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Performances of Pre-Trained Models in Classification of Body Cavity Fluid Cytology Images

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Abstract – Using deep learning architectures, disease detection from medical images such as brain images, chest X-rays, and cytology images is used in many areas. With the use of deep learning architectures in the faster detection of diseases, the possibility of starting treatment early increases. Benign and malignant cell clusters are formed from body cavity effusions. Diagnosis is made by visual inspection of images of centrifuged body fluid effusions deposits. Bad cells are usually abundant in body cavity fluids. Here, separating malignant cells from the proliferation of mesothelial cells or inflammatory cells is the problematic part. In this case, a classifier can be used to distinguish benign mesothelial or inflammatory cells from malignant carcinoma cells. In this study, using Convolutional Neural Network (CNN) based models, the detection of benign and malignant cells from cytology images consisting of fluids in the body cavity will be an aid to pathologists by detecting early and accurately. The dataset contains 693 images with two classes of 256x192 benign and malignant cells. These images are trained using AlexNet, ResNet50, DarkNet53, GoogleNet, MobileNetv2, and EfficientNetb0 architectures. As a result of the test phase, the highest classification accuracy was obtained in the DarkNet53 architecture with 98.56%.

Keywords – Classification, CNN, Cytology Image, Deep Learning, Effusion

I. Introduction

The pleural space is the space between the outer pleura attached to the chest wall and the inner pleura on the lung surface. Pleural effusion, on the other hand, is the excessive accumulation of fluid between the layers of the pleura covering the surface of the lungs. Pleural effusion may occur due to various reasons such as inflammation, infection or malignancy. Mesothelial cells, inflammatory cells, and malignant cells may be involved in these effusions between the pleural layers [1,2]. Fluid samples taken from the pleural space are centrifuged and the residue is spread on a glass slide and stained with various dyes. Microscopic images of pleural effusion cytology stained with Leishman stain in the study are given in Figure 1.

Examination of body fluid cytology is a complete diagnostic method that is widely used in both the diagnosis and staging of malignant cells. The process of examining body fluid smears can be time-consuming and prone to error. Cytological examination is usually performed to diagnose the disease in pleural effusion. Carcinoma can be diagnosed with malignant epithelial cell clusters sought in body fluids that are microscopically examined by pathologists [3].

Deep learning in cytological examinations will help to increase the overall survival rate of cancer patients by producing fast and highly accurate results in early and effective diagnosis.

Aboobacker et al. [1] proposed an integrated approach based on deep learning that learns to detect malignant cells in effusion cytology images. In their architecture called U-Net, they obtained an accuracy of 96% and AUC of the ROC curve of 97%, precision 96% Recall 96% and Specificity

97% from images containing malignant cell detection.

Uca et al. [4] trained and tested 21 patients using a dataset of 693 images using the ResNet50, GoogleNet and AlexNet classification architectures, as a result of the images they subjected to training and testing, AlexNet architecture was 97.26%, GoogleNet architecture was 98.12% and ResNet50 architecture was 99%, 13 classification accuracies were obtained. They contrasted the classification outcomes they obtained with those from other studies that used the same dataset.

The continuation of the article is organized as a Material and Methods section, Result section, and Conclusion section.

II. Materials and Method

The dataset and CNN architectures used in the study are discussed in this section.

A. *Dataset*

A publicly available dataset was used to classify Cytology images [5]. This two-class dataset consists of benign (mesothelial cell proliferation, inflammatory cell, etc.) cells with 160 images and malignant carcinoma (malignant epithelial) cells with 533 images. The images in the dataset were created by resizing the smears (smears) prepared from centrifuged deposits of body fluids to 256x192 pixels at 40X magnification after staining with Leishman. Figure 1 shows examples of the cytology images used in the paper.

