Original Article

Effective Classification of Colon Cancer using Resnet-18 in Comparison with Squeezenet

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Abstract

Aim: The work aims to find out a better way to perform colon cancer identification with the help of Resnet-18 algorithm in comparison with a Squeezenet algorithm to maximize the accuracy in finding rather than the existing method of prediction. **Materials and Methods:** A collection of 30 samples were picked for consideration; group 1 visualizing Resnet-18 classifier algorithm and finally group 2 is responsible for the Squeezenet algorithm. Thus G power calculation is done with a power of 80.5 and the alpha value is equivalent to 0.061. **Results:** When compared to the Squeezenet algorithm, the Resnet-18 classifier algorithm has attained an accuracy of 86.5060 % and 0.32754 which is somewhat greater than the existing method. (Squeezenet algorithm attained an accuracy of 83.5433% and 0.28975) respectively.

Conclusion: From the above statement it is evident that the Resnet-18 algorithm would be a better choice for predicting colon cancer and it is more effective.

Keywords: Novel texture analysis, Colon Cancer, Resnet-18, Squeezenet, Machine Learning (ML), Artificial Intelligence (AI), Accuracy.

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INTRODUCTION

Colorectal cancer (CRC) is the third most frequent type of cancer in the world, accounting for roughly 10% of all occurrences (Egeblad, Nakasone, and Werb 2010). A more precise classification of medical images can effectively predict the development of colorectal cancer, according to the findings of numerous research (Kather et al. 2019). Many common tissue types, including normal colon mucosa (NORM), adipose tissue (ADI), polyps, cancer-associated stroma (STR), and lymphocytes (LYM), can extract prognosticators directly from hematoxylin and eosin stains (HE stains), which are the most often used tissue stains in histology (Kather et al. 2016). One of the most reliable approaches for identifying CRC is pathological diagnosis, which needs a pathologist to physically evaluate digital full-scale entire slide images are Wafer Scale Integration (WSI). Furthermore, in contrast to the increasing collection of WSI data, there is a worldwide lack of pathologists, and pathologists' daily workload is intense, which could lead to inadvertent misdiagnosis owing to fatigue (Sayed, Lukande, and Fleming 2015). As a result, utilizing recent Artificial intelligence (AI) progress, it is critical to build diagnosis procedures that are both successful and low-cost. The recommended system has the potential to support and speed pathological investigation (Komura and Ishikawa 2018) in tumors such as lung (Coudray et al. 2018; Hua et al. 2015), breast (Veta et al. 2015), lymph node (Ehteshami Bejnordi et al. 2017), and skin (Zhang et al. 2020; Esteva et al. 2017). Deep learning has made progress in the field of CRC, including categorization, tumor cell detection, and outcome prediction.

There is numerous research work carried out in colon cancer identification using various algorithms. It is somewhat essential to understand what are all the steps taken and carried out in each algorithm. Other than that it is essential to understand the operation and functional behavior of the individual algorithm. This is the essential step and much-needed strategy to define which one is better and easy to select an effective algorithm among a group of algorithms already available. For this concern, a lot of research works are analyzed between 2013 to 2021. Among that nearly 73 research works were the artificial intelligence of analyzed and picked selectively few research works from that. Most of them dealt with a comparative analysis to visualize the effectiveness and prediction rate as well as conveying several ways to simplify and improve prediction. There are few research works which were repeatedly reviewed to perform colon cancer detection with the sense of various topologies. For systematic analysis and implementation, the articles that lie in between (Ko 2018; Williams 2017; Loktionov, n.d.; Al-Haija and Manasra 2020; Demir, Yilmaz, and Kose 2019; Gupta et al. 2021) are reviewed several times. Among numerous research works, the work which was done by (Sarwinda et al. 2021) is the best one because of its depth in action and viable contents are more and more represented.

Our institution is passionate about high quality evidence based research and has excelled in various fields (Parakh et al. 2020; Pham et al. 2021; Perumal, Antony, and Muthuramalingam 2021; Sathiyamoorthi et al. 2021; Devarajan et al. 2021; Dhanraj and Rajeshkumar 2021; Uganya, Radhika, and Vijayaraj 2021; Tesfaye Jule et al. 2021; Nandhini, Ezhilarasan, and Rajeshkumar 2020; Kamath et al. 2020). The major goal of this study is to create an effective and straightforward architecture for classifying histological colon cancer images. In terms of the number of layers and trainable parameters, simplicity is taken into account. We discovered that a careful assessment of the number of trainable layers and trainable parameters can result in an efficient Resnet-18 model in this study. Through Google colab, the existing and proposed algorithm has functioned over the input data set. And finally, the result obtained is compared.

