ECE 9202: Advanced Image Processing - Assignment 3

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1 Objective

The objective of this assignment is to apply morphological operations such as dilation, erosion, opening, etc. for medical image classification; compare classification performance with and without morphological preprocessing on a fine-tuned VGG16, and analyze the effect of the preprocessing techniques using quantitative metrics.

2 Dataset

The BloodMNIST dataset consists of images of individual normal cells, captured from individuals without infection or ongoing pharmacological treatment. It contains 17,092 images organized into 8 classes. The dataset is split into 70% training, 10% validation, and 20% test sets. The source images with a resolution of 3x360x360 are center-cropped to 3x200x200 and then resized to 3x28x28.

3 Methodolgy

The first task is implementing transfer learning for image classification on raw images 1. The implementation environment is Python and PyTorch. The images are resized to 224x224 to meet model requirements and then normalized. The training, validation, and test datasets are loaded. The pre-trained VGG16 with weights from IMAGENET1K_V1 is used. Cross entropy loss and Adam optimizer are used and model is trained for 25 epochs.The model architecture is described below in Table1.

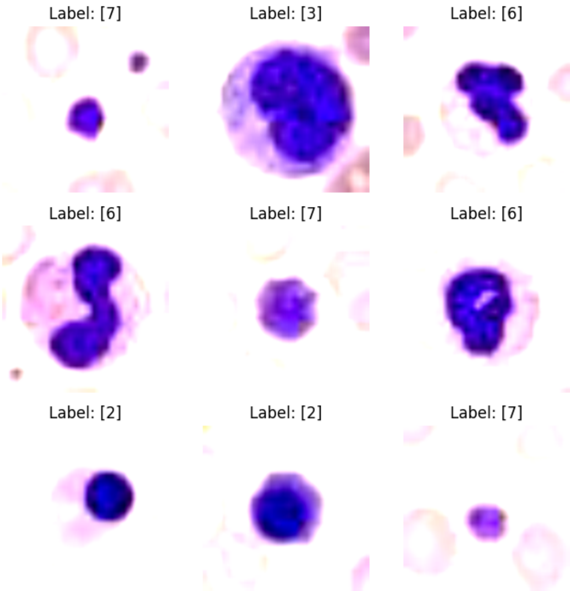
Layer	**Features/Dropout Value**
Linear	(25088,4096)
ReLU	-
Dropout	0.5
Linear	(4096,256)
ReLU	-
Dropout	0.5
Linear	(256,8)
Softmax	-

Table 1: Fine-tuned VGG 16 architecture

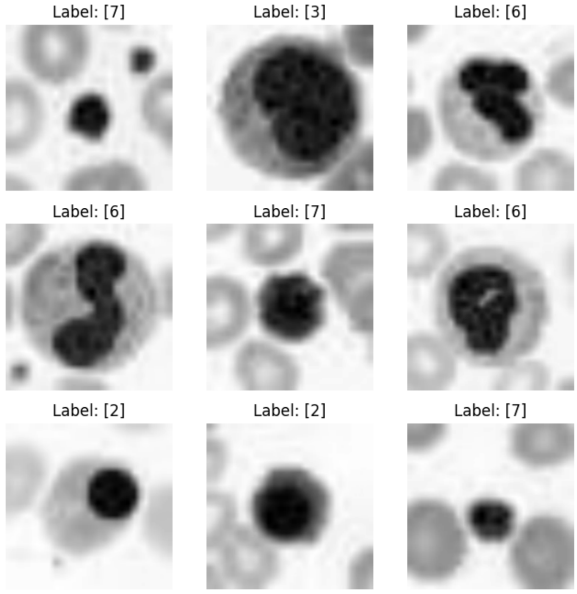
For task 2, the dataset is converted to grayscale, normalized, and morphologically processed. The structuring element is defined to be of size 3x3. Erosion removes small noise and refines the fracture edges as shown in 3b. Dilation expands the bright areas and hence improves their visibility and opening reduces small noise while preserving edges as shown in Figure 3c . Cross entropy loss and Adam optimizer are used and model is trained for 25 epochs. The model architecture is similar to Table1. In the first experiment, erosion is performed and then image classification is conducted. In experiment 2, the opening operation is performed before classification. For task 3, the saved models from task 1 and task 2 are loaded, and classification performance is compared for raw images and morphologically processed images using accuracy, precision, recall, and F1-score.

