision Results

Here, we show the accuracy results of training and inference on full precision, 32-bit. Without quantization or lowering the bit-width, the results are as shown in Table 4. It is shown that for the PCam dataset, Sparsity on Grayscale color mode produces the best accuracy of 90%. For MHIST, the best accuracy of 76% is acquired by RGB color mode.

6.2 Low Bit-Width Precision Results

In this section, we present the results of low bit-width model training. It is worth noting that training of low bit-width models was not performed from scratch, but the train-ing benefited from the knowledge acquired from the 32-bit-width training mentioned in the previous Section 5.1.1. Hence, the status of the models reported in Table 4 is saved and loaded, and training is continued with low bit-width. This pipeline of first training on 32-bit, and then continuing training with lower bit-width, is the pipeline suggested by [2]. The final inference accuracy results with low bit-width training are shown in Table 3. The highest accuracy achieved is 0.77 for RGB and grayscale, 0.73 for sparsity on grayscale, and 0.76 for sparsity on RGB, where the weight parameter bit-width is 4 and activation bit-width is also 4, i.e., bit-width configuration $\langle W:A \rangle = \langle 4:4 \rangle$. This is for the MHIST dataset. On the other hand, for the PCam dataset, the inference accuracy was 0.85 for RGB on $\langle 8:8 \rangle$. For grayscale color mode, the accuracy achieved 0.89 on $\langle 4:4 \rangle$ and $\langle 8:8 \rangle$. For sparsity on grayscale, the accuracy became 0.90 on $\langle 8:8 \rangle$. Finally, for sparsity on RGB, the accuracy was 0.86 on $\langle 2:2 \rangle$.

6.3 Energy Estimation

To validate our approach from an energy efficiency perspective, the deep neural net-work energy estimation tool developed by MIT [30] is utilized. Figure 3 depicts the break- down of the normalized energy consumption of various implementations of ResNet20, including different bit-widths, sparsity, and color modes, for the MHIST dataset. Each bar consists of communications for input feature map (ifmap), output feature map (ofmap), weight, and total computation. Moreover, from left to right, by applying sparsity or/and dif-ferent color modes, normalized energy is reduced significantly, whereas, from top to bottom, by increasing the bit-



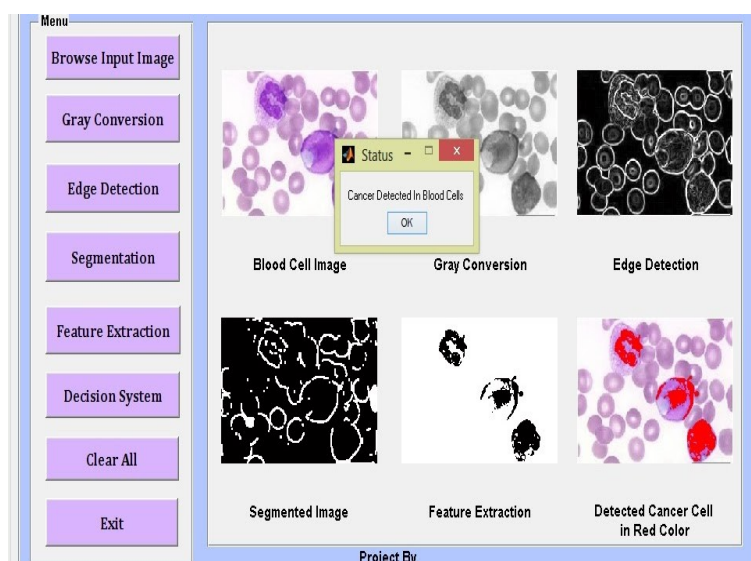
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width for an identical color mode, energy consumption is increased. This means that the settings in Figure 3d,m consume the least and most energy, respectively. Although, here in, the first three layers consume considerably higher energy than the other layers, this figure could be varied for different neural network architectures. It is worth noting that, for the PCam dataset, similar behavior is expected as the architecture remains unchanged.

