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Impact of Adaptive Mean Filter as the Preprocessing Stage of Histopathological Image Classification of Breast Tumor Using Transfer Learning VGG16 for Various Magnifications

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ABSTRACT

This study assesses the impact of using an Adaptive Mean Filter (AMF) as a preprocessing stage for classification of breast tumor histopathological images at various magnifications. The histopathological image was converted from red-green-blue (RGB) into grayscale before AMF is applied. In this study, AMF was performed with kernel sizes of 3 × 3 and 5 × 5 pixels. The datasets were extracted using transfer learning VGG16 before being classified using Bagging classifier. To obtain unbiased performance of the model, stratified K fold cross-validation with K = 10 was used. The dataset was divided into K-equal-sized folds. For each fold, the model was trained on the remaining K-1 folds then evaluated on the held-out fold. This process was repeated K times, with each fold used once as the validation set. The accuracy of the model was then averaged over the K folds to estimate its generalization performance. The AMF with a kernel size of 3 × 3 pixels improves the multi-class classification accuracy for magnifications of 40× and 200×, resulting in accuracy increases of 0.20% and 0.89%, respectively. However, at a magnification of 100×, the model's performance decreases. While the use of AMF with a kernel size of 3 × 3 pixels did not raise the accuracy at magnification 400×, it resulted in a lower standard deviation by 0.24%. In binary-class classification, the use of the AMF with a kernel size of 3 × 3 pixels improves accuracy by 1.10% for magnification 40× and by 0.85% for magnification 200×. However, when implemented at magnifications of 100× and 400×, the AMF filter results in decreased performance. In conclusion, the use of the AMF with a kernel size of 3 × 3 pixels as a preprocessing stage for the histopathological image classification of breast tumor has shown to have a positive impact on the accuracy of multi-class and binary-class classifications for magnifications of 40× and 200×, but not for magnifications of 100× and 400×. The results also indicate that the use of

AMF filter can reduce the standard deviation compared to without AMF for some magnifications. However, caution should be considered when applying the AMF filter, as it can decrease the model performance in some cases.

Keywords: Histopathological images, breast tumor, adaptive mean filter (AMF)

I. INTRODUCTION

Cancer is a disease caused by the uncontrolled growth of abnormal cells in the body. In 2020, there were approximately 19.3 million newly diagnosed cases and close to 10 million fatalities due to cancer on a worldwide [1]. Breast cancer is the most commonly diagnosed cancer and the fifth cause of cancer deaths worldwide in 2020, with 2.3 million new cases and 685,000 deaths [2]. If the current trend remains unchanged, the burden of the breast cancer is projected to grow to over 3 million new cases and 1 million deaths per year by 2040 [3]. Mortality from breast cancer can be reduced through early detection and appropriate treatment [4].

In choosing the appropriate treatment, a cancer diagnosis including staging, grading, and determination of cancer type is required. The accurate method to determine the staging, grading, and determination of breast cancer type is through a biopsy [5]. Biopsy is a diagnostic technique involving the collection of the tissue samples and investigation using a microscope. The examination of tissue related to disease is called histopathology [6]. The diagnosis of breast cancer in terms of grading and staging is carried out by a pathologist through visual inspection of histopathological samples using a microscope [7].

Histopathological image analysis can detect almost all cancers in the body [8]. However, this method is complex and requires extensive knowledge, high accuracy, time consuming, and experienced pathologists to obtain accurate diagnosis results [9]. The accuracy can also be affected by other factors, such as fatigue and decreased attention of pathologists [10]. In order to address these challenges, computer-aided diagnosis (CAD) technology has been introduced to assist pathologists in analyzing histopathological images. CAD improves accuracy, reduces the time taken, and enables early diagnosis of cancer [11].

In recent years, there has been significant research into classifying breast cancer using histopathological images, with a particular emphasis on creating effective algorithms by using diverse datasets, architectures, and machine learning methods [12]. However, relatively little study in trying to explore algorithms with combination of filters in breast cancer classification via histopathological images. It is well-known that histopathological images can be subject to noise that could compromise diagnostic accuracy [13]. Therefore, it is necessary to incorporate noise filtering in a preprocessing stage.

An adaptive mean filter (AMF) is a well-known filter and commonly used technique for reducing noise in medical images. The AMF adapts to the local variations in the image, allowing it to distinguish between noise and important image features [14]. This ability preserves the edges and features in the image while reducing noise [15]. Another advantage of using an AMF is that it is computationally efficient and can be applied in real-time, making it useful for application where speed is important [16]. In this study, we examined the impact of AMF as a preprocessing stage in classification of histopathological breast cancer for four magnifications.