Material and Methods

This research work was conducted at the Department of Electronics and Communication Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. This study consisted of the Resnet-18 and Squeezenet algorithm and also 30 samples were taken. For colon cancer analysis, the Matlab online simulation program is used. The IBM Statistics Package for Social Sciences (SPSS) software version 26 was used to conduct the statistical analysis for our study. The sample size for every group was calculated using a G Power calculator having 80% pretest power, an alpha error of 0.95, a threshold value of 0.05, and a 86% confidence level. Accuracies of both models are tested with a sample size of 10 using Matlab(Subramanian et al. 2016)**.**

Resnet-18 algorithm

Resnet design, which is more efficient and powerful, was recently proposed (Cao et al. 2022). Very deep convolutional neural networks can be efficiently taught with this design. Resnet uses residual blocks to construct its design. There are a total of 18 layers, including the initial convolutional layer and the final fully linked layer . We use the residual Convolution Neural Networks (CNN) Resnet-18 to produce multi-class classification for colon cancer detection in this paper. A total of 1125 photos are stored in the multi-class weather recognition dataset (Brownlee 2019), which is classified into four categories: sunrise, shine, rain, and cloudy. A Resnet-18 network is trained via transfer learning with many preprocessing stages, fine-tuning, and configuration based on the gathered images. We demonstrate that the model's validation (testing) accuracy is superior.

Squeezenet algorithm

We chose Residual Network (Squeezenet) for examination because of the model's solid performance. The short version of Residual Network with 50 Layers is Squeezenet. When researchers used deep learning models to follow the statement "the deeper the better", they ran into some issues. The assumption that "the deeper the network, the greater the network's performance" was disproved when a deep network with 52 layers had poor results when compared to networks with 20–30 layers (He et al. 2016). Jump connection and residual learning structure are distinct features of the Squeezenet algorithm (Liu et al. 2021). Deep network training, gradient disappearance, and gradient explosion are all challenges that it can help with. In this research, the algorithm for image classification and recognition was chosen. Squeezenet is trained on Imagenet, a database of around 1.2 million images whose characteristics and weights are transmitted from one job to the next using the same pre-trained network. Fine-tuning works on and processes a new task that has a variety of classes and categories. When compared to building a model from scratch, the number of iterations used to train a fine-tuned network is smaller. The goal of employing pretrained networks is to improve accuracy by utilizing the idea of "transfer learning." Transfer learning is a machine learning to approach that allows you to apply what you've learned in one area to similar challenges in another. It is suggested that you utilize the model that you generated and trained for a task as a starting point for a task that is similar to the one you trained (Yang et al. 2020).

Statistical Analysis

For evaluating the efficiency of the algorithm, the statistical analysis of the suggested model was carried out using Statistical Package for Social Sciences (SPSS)(Verma 2013) .Colon cancer detection is the independent variable, where accuracy variables are the dependent variables (output parameters). To compare the results of the resnet-18 and squeezenet algorithms, an independent t-test was used.

Result

The colon cancer identification using a Resnet-18 algorithm is able to locate the cancer and provide better performance rather than a Squeezenet.

Figure1 displays a graph evaluation of the average accuracy variance among Resnet-18 and Squeezenet approaches. X-axis represents Resnet-18 and Squeezenet; Y-axis represents average losses observed from two different groups and it possesses a standard deviation of ±1SD.

Figure 2 displays a graph evaluation of the average loss variance among Resnet-18 and Squeezenet approaches. X-axis represents Resnet-18 and Squeezenet; Y-axis represents average losses observed from two different groups and it possesses a standard deviation of ±1SD.

Figure 3 Training process taken over sample images

Table1 represents the accuracy of colon cancer detection for 30 samples using Resnet-18 and Squeezenet algorithms.

Table 2 represents mean and standard deviation of the group and accuracy of the novel texture analysis Resnet-18 and Squeezenet algorithms were 86.5060% and 0.30049, 83.5433% and 0.28975, respectively. In comparison to the Squeezenet approach, the resnet-18 technique had a lower standard error mean of 0.07759. Applying independent sample t-tests, there is a large discrepancy in accuracy between the two methods.

Table 3 visualizes the group and accuracy of the Resnet-18 and Squeezenet approach are compared. When utilizing independent sample t-tests to compare Resnet-18 and Squeezenet algorithms, there is a statistically significant difference. The accuracy of the resnet-18 (86.5060%) was the greatest, while the squeezenet algorithm was the poorest (83.5433 %).