Benign

Malignant

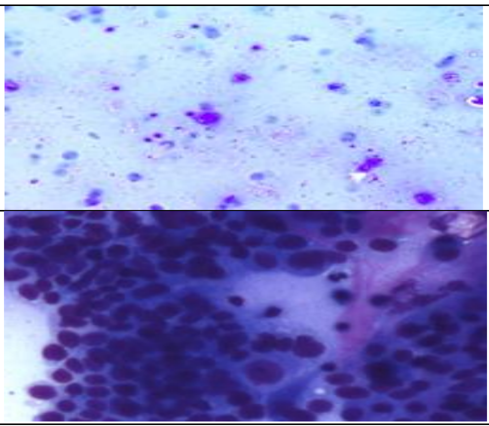

Fig. 1 Cytology image examples

B. CNN Architectures

Convolutional Neural Network architecture (CNN), which has been accepted as a basic architecture of deep learning neural networks, is the most common neural network architecture applied to image classification and signal processing problems. Unlike traditional machine learning architectures, deep learning models perform these operations independently, without the need for feature extraction and pre-processing. While expert knowledge is required for feature extraction with machine learning methods, the feature extraction process with CNN architectures is directly extracted by the model, not an expert, and the learning process is carried out on the model. In this way, the use of CNN architectures has increased in recent years, since it eliminates the problems in feature extraction [6]. Six different pre-trained models were used in the paper. These models are AlexNet [7], ResNet50 [8], GoogleNet [9], DarkNet53 [10], EfficientNetb0 [11], and MobileNetv2 [12].

III. Results

On a computer with an i7 CPU, 8 GB of RAM, and a video card, this investigation was conducted for the classification of cytological images made up of bodily cavity fluids. Six different CNN architectures were used in the study. In addition to the accuracy metric, sensitivity, specificity, and F1 score metrics were also used to compare the performance of these architectures. Additionally, in this study, 30% of the dataset's data was utilized to test the models, while 70% of it was used to train the models. Accuracy, sensitivity, specificity and F1 score parameters were used to calculate the performance metrics of the pre-trained models used in the classification of Body Cavity Fluid Cytology images [13,14]. In Table 1, the confusion matrices from the AlexNet architecture are presented.

Table 1. AlexNet's confusion matrix

AlexNet		BENIGN	MALIGNANT
True Class	BENIGN	44	4
	MALIGNANT	1	159
		Predicted Class	

Table 1 shows that, of the 208 images used for the test, 203 were accurately predicted by the AlexNet architecture, while 5 were wrongly predicted. The accuracy value of the AlexNet architecture is 97.60%. Table 2 presents the AlexNet's performance evaluation metrics.

Table 2. Performance metrics of AlexNet

Accuracy	Sensitivity	Specificity	F1-Score
97.60%	97.78%	97.55%	94.62%

Table 3 shows the ResNet50 architecture's confusion matrix.

Table 3. Resnet50's confusion matrix

ResNet50		BENIGN	MALIGNANT
True Class	BENIGN	41	7
	MALIGNANT	1	159
		Predicted Class	

Table 3 shows that, of the 208 images used for the test, 200 were accurately predicted by the ResNet50 architecture, while 8 were wrongly predicted. The accuracy value of the ResNet50 architecture is 96.15%. Table 4 presents the ResNet50's performance evaluation metrics.

Table 4. Performance metrics of ResNet50

Accuracy	Sensitivity	Specificity	F1-Score
96.15%	97.62%	95.78%	91.11%

Table 5 shows the GoogleNet architecture's confusion matrix.

Table 5. GoogleNet's confusion matrix

GoogleNet		BENIGN	MALIGNANT
True Class	BENIGN	38	10
	MALIGNANT		160
		Predicted Class	

Table 5 shows that, of the 208 images used for the test, 198 were accurately predicted by the GoogleNet architecture, while 10 were wrongly predicted. GoogleNet correctly predicted all of the Malignant Cytology test images. The accuracy value of the GoogleNet architecture is 95.19%. Table 6 presents the GoogleNet's performance evaluation metrics.

Table 6. GoogleNet's confusion matrix

Accuracy	Sensitivity	Specificity	F1-Score
95.19%	100%	94.12%	88.37%

Table 7 shows the EfficientNetb0 architecture's confusion matrix.