II. METHODS AND MATERIAL

BreakHis Dataset

The breast cancer histopathological database (BreakHis) consisted of 7,909 images of breast tumor tissue from 82 patients using magnifications of 40×, 100×, 200×, and 400× [17, 18]. The total data consisted of 2,480 benign tumor images and 5,429 malignant or cancerous tumor images measuring 700 × 460 pixels, stored in 8-bit red-green-blue (RGB)-portable network graphics (PNG) format. The dataset contained four histological distinct types of benign tumors: adenosis (A), tubular adenoma (TA), phyllodes tumor (PT), and fibroadenoma (F); and four malignant tumors (breast cancer): ductal carcinoma (DC), mucinous carcinoma (MC), lobular carcinoma (LC), and papillary carcinoma (PC) [19]. These datasets were the result from a collaboration between the P&D laboratory and Pathological Anatomy and Chitopathology, Parana, Brazil. BreakHis dataset are available as an open source and can be obtained from the official website of the dataset at http://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/. The image distribution from the BreakHis based on class and subclasses can be seen respectively in Table I and Table II.

TABLE I

THE IMAGE DISTRIBUTION FROM BREAKHIS BASED ON MAGNIFICATION AND CLASS

Magnification	Benign	Malignant	Total
40×	625	1370	1995
100×	644	1437	2081
200×	623	1390	2013
400×	588	1232	1820
Total	2480	5429	7909

TABLE II

THE IMAGE DISTRIBUTION FROM BREAKHIS BASED ON MAGNIFICATION AND SUBCLASSES

Magnification	Benign				Malignant				Total
	A	F	PT	TA	DC	LC	MC	PC	
40×	114	253	109	149	864	156	205	145	1995
100×	113	260	121	150	903	170	222	142	2081
200×	111	264	108	140	896	163	196	135	2013
400×	106	237	115	130	788	137	169	138	1820
Total	444	1014	453	569	3451	626	792	560	7909

adenosis (A), tubular adenoma (TA), phyllodes tumor (PT), and fibroadenoma (F), ductal carcinoma (DC), mucinous carcinoma (MC), lobular carcinoma (LC), and papillary carcinoma (PC)

Adaptive mean filter (AMF)

AMF is a class of filters for which filtering power is adapted based on local image statistics. The AMF is a spatial based on a moving kernel [14]. The original image ($I(x, y)$) is filtered using Equation (1).

$$I_{AMF}(x,y) = I_{MF}(x,y) + \frac{\sigma_L^2 - \sigma_g^2}{\sigma_L^2}(I(x,y) - I_{MF}(x,y)) \quad (1)$$

where σ_g^2 is the global variance of image noise, and σ_L^2 is the local variance. In a relatively homogeneous area, σ_L^2 will be small and the filter behaves more aggressively so that the equation tends to the value of $I_{MF}(x,y)$. While in the edge region, σ_L^2 will be high and the filter reduces less noise so that the equation tends to the value $I(x,y)$. AMF produces images with low noise, but spatial resolution can be significantly compromised [15].

Feature extraction using transfer learning

Due to the privacy issue in the medical domain, the provided datasets are not large enough to sufficiently train a convolutional neural network (CNN) [20]. Transfer learning strategy was used to deal with this problem. Transfer learning is a machine learning method which utilize a pre-trained model as basis for a new task-specific model [21]. Transfer learning has advantages such as accelerating convergence, reducing computational resources, and enhancing network performance [22].

Transfer learning using several kinds of architectures like InceptionV3, Xception, ResNet50, InceptionResNetV2, and VGG16 has been used to classify four datasets histopathological images of breast cancer [17]. For BreakHis dataset, the topmost result was obtained by architecture VGG16 with 93.54% accuracy. VGG16 consist of five blocks, each of two or three convolution layers and a pooling layer, and three fully connected layers connected in the final blocks. The biggest feature of VGG16 is that it uses a small convolution kernel with a size of 3 × 3, which makes the model easily to converge [23].

Model evaluation

Processed dataset were extracted using the VGG16 architecture. To avoid any feature loss, all the data were resized to 700 × 700 pixels. At the end of the architecture, we included a global average pool layer to avoid memory overflow and simplify the classification process. The process of extraction features can be seen in Fig. 1.