Discussion

An independent sample t-test found a statistically significant variation (p= 0.610) between the Resnet-18 and Squeezenet classifier methods. Resnet-18 techniques have a greater classification accuracy and precision rate than Squeezenet.

A Spatially Constrained CNN (SC-CNN) technique was approved in 2016 for detecting and classifying four nucleus types in colon tumors based on histological images (Sirinukunwattana et al. 2016). Their proposed method does not require nuclei segmentation and can classify them with an F-measure of up to 80.2 percent. A label-free classification approach for grading colon cancer has been presented (Sirinukunwattana et al. 2016; Kuepper et al. 2016). They used infrared spectral histopathology images and various dedifferentiation states of colon cancer in this study. Random Forest, a supervised learning method based on Decision Trees (DT), was used to classify the data (RF). A CAD technique for detecting and staging lung cancer has been proposed (Masood et al. 2018). In their work, the authors used CNN and DFCnet and evaluated their model on six different datasets. By examining histopathological cancer images, (Babu et al. 2018) developed an RF-based classification algorithm to predict the existence of colon cancer. (Urban et al. 2018) describes a method for detecting polyps from colonoscopy pictures with a 96 percent classification accuracy. The authors hand-labeled 8641 colonoscopy pictures from 2000 patients and used them to train a CNN model. They next put their strategy to the test on 20 colonoscopy movies that lasted a total of five hours. A CNN-based classification system with binarized weights is presented for detecting colorectal cancer from colonoscopy footage (Akbari et al. 2018).

A comparison of the suggested method to other cancer diagnosis methods demonstrates that artificial intelligence outperforms the majority of them. Pathologists will be able to diagnose more colon cancer patients with less effort, expense, and time if they use this computer-based identification method in medical centers. To improve the classification model's performance, we want to expand on its design and engineer additional sets of features from more histopathology pictures in the future.

CONCLUSION

From the above statement it is evident that the novel texture analysis Resnet-18 algorithm would be a better choice for predicting colon cancer and it is more effective. It is clear from the preceding statement that the Resnet-18 algorithm is a better option for predicting colon cancer and is more successful. Based on the experimental results, the Resnet-18 model has been proved to predict colon cancer diseases more significantly than the Squeezenet.

Further research is needed on how to predict colon cancer diseases under these extreme conditions. In addition, for the Squeezenet, it is necessary to collect as many samples as possible and make the trained network have a good generalization performance.The Resnet-18 model gives better accuracy 86.5% than the Squeezenet model 83.5%.

Declaration

Conflicts of Interest
The submission has no potential conflicts.

Author Contributions
Data collection, data analysis, and manuscript preparation were all done by author KV. Conceptualization, data validation, and critical assessment of papers were all done by author SPK.

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Tables and Figures

Table 1. Accuracy of colon cancer detection for 30 samples using Resnet-18 and Squeezenet algorithm.

Training Size	Epochs	Iterations	Accuracy (%)		Loss (%)	
			Squeezenet	Resnet-18	Squeezenet	Resnet-18
60:40	20	391	83.3	86.1	1.32	2.54
	40	600	83.5	86.24	1.23	2.35
	60	798	83.7	86.22	1.54	2.44
	80	998	83.4	86.45	1.11	2.87
	100	1363	83.9	86.78	1.29	2.89
70:30	20	567	83.78	86.23	1.35	2.20
	40	779	83.90	86.17	1.88	2.10
	60	979	83.45	86.66	1.90	2.33
	80	1380	83.34	86.79	1.89	2.77
	100	2165	83.22	86.76	1.20	2.98
80:20	20	979	83.14	86.11	1.98	2.88
	40	1400	83.76	86.99	1.77	2.27
	60	1770	83.67	86.66	1.99	2.34
	80	2540	83.98	86.65	1.65	2.23
	100	3135	83.11	86.78	1.98	2.21

Table 2. The mean and standard deviation of the group and accuracy of the novel texture analysis Resnet-18 and Squeezenet algorithms were 86.5060% and 0.32754, 83.5433% and 0.28975, respectively. In comparison to the Squeezenet approach, the Resnet-18 technique had a lower standard error mean of 0.07759. Applying independent sample t-tests, there is a large discrepancy in accuracy and loss between the two methods.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	Resnet-18	15	86.5060	.30049	.07759
	Squeezenet	15	83.5433	.28975	.07481
Loss	Resnet-18	15	2.4933	.30215	.07802
	Squeezenet	15	1.6053	.32754	.08457

Table 3. The group and accuracy of the novel texture analysis resnet-18 and squeezenet approach are compared. When utilizing independent sample t-tests to compare resnet-18 and squeezenet algorithms, there is a statistically significant difference. The accuracy of the resnet-18 (86.5060%) was the greatest, while the squeezenet algorithm was the poorest (83.5433 %).

