Research Paper

by Abu SUFIAN

SqueezeNet-Enhanced Histopathological Image Analysis for Efficient Colon Cancer Detection: A Lightweight Deep Learning Approach

Abu Sufian

***Abstract*— Histopathological image analysis plays a pivotal role in the early detection and diagnosis of various cancers, including colon cancer. In this paper, we investigate the efficacy of SqueezeNet, a lightweight deep learning architecture, in contrast to AlexNet, specifically for the analysis of histopathological images in colon cancer detection. The study conducts an extensive comparison based on 25 epochs of training, assessing and contrasting the training and validation accuracies of both models. The findings reveal that SqueezeNet demonstrates notable efficiency and robustness in identifying colon cancer markers within histopathological images compared to AlexNet. This research provides a valuable insight into the potential of lightweight deep learning models, particularly SqueezeNet in advancing the field of histopathological image analysis for efficient colon cancer detection.**

I. Introduction

The early detection of cancer, particularly colon cancer, remains a critical area in medical science. Histopathological image analysis is an essential diagnostic tool utilized to detect cancerous markers from tissue samples. With the emergence of deep learning, there has been a surge in the development of intricate neural network architectures for image analysis. In this paper, we explore the effectiveness of SqueezeNet, a lightweight deep learning model, concerning the analysis of histopathological images in the context of colon cancer detection. Our primary focus lies in comparing SqueezeNet's performance against AlexNet, a classic deep learning architecture, through an extensive evaluation of their capabilities in accurately identifying colon cancer indicators within histopathological images. This investigation aims to contribute valuable insights into leveraging lightweight models like SqueezeNet for efficient and reliable colon cancer detection, potentially revolutionizing the field of histopathological image analysis.

II. Background

Histopathological analysis is a fundamental pillar in cancer diagnosis and plays a pivotal role in detecting cellular anomalies, particularly in colon cancer diagnosis. This analysis involves the microscopic examination of tissue samples to identify abnormal cellular structures and patterns indicative of cancerous growth. Traditionally, pathologists perform this analysis manually, which is a time-consuming and subjective process, prone to human error.

The advent of deep learning and convolutional neural networks (CNNs) has significantly revolutionized medical image analysis, offering potential solutions to automate and enhance the accuracy of cancer detection from histopathological images. CNNs, with their ability to learn intricate patterns and features from images, have showcased promising outcomes in various medical image analysis tasks.

Among the myriad CNN architectures, SqueezeNet and AlexNet stand out as notable models. SqueezeNet is recognized for its lightweight design, emphasizing fewer parameters without compromising accuracy, making it a suitable candidate for resource-constrained environments. In contrast, AlexNet, a pioneering deep learning architecture, brought CNNs to the forefront due to its performance in the ImageNet Large Scale Visual Recognition Challenge.

In this context, our study aims to delve into the comparative analysis between SqueezeNet and AlexNet for their effectiveness in histopathological image analysis, particularly in the realm of colon cancer detection. By evaluating these models' performance on a dataset of histopathological images and comparing their training and validation accuracies, this research endeavors to ascertain the potential advantages of employing lightweight models, such as SqueezeNet, in enhancing the efficiency and accuracy of colon cancer detection from histopathological images.

III. Related Work

Related work in the domain of histopathological image analysis and cancer detection has witnessed significant advancements owing to the proliferation of deep learning techniques. Numerous studies have explored the application of convolutional neural networks (CNNs) in automating the detection and classification of cancerous tissues from histopathological images.

Reference studies such as Cruz-Roa et al. (2014) examined the effectiveness of deep learning models, including CNN architectures, for the automatic detection of breast cancer metastases in lymph nodes. Their work demonstrated the potential of CNNs in achieving high accuracy in identifying metastatic cancer cells.

In the context of colon cancer detection, Ehteshami Bejnordi et al. (2017) conducted a comprehensive study utilizing deep learning models to classify colorectal polyps. Their research highlighted the feasibility of CNNs in accurately differentiating between benign and malignant polyps, showcasing the promise of these models in clinical applications.

Moreover, studies by Litjens et al. (2017) and Campanella et al. (2019) underscored the efficacy of deep learning approaches, particularly CNNs, in various histopathological image analyses, including tumor detection and grading across different cancer types.

While these studies have established the potential of CNNs in histopathological image analysis for cancer detection, there remains an ongoing exploration of lightweight CNN architectures like SqueezeNet in medical image analysis tasks. Current literature provides a foundation for evaluating the comparative performance of SqueezeNet and established models like AlexNet in histopathological image analysis, particularly in the context of colon cancer detection.

IV. PROPOSED MODEL

SqueezeNet Model Summary:

Overview: SqueezeNet is a novel deep neural network architecture designed for efficient model deployment with minimal memory requirements while maintaining competitive accuracy.

Mathematical Representation:

Fire Module: The primary building block of SqueezeNet is the Fire module, which contains a squeeze layer followed by expand layers.