Bagging classifier is the machine learning algorithm used in this model with n estimators = 100. Bagging or Bootstrap Aggregating, is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of supervised learning algorithms [24]. It works by creating multiple subsets of the original training dataset, each of which is then used to train a separate instance of the same learning algorithm. These models were then combined in some way to produce a final prediction.

To validate the performance of the proposed model, we used stratified K-fold cross-validation with K=10. The performance of the proposed model was evaluated in terms of accuracy and standard deviation from cross-validation. Stratified K-fold cross-validation is a technique used in machine learning to evaluate the performance of a model on a dataset [25]. It is a variation of K-fold cross-validation that ensures that each fold of the data contains the same proportion of target class labels as the entire dataset. This helps to avoid bias in the model evaluation process that can arise when the distribution of target classes in the folds is not representative of the overall distribution in the dataset.

The process of the stratifies K-fold cross-validation involved dividing the dataset into K-equal-sized folds. For each fold, the model was trained on the remaining *K-1* folds and then evaluated on the held-out fold. This process was repeated *K* times, with each fold used once as the validation set. The performance of the model was then averaged over the *K* folds to give an estimate of its generalization performance.

In this study, a computer with Windows 10 Pro 64-bit operating system and Intel® core ™ i7-10700 CPU @ 2.90GHz, 8GB RAM were used. MATLAB 2015a was used to implement grayscale transformation and AMF, and Jupyter Notebook was used for feature extraction and classification.

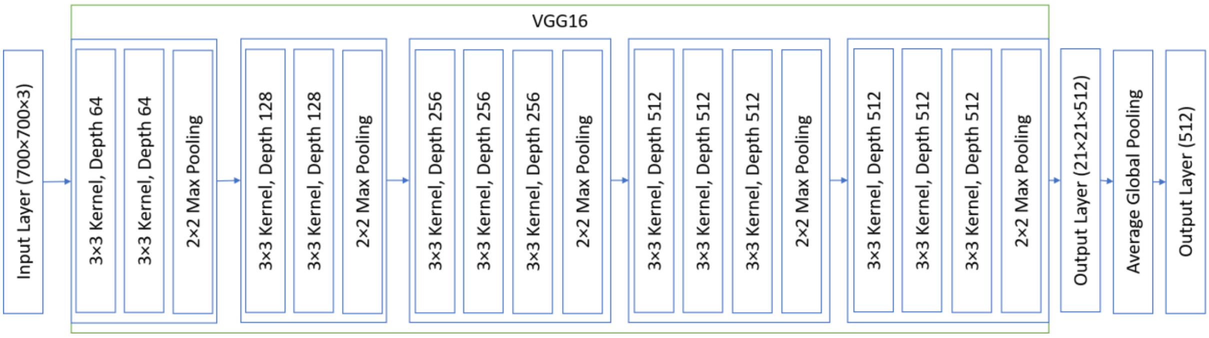

Figure 1: The process of extraction features in this study

III.RESULTS AND DISCUSSION

Figure 2 displays samples from datasets evaluated in this study. As AMF is used for medical imaging with 1 channel or grayscale, the RGB image or original dataset was transformed using grayscale conversion to produce Figure 2a. The AMF filter with kernel sizes 3 × 3 and 5 × 5 pixels was then applied to the original image to produce the samples in Figure 2b and 2c, respectively.

Table III presents the results of multi-classification and Table IV presents the results of binary-classification for different magnifications. Table III indicates the AMF filter with a kernel size of 3 × 3 pixels improve the accuracy for magnifications of 40×, 200×, and 400x. At a magnification of 40×, the model accuracy is increased by 0.20%. The accuracy improvement is 0.89% for magnification of 200×. While the accuracy for a magnification of 400× remains the same as for original image, the use of AMF filter with a kernel size of 3 × 3 pixels resulted in a lower standard deviation than original image. However, for a magnification of 100×, the use of AMF filter decreases the model performance.

When the AMF with a kernel size of 3 × 3 pixels was used in the preprocessing stage, it resulted in improved performance for datasets with magnifications of 40× and 200×, as shown in Table IV. Specifically, the accuracy is increased by 1.10% for magnification 40× and by 0.85% for magnification of 200×. On the other hand, AMF filter decreases the model performance in magnifications of 100× and 400×.

Datasets with different magnifications have unique characteristics. The performance accuracy can be impacted by the use of a noise reduction filter, especially AMF. Since RGB dataset is converted into gray-scale dataset to apply AMF, it is expected there's some loss information which result in lower accuracy. Further research should consider applying AMF to RGB images.