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Accuracy	Equal variances assumed	.171	.682	27.488	28	.000	2.96267	.10778	2.74189	1.84345
	Equal variances not			27.488	27.96	.000	2.96267	.10778	2.74188	3.18435

	assumed									
Loss	Equal variances assumed	.422	.154	2.835	28	.000	1.88800	.11506	1.65231	1.12369
	Equal variances not assumed			2.835	27.82	.000	1.88800	.11506	1.65224	1.12376

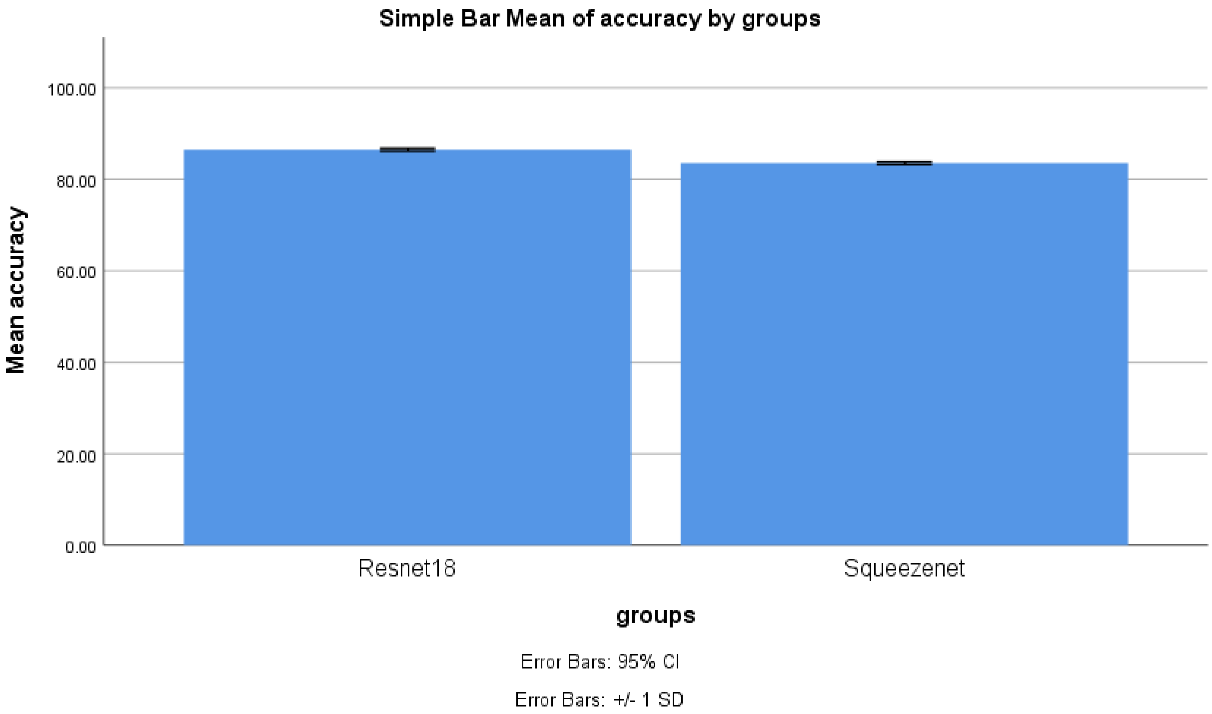

Figure 1. It displays a graph evaluation of the average accuracy variance among Resnet-18 and Squeezenet approaches. X-axis represents Resnet-18 and Squeezenet; Y-axis represents average accuracy observed from two different groups and it possesses a standard deviation of ±1SD.