4 Results

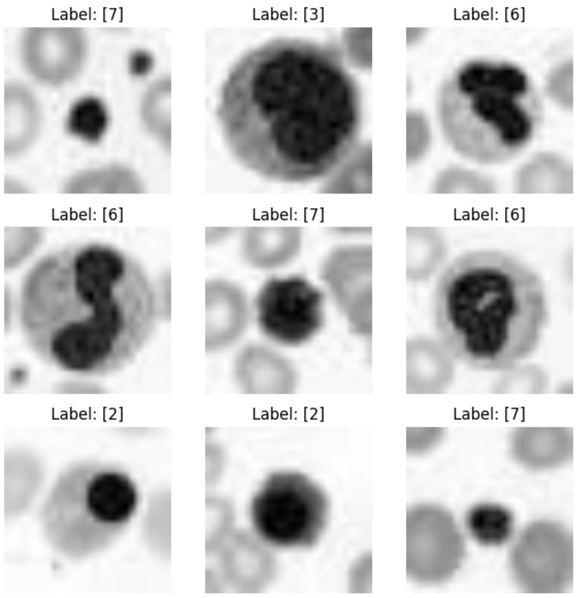
Figure 2 shows the images before classification and 3 shows the raw and preprocessed images that are misclassified.Figure 4 compares the performance of classification model on raw images and morphologically processed images.



(a) Raw images used for classification

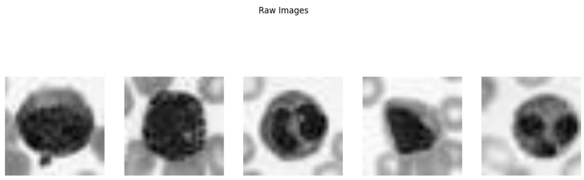


(b) Erosion operation performed for morpholigical processing

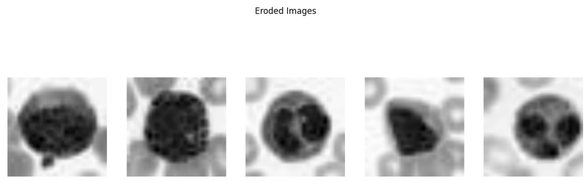


(c) Opening operation performed for morpholigical processing

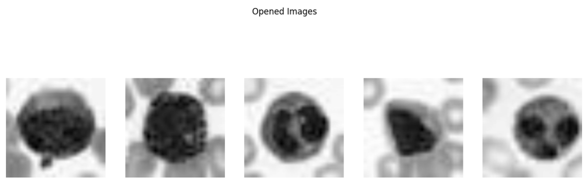
Figure 1: Raw and Preprocessed Images



(a) Raw images used for classification

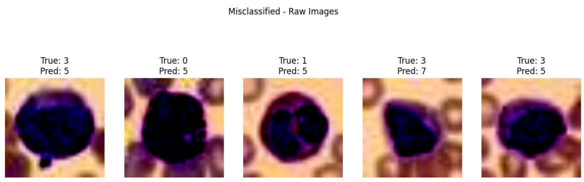


(b) Erosion operation performed for morpholigical processing

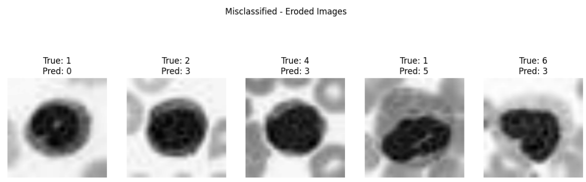


(c) Opening operation performed for morpholigical processing

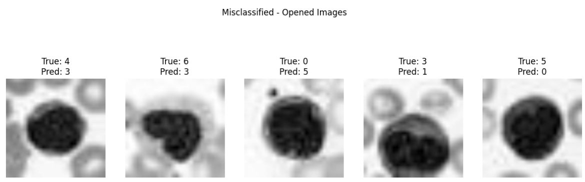
Figure 2: Raw and morphologically processed images



(a) Misclassified raw images



(b) Misclassified images after erosion operation



(c) Misclassified imaged after opening operation

Figure 3: Misclassified raw and morphologically processed images

	Task	Accuracy	Precision	Recall	F1-score
0	Raw Images	0.402222	0.512685	0.402222	0.318992
1	Erosion Processed	0.926045	0.930398	0.926045	0.926955
2	Opening Processed	0.927799	0.929249	0.927799	0.927738

Figure 4: Comparison of performance metrics

5 Discussion

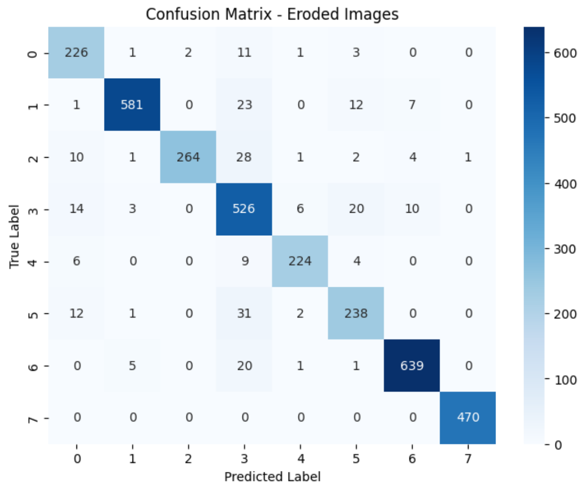
In this study, the performance of a VGG16 model trained on raw BloodMNIST images versus images that underwent morphological preprocessing (erosion and opening operations) is compared. The performance of the models was analyzed using standard classification metrics such as accuracy, precision, recall, and F1-score.