The results indicate that the use of the AMF with a kernel size of 3 × 3 pixels leads to improved classification accuracy for magnifications of 40×, 200×, and 400× in both multi-class and binary-class classifications. However, a negative impact on performance was observed for magnification of 100× and 400× when using the AMF. In contrast, a kernel size of 5 × 5 pixels resulted in an overall negative impact on classification accuracy, indicating that a kernel size of 3 × 3 pixels is the optimal choice for this dataset.

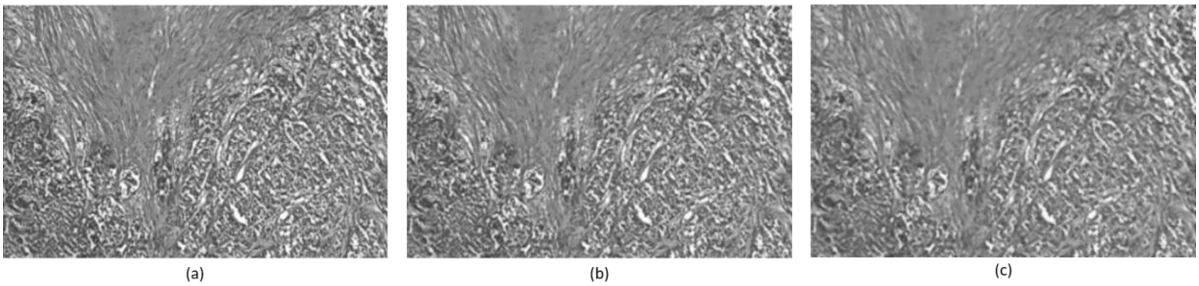

Figure 2: Sample of each datasets that evaluated in this study (a) original image in grayscale format; (b) filtered image by AMF filter with kernel size 3 × 3 pixels; (c) filtered image by AMF with kernel size 5 × 5 pixels

TABLE III

ACCURACY FOR MULTI-CLASS CLASSIFICATION ACROSS VARIOUS MAGNIFICATIONS

	Accuracy for Various Magnification (%)			
Dataset	40×	100×	200×	400×
Original image	71.23±2.22	**67.09**±1.78	61.75±2.03	56.87±2.69
AMF (3 × 3)	**71.43**±2.31	66.51±3.32	**62.64**±2.0	**56.87**±2.45
AMF (5 × 5)	70.62±2.4	65.16±2.89	60.06±2.84	54.89±2.28

TABLE IV

ACCURACY FOR BINARY-CLASS CLASSIFICATION ACROSS VARIOUS MAGNIFICATIONS

	Accuracy for Various Magnification (%)			
Dataset	40×	100×	200×	400×
Original image	87.52±1.45	**85.78**±1.79	83.11±2.23	**80.82**±3.15
AMF (3 × 3)	**88.62**±2.61	85.15±2.19	**83.96**±1.58	80.27±2.87
AMF (5 × 5)	88.22±2.39	84.72±2.9	83.21±1.84	78.74±2.62

Table III and Table IV show that applying the AMF with kernel size of 5 × 5 pixels to the original image dataset result in lower model performance. This indicates that a kernel size of 5 × 5 pixels led to over-smoothing or blurring of the image. The larger kernel size considers more pixels in the surrounding area during the filtering operation, resulting in a larger averaging effect. Consequently, high-frequency details such as edges and contrast may be lost, leading to a loss of important information in the image.

According to Calvo et al. [26], transfer learning models' feature extraction approach may not be effective for datasets with high levels of noise. They used the adaptive unsharp mask (AUM) filter to enhance color contrast in images from the BreakHis dataset. The AUM filter can increase contrast in areas with high detail and does not amplify noise much [27]. However, when the AUM filter was used as a preprocessing step, the model's accuracy decreased. Therefore, it is suggested that denoising filters should be used after color or contrast enhancement filters to reduce noise's impact on the model performance in future research.

IV. CONCLUSION

In conclusion, the use of the AMF with a kernel size of 3 × 3 pixels as a preprocessing stage for the histopathological image classification of breast tumor has shown to have a positive impact on the accuracy of multi-class and binary-class classifications for magnifications of 40× and 200×, but not for magnifications of 100× and 400×. The results also indicate that the use of AMF can reduce the standard deviation compared to the original image for some magnifications. However, caution should be exercised when applying the AMF, as it can decrease the model performance in some cases.

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