7 Proposed System

Here in, the two datasets are first loaded, and then preprocessing is applied as described in Section 4.3. The deep learning model is trained on 32-bit precision. The same model is trained on lower bit-widths. We use EWGS, an element-wise gradient scaling method for training a quantized network [2]. Different bit-widths are employed for CNN weight parameters $\langle W \rangle$ and activation parameters $\langle A \rangle$, or, in short, $\langle W:A \rangle$. These bit widths are $\langle 32:32 \rangle$, $\langle 8:8 \rangle$, $\langle 4:4 \rangle$, and $\langle 2:2 \rangle$. Lowering bit-width is a form of quantization that offers faster and low-power inference, which is more suitable for low-energy devices. Other than decreasing the bit-width, we create four color modes for each dataset. Besides the original RGB (red, green, blue), we create three different color modes by applying compression methods such as channel reduction and sparsity. The color modes are RGB, grayscale, sparsity on RGB, and sparsity on grayscale. The reason for using four color modes is to evaluate the effectiveness of these color modes in reducing the complexity of image representation, which in turn lowers the computational power. Thus, low-energy devices can process these images because the power requirements are reduced. Finally, we compare and contrast the results.

8 Result





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9 Discussion

In this section, we present our experimental results. We first compare the inference results of the 32-bit precision model with various low bit-width models investigated in this paper. Then, we discuss how lowering the bit-width may affect the final classification accuracy results. We use the following bit-width values for weight and activation parameters $\{W, A\}$: $\{32:32\}$, $\{8:8\}$, $\{4:4\}$, and $\{2:2\}$. As shown in Table 4, for 32 bit-width on MHIST, the highest inference accuracy achieved is 76% in RGB color mode. The other color modes produce lower accuracy when the bit widths are reduced to $\{2:2\}$, $\{4:4\}$, and $\{8:8\}$. The accuracy, as reported in Table 3, is 77% for RGB on MHIST on the $\{4:4\}$ configuration, which is slightly higher than the full 32-bit-width result. In fact, grayscale color mode reached similar accuracy on $\{4:4\}$. This shows that converting RGB images to grayscale may be used to normalize cancerous patterns. Grayscale images can sometimes produce equally accurate or better results than RGB. On the other hand, for the PCam dataset, Table 4 shows the highest accuracy of 90% for sparsity on grayscale with 32-bit precision. This result is much higher than 84% for the RGB color mode. This confirms our hypothesis that compression methods such as sparsity, and channel reduction such as grayscale, would give comparable or even better results than the original RGB color mode. Moreover, as seen in Table 3, the same accuracy of 90% was achieved when lowering the bit-width to $\{8:8\}$ with sparsity on grayscale. This proves our hypothesis that a lower bit-width can produce results comparable to the full 32 bit-width. Finally, the results presented in Table 6 show the detailed classification results of all color modes concerning the two datasets. The true positive rate (TPR) is shown as the sensitivity rate. This rate indicates the number of sick people that are correctly identified as sick. Additionally, the true negative rate (TNR) is presented. This is the specificity rate, which measures the number of healthy people correctly identified as healthy. We have added our baseline method, RGB (original), with a $\{32:32\}$ configuration that contains no optimization and no quantization. For PCam, the baseline achieved 93% TP on 32 bit-width. The same level of TP is also achievable in the same color mode when lowering the bit-width to $\{8:8\}$. Moreover, the same TP is achieved in grayscale with $\{4:4\}$. For MHIST, the baseline reached 63% TP on 32 bit-width. However, with a lower bit-width and compressed color mode, a better TP of 77% is achieved.

10 Conclusion

In this paper, we have used low-bit-width training of ResNet20 based on [11]. Using a lower bit-width reduces the complexity of the model and therefore uses low power, which is suitable for low-power medical devices. We applied this method to two histopathology datasets: PCam and MHIST. We found that lowering the bit-width, and thus using low power, can achieve results comparable to full-bit-width training of the same model. A specific challenge in the MHIST dataset is the lack of balance in the cases between the two classes. As shown in Table



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2, one class represents 69% of the dataset. This makes it difficult to recognize cases of the minority class. There is an inherent limitation in every medical imaging dataset, which is the diversity of the patterns. Some malignant patterns appear similar to benign ones. Both humans and machines have difficulty diagnosing cases due to this.

However, humans and machines need to work together to produce a higher-quality diagnosis. Some patterns are more difficult to notice for humans but easier for machines, and vice versa. Thus, machine diagnosis gives another perspective and preliminary recommendation to physicians and pathologists.

In the future, we plan to evaluate the effectiveness of different sparsity thresholds. We used 200 pixels in this paper, as described in Section 4.2. We plan to evaluate 180 and 220 pixels. This should test whether the general pattern is affected if more white pixels are removed. We also plan to implement the model on mobile phones and evaluate the accuracy, energy, and hardware utilization. Author Contributions: All authors have equally contributed to the development of this work. All authors have read and agreed to the published version of the manuscript.

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