Table 7. EfficientNetb0's confusion matrix

EfficientNetb0		BENIGN	MALIGNANT
True Class	BENIGN	38	10
	MALIGNANT	4	156
		Predicted Class	

Table 7 shows that, of the 208 images used for the test, 194 were accurately predicted by the

EfficientNetb0 architecture, while 14 were wrongly predicted. Efficientnetb0 predicted 38 of the 48 benign Cytology test images correctly and 10 of them incorrectly. Similarly, out of 160 malignant Cytology test images, it predicted 156 correctly and 4 incorrectly. The accuracy value of the EfficientNetb0 architecture is 93.27%. Table 8 presents the EfficientNetb0's performance evaluation metrics

Table 8. Performance metrics of EfficientNetb0

Accuracy	Sensitivity	Specificity	F1-Score
93.27%	90.48%	93.98%	84.44%

Table 9 shows the MobileNetv2 architecture's confusion matrix.

Table 9. MobileNetv2's confusion matrix

MobileNetv2		BENIGN	MALIGNANT
True Class	BENIGN	38	10
	MALIGNANT	1	159
		Predicted Class	

Table 9 shows that, of the 208 images used for the test, 197 were accurately predicted by the MobileNetv2 architecture, while 11 were wrongly predicted. The accuracy value of the MobileNetv2 architecture is 94.71%. Table 10 presents the MobileNetv2's performance evaluation metrics.

Table 10. Performance metrics of MobileNetv2

Accuracy	Sensitivity	Specificity	F1-Score
94.71%	97.44%	94.08%	87.36%

Table 11 shows the DarkNet53 architecture's confusion matrix.

Table 11. DarkNet53's confusion matrix

DarkNet53		BENIGN	MALIGNANT
True Class	BENIGN	46	2
	MALIGNANT	1	159
		Predicted Class	

Table 11 shows that, of the 208 images used for the test, 205 were accurately predicted by the DarkNet53 architecture, while 3 were wrongly predicted. The accuracy value of the DarkNet53 architecture is 98.56%. The performance evaluation metrics of the DarkNet53 architecture, where the highest accuracy value was obtained in the study, are presented in Table 12.

Table 12. Performance metrics of DarkNet53

Accuracy	Sensitivity	Specificity	F1-Score
98.56%	97.87%	98.76%	96.84%

When the 6 different architectures used in the study were examined, the highest accuracy value was obtained in the DarkNet53 architecture with 98.56%. DarkNet53 was followed by AlexNet with 97.6%, ResNet50 with 96.15%, GoogleNet with 95.19%, MobileNetv2 with 94.71% and EfficientNetb0 with 93.27%, respectively. The accuracy values of these architectures are given in Figure 2.

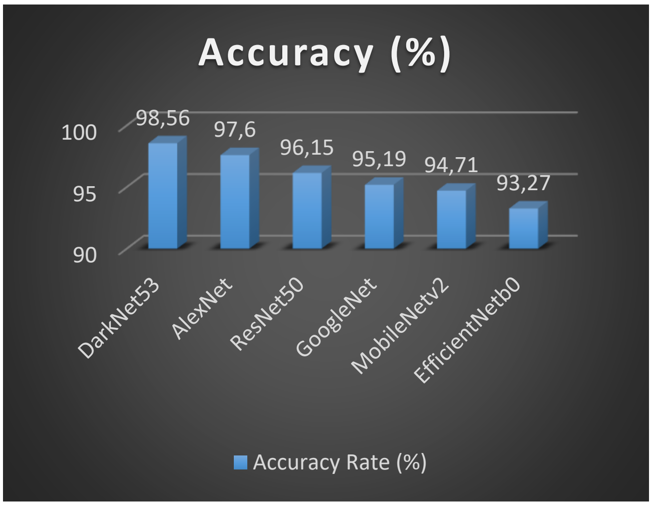

Fig. 2 Accuracy rates of pre-trained models

IV. CONCLUSION

Artificial intelligence methods have been used frequently in recent years, especially in the biomedical field. Thanks to artificial intelligence-supported systems, the workload of experts will be lightened. At the same time, these systems can be used in non-expert centers. In this study, pre-trained models were used for the Classification of Body Cavity Fluid Cytology Images. DarkNet53 architecture has reached the highest accuracy value among the models used.

CONFLICT OF INTEREST

There is no conflict of interest.

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