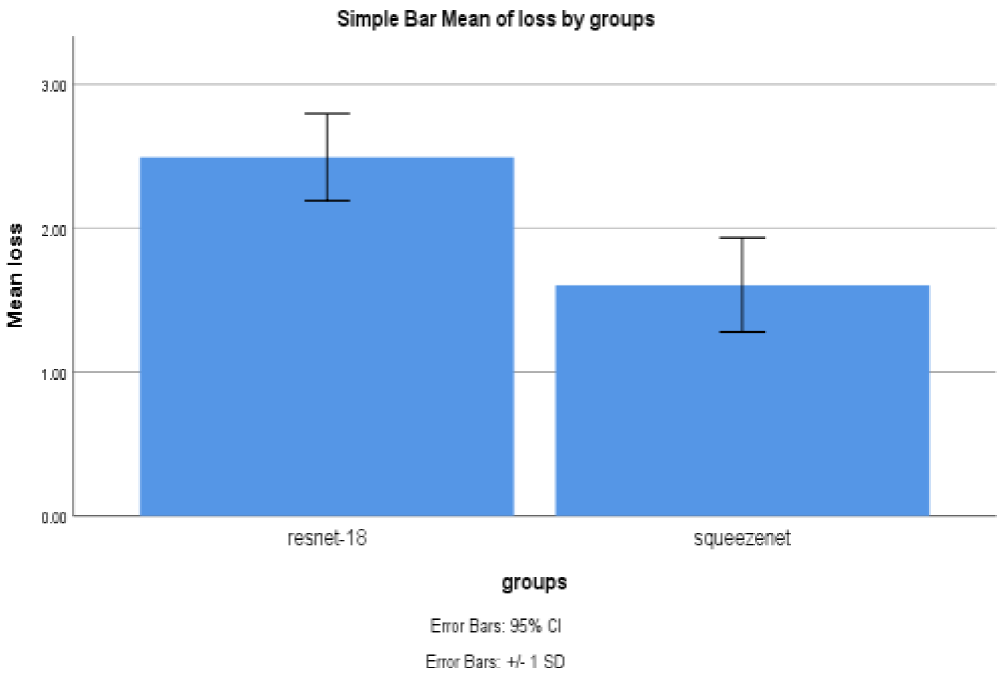

Figure 2. It displays a graph evaluation of the average loss variance among Resnet-18 and Squeezenet approaches. X-axis represents Resnet-18 and Squeezenet; Y-axis represents average losses observed from two different groups and it possesses a standard deviation of ±1SD.

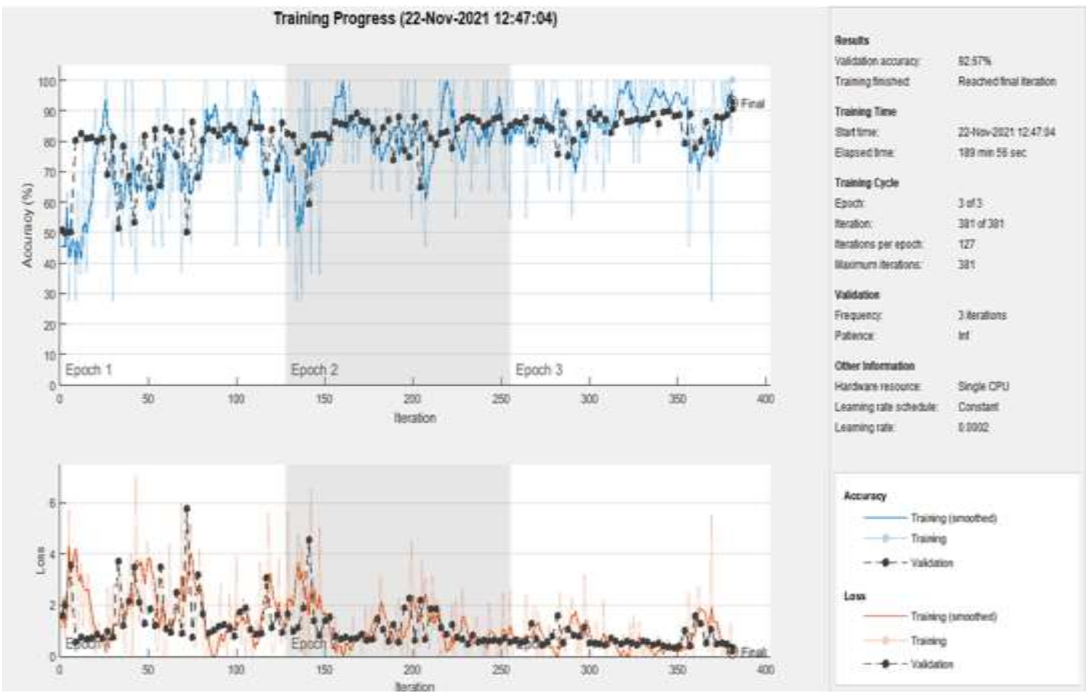

Figure 3. Training process taken over sample images