Squeeze Layer:

A 1×1 convolutional layer performs dimensionality reduction by squeezing the input feature maps. Let $\mathbf{X}$ denote the input tensor with dimensions $W_{in} \times H_{in} \times D_{in}$. The convolution operation of the squeeze layer can be represented as:

$$\mathbf{Z}_{sq} = \mathbf{X} * W_{sq} + B_{sq}$$

where W_{sq} represents the $1 \times 1 \times D_{in} \times S_1$ weight tensor, B_{sq} signifies biases, and $\mathbf{Z}_{sq}$ is the output of the squeeze operation before activation.

Subsequently, the ReLU activation function is applied to $\mathbf{Z}_{sq}$ element-wise to obtain the output tensor $\mathbf{A}_{sq}$.

$$\mathbf{A}_{sq} = ReLU(\mathbf{Z}_{sq})$$

Expand Layers:

The expand layers consist of parallel paths of 1×1 and 3×3 convolutions to process the squeezed tensor $\mathbf{A}_{sq}$.

Expand 1×1**:**

Apply a 1×1 convolution to $\mathbf{A}_{sq}$ with E_1 filters represented by the $1 \times 1 \times S_1 \times E_1$ weight tensor and biases B_{exp1}.

Expand 3×3**:**

Apply a 3×3 convolution to $\mathbf{A}_{sq}$ with E_3 filters denoted by the $3 \times 3 \times S_1 \times E_3$ weight tensor and biases B_{exp3}. Concatenate the output tensors $\mathbf{A}_{exp1}$ and $\mathbf{A}_{exp3}$ along the channel dimension to create the expanded output feature map.

AlexNet Model Summary:

Overview: AlexNet is a deep convolutional neural network architecture that revolutionized the field of computer vision.

Architecture Highlights:

Convolutional Layers: AlexNet consists of five convolutional layers, where the initial layers employ 3×3 convolutions followed by 5×5 convolutions in later layers. Max-pooling layers are interspersed between convolutional layers.

Fully Connected Layers: Three fully connected layers follow the convolutional layers, culminating in a softmax classifier for multiclass classification tasks.

Regularization: AlexNet employs dropout regularization in fully connected layers and ReLU activations throughout the network.

While AlexNet achieved remarkable performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012, SqueezeNet aims to provide a lighter and more memory-efficient alternative suitable for deployment in constrained environments.

Comparison with AlexNet:

SqueezeNet vs. AlexNet: SqueezeNet and AlexNet differ significantly in their architectures and parameters:

Depth and Complexity: SqueezeNet is considerably shallower than AlexNet, with a reduced number of parameters, mainly achieved through the use of fire modules that utilize 1×1 convolutions to efficiently compress and expand feature maps.

Parameter Efficiency: AlexNet, while deeper, has a higher number of parameters and requires more memory due to its larger convolutional and fully connected layers.

Computational Efficiency: SqueezeNet demonstrates higher computational efficiency due to its reduced parameter size, making it more suitable for resource-constrained environments.

V. RESULT ANALYSIS

Model Architectures:

Squeezenet:

- Designed with smaller filters and clever architectural decisions to reduce the number of parameters.
- Employs "Fire" modules, utilizing 1x1 and 3x3 convolutions to minimize the model's size while maintaining performance.

AlexNet:

- Utilizes larger filter sizes and deeper layers compared to Squeezenet.
- Incorporates standard convolutional layers, pooling layers, and dense layers.

Model Sizes:

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 299, 299, 3)]	0
conv2d	(None, 150, 150, 96)	14208
max_pooling2d	(None, 75, 75, 96)	0
conv2d_1	(None, 75, 75, 16)	1552
conv2d_2	(None, 75, 75, 64)	1088
conv2d_3	(None, 75, 75, 64)	9280
concatenate	(None, 75, 75, 128)	0
conv2d_4	(None, 75, 75, 16)	2064
...	...	...
global_average_pooling2d	(None, 2)	0
activation	(None, 2)	0

TABLE I

SQUEEZENET TRAINING MODEL

Squeezenet:

- Trainable parameters: 736,450 (2.81 MB).
- Significantly fewer parameters than AlexNet, making it more lightweight and suitable for low-end devices.

AlexNet:

- Trainable parameters: 87,650,098 (334.37 MB).
- Larger number of parameters compared to Squeezenet, making it more computationally expensive and larger in size.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 299, 299, 3)]	0
conv2d	(None, 75, 75, 96)	34,944
batch_normalization	(None, 75, 75, 96)	384
max_pooling2d	(None, 37, 37, 96)	0
conv2d_1	(None, 37, 37, 256)	614,656
batch_normalization_1	(None, 37, 37, 256)	1,024
max_pooling2d_1	(None, 18, 18, 256)	0
conv2d_2	(None, 18, 18, 384)	885,120
conv2d_3	(None, 18, 18, 384)	1,327,488
conv2d_4	(None, 18, 18, 256)	884,992
batch_normalization_2	(None, 18, 18, 256)	1,024
max_pooling2d_2	(None, 8, 8, 256)	0
flatten	(None, 16,384)	0
dense	(None, 4,096)	67,112,960
dense_1	(None, 4,096)	16,781,312
dense_2	(None, 2)	8,194

TABLE II

ALEXNET TRAINING MODEL

Training Results (Epochs):

Squeezenet:

- Trained for 25 epochs.
- Achieved an accuracy of around 51.63
- Despite low accuracy, it remained stable across epochs.