The VGG16 model trained on raw images performed with a baseline accuracy of 0.402%, precision of 0.512%, recall of 0.402%, and an F1-score of 0.318%. Eventhough these observations are satisfactory, it shows room for improvement, particularly in noisy images with poorly defined features.

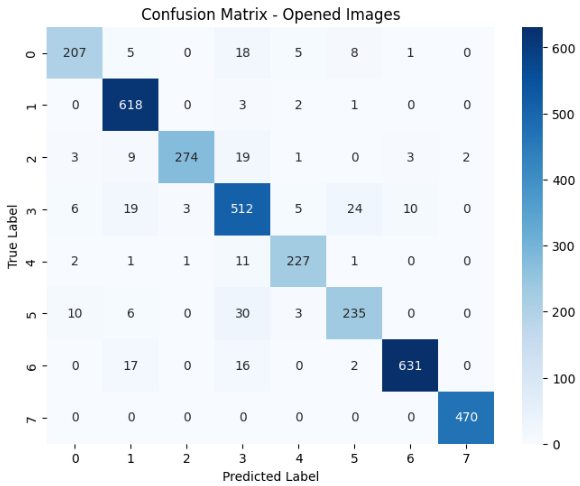
However, when the models trained on morphologically processed images were able achieve notably high performance as shown in table 4. Morphological operations are designed to enhance specific features in an image by manipulating the shape of structures within it. They can reduce noise and enhance the important features in the images, such as cell boundaries and structures. In this assignment, the preprocessing operations applied were:

- Erosion: It helped remove small noise and refined the edges of the blood cells, which is particularly useful in medical images where subtle features can easily be overwhelmed by noise. While the reduction in noise improve the model's ability to focus on important features, it may also lead to the loss of finer details, which could negatively affect classification in cases where small features are important.
- Opening: This operation operation, first erodes and then dilates the image, effectively reducing noise while

(a) Confusion matrix for classification results of raw images



(b) Confusion matrix for classification results of images after performing erosion operation



(c) Confusion matrix for classification results of images after performing opening operation

Figure 5: Confusion matrices for comparison

preserving the core features of the blood cells. The model performed better on images preprocessed with opening because this operation maintains important structural features while eliminating minor distractions. This preprocessing technique helps the model better focus on the relevant features of blood cells, resulting in improved classification metrics across all evaluation measures.

Eventhough the use of morphological preprocessing shows significance improvement in the results, they also have limitations. While erosion reduces noise, it also eliminates fine details, which affects the model's ability to accurately classify certain blood cells, particularly smaller ones. There is the risk of over simplification when using erosion, especially in medical images where subtle details are crucial. Comparatively, opening offers better balance by reducing noise while preserving key structural features. Therefore, it was the most effective preprocessing technique for enhancing the model's performance on BloodMNIST images.

Furthermore, The use of transfer learning with a pre-trained VGG16 model on the ImageNet dataset proved beneficial for BloodMNIST classification. The model leveraged learned features, such as edge detection and texture recognition, which are crucial for identifying patterns in medical images like blood cells. Fine-tuning the model on the BloodMNIST dataset allowed it to adapt to the unique features of blood cells, leading to effective classification.

Despite the advantages of transfer learning, the preprocessing steps played a significant role in the model's performance. The application of erosion and opening improved the model's ability to classify cells in noisy or unclear images. However, the morphological preprocessing also introduced trade-offs, as seen in the slight reduction in accuracy for the erosion-preprocessed images. This suggests that while transfer learning provided a strong foundation, preprocessing could further refine feature extraction and improve model performance, especially in complex cases.

6 Conclusion

This study examined the application of morphological preprocessing techniques, including erosion and opening, to enhance the performance of a VGG16 model in classifying BloodMNIST images. While the model trained on raw images performed reasonably well, preprocessing enhanced the model's ability to detect and classify blood cells, particularly in noisy or poorly defined images. Among the preprocessing methods, opening proved to be the most effective, improving the model's accuracy, precision, and recall by reducing noise while preserving critical features of the blood cells. In contrast, erosion, while effective in cleaning up small noise, led to some loss of critical details, which occasionally impacted classification accuracy. Overall, this study proves the value of applying morphological preprocessing for medical image classification and highlights the need for careful selection of preprocessing techniques to balance feature enhancement and noise reduction.