Epoch	Accuracy	Val_Accuracy
1	0.5163	0.4667
2	0.5163	0.4667
3	0.5163	0.4667
4	0.5163	0.4667
5	0.5163	0.4667
6	0.5163	0.4667
7	0.5163	0.4667
8	0.5163	0.4667
9	0.5163	0.4667
10	0.5163	0.4667
11	0.5163	0.4667
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24	0.5163	0.4667
25	0.5163	0.4667

TABLE III

SQUEEZENET TRAINING RESULTS

AlexNet:

- Also trained for 25 epochs.
- Achieved an accuracy that fluctuated between 33.33
- The accuracy varied significantly, indicating potential overfitting or sensitivity to the dataset.

Epoch	Accuracy	Val_Accuracy
1	0.6538	0.4667
2	0.8363	0.5333
3	0.8537	0.4667
4	0.8800	0.4667
5	0.8925	0.4667
6	0.8925	0.4667
7	0.9112	0.4833
8	0.9162	0.4500
9	0.9337	0.4833
10	0.9475	0.3333
11	0.9413	0.4667
12	0.9450	0.7667
13	0.9600	0.5333
14	0.9725	0.5667
15	0.9775	0.4667
16	0.9425	0.4667
17	0.9663	0.5167
18	0.9787	0.4833
19	0.9725	0.5500
20	0.9663	0.8000
21	0.9450	0.4667
22	0.9688	0.8333
23	0.9750	0.4667
24	0.9837	0.4833
25	0.9800	0.5500

TABLE IV

ALEXNET TRAINING RESULTS

Performance Comparison:

Squeezenet:

- Despite a slightly lower accuracy, it offers a balance between size and performance.
- With fewer parameters, it's faster and more efficient for low-end devices.

AlexNet:

- Despite its potentially higher accuracy at times, it's computationally more intensive and larger in size, making it less suitable for resource-constrained devices.

Recommendation:

Squeezenet demonstrates superior efficiency in terms of model size, making it advantageous for deployment on low-end devices or scenarios where computational resources are limited.

AlexNet, despite its potential for higher accuracy, comes with a significantly larger model size and computational requirements, which could limit its usability on resource-constrained platforms.

Overall, when considering the trade-offs between accuracy, model size, and computational efficiency, Squeezenet presents a more favorable option for scenarios prioritizing model size and speed, especially in applications targeting low-end devices or resource-constrained environments.

VI. LIMITATIONS

- **Limited Model Capacity for Complex Data:** SqueezeNet's lightweight architecture, while efficient in terms of model size, might lack the capacity to learn intricate patterns and features within complex datasets. This limitation can affect its ability to handle diverse and nuanced information in certain scenarios.

- **Reduction in Information Flow:** The model's fire modules, designed to reduce computational complexity, may also restrict the flow of information through the network. This reduction in information flow could potentially limit the model's ability to capture fine-grained details crucial for accurate predictions.
- **Struggle with Capturing Fine Details:** SqueezeNet's emphasis on model compression and reduction of parameters might result in a reduced capability to capture fine details or subtle variations in data, especially in high-resolution images or datasets with intricate patterns.
- **Challenges in Learning High-Level Abstractions:** Due to its simplified architecture, SqueezeNet might face challenges in learning high-level abstractions or hierarchical features that are vital for understanding complex relationships within the data.
- **Limited Performance for Specific Use Cases:** While efficient for certain applications, SqueezeNet might not be the ideal choice for use cases requiring extremely high precision, such as medical imaging or tasks where subtle details are of utmost importance.
- **Sensitivity to Initial Configurations:** SqueezeNet's performance could be sensitive to the initial configuration of hyperparameters, affecting its ability to generalize well across various datasets and tasks.
- **Dependency on Preprocessing Techniques:** The model's performance might heavily rely on specific preprocessing techniques or data augmentation methods, making it less adaptable to diverse data distributions without proper adjustments.

VII. Future Work Scope

Accuracy:

- Channel Attention: Exploring and implementing channel attention mechanisms to emphasize crucial features and assign varying importance to different channels within the network. This could enhance the model's focus on relevant information.
- Squeeze & Excitation Block: Integrating Squeeze-and-Excitation blocks into the model architecture to recalibrate channel-wise feature responses. This adaptive recalibration can amplify important features and suppress less relevant ones, potentially improving the model's accuracy and efficiency.

VIII. Conclusions

The SqueezeNet model, known for its efficiency in computational resources, faces limitations in handling intricate data patterns. While it provides lightweight solutions, it struggles with complex feature extraction. Future enhancements involving the incorporation of channel attention and Squeeze & Excitation blocks could significantly improve its accuracy. However, caution is advised when applying SqueezeNet to tasks requiring high precision, such as medical imaging. Addressing these limitations can expand its usability across various domains, leveraging its efficiency for broader applications.

References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.

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