Original Article

Effective Classification of Colon Cancer using Resnet-50 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-50 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-50 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-50 classifier algorithm has attained an accuracy of 87.5060 % which is somewhat greater than the existing method. (i.e. Squeezenet algorithm obtained an accuracy of 85.5433 %).

Conclusion: From the above statement it is evident that the Resnet-50 algorithm would be a better choice for predicting colon cancer and it is more effective.

Keywords: Novel texture analysis**,** Colon Cancer, Resnet-50, Squeezenet, Machine Learning (ML), Artificial Intelligence (AI), Accuracy.

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INTRODUCTION

According to recent figures, cancer is responsible for 8.8 million deaths worldwide, making it the second most deadly disease and the leading cause of roughly one in every six fatalities (World Health Organization 1982). Colorectal cancer (CRC) is the third most prevalent type of cancer, trailing only lung and breast cancers in terms of incidence rates (Ganz, Xiaoyun Yang, and Slabaugh 2012). Because, according to the American Cancer Society, 56 percent of patients with colorectal cancer are diagnosed at a regional or distant stage, where the cancer has spread out from the primary tumor to other parts of the body (Rogers et al. 2021), timely detection and classification of cancerous cells is critical for effective treatment (Oh et al. 2009). Rapid technical breakthroughs in the fields of image processing and machine learning have resulted in the development of a slew of low-cost, quick computer-assisted diagnostic methods. Deep learning 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.

Colon cancer detection using various algorithms has been the subject of a lot of research. Understanding all of the stages taken and carried out in each algorithm is relatively necessary. Aside from that, it is critical to comprehend the operation and functional behavior of each algorithm. This is the most important stage and technique and artificial intelligence for determining which algorithm is better and selecting an effective algorithm from a group of algorithms currently accessible. Between 2011 and 2022, a large number of research studies were examined in this regard. Nearly 1903 study papers were analyzed, and just a handful of research works were chosen at random. The majority of them included a comparison analysis to display the effectiveness and prediction rate, as well as many methods to simplify and improve prediction. There are a few research papers that have been evaluated several times in order to perform colon cancer detection in the context of diverse topologies. The publications in between (Ko 2018; Williams 2017; Loktionov, n.d.; Al-Haija and Manasra 2020; Demir, Yilmaz, and Kose 2019; Gupta et al. 2021) are evaluated numerous times for systematic analysis and implementation. Among several study works, the work of (Sarwinda et al. 2021) is the best because of its depth in action and the increasing representation of viable contents.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)

This study gives a complete review and insight into a specific component of these methodologies, such as preprocessing, network design selection, training procedures, and training data. In our experiment, we used the Squeezenet and Resnet-50 models to categorize CRC histopathology pictures. To boost the accuracy, we also used transfer learning and fine-tuning approaches.

Materials 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-50 and Squeezenet algorithm and also 64 samples were taken. For colon cancer analysis, the Google Colab online simulation program is used. The IBM Statistical 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 87% confidence level. Accuracies of both models are tested with a sample size of 10 using Matlab (Subramanian et al. 2016)**.**

Resnet-50 algorithm

A more efficient and powerful Resnet design was recently introduced (Cao et al. 2022). This method makes it possible to teach very deep convolutional neural networks quickly. Resnet uses residual blocks in its formation. Two of the 50 layers are the first convolutional layer and the last completely linked layer.

We use the residual Convolutional Neural Networks(CNN) ResNet-50 to develop multi-class classification for colon cancer diagnosis in this study. The 1125 photos in the multi-class weather recognition dataset (Brownlee 2019) are grouped into four categories: sunrise, shine, rain, and cloudy. A Resnet-50 network is trained using transfer learning, which requires multiple preprocessing rounds, fine-tuning, and configuration based on the acquired pictures. The validation (testing) accuracy of the model is demonstrated to be superior.

Squeezenet algorithm

The Resnets (He et al. 2016) model was inspired by the VGG-19 (Yang et al. 2016) model. It's one of Imagenet's (Object detection and Image classification Challenge) deepest proposed architectures. Typically, in a CNN, numerous layers are connected and trained to execute the artificial intelligence of the different tasks. At the conclusion of each layer, the network learns many levels of features. In this model, the convolutional layers are generally 33 filters in size. The layers in Resnet have the same number of filters for the same output feature map size, and the number of filters is doubled if the feature map size is halved to keep the time complexity for each layer constant. It does direct downsampling by convolving layers with a two-step stride. A global average pooling layer and a Softmax triggered fully connected layer complete this Resnet.

Statistical Analysis

The statistical study of the suggested model was carried out using SPSS (Verma 2013) to evaluate the algorithm's efficiency. The independent variable is colon cancer detection, while the dependent variables are accuracy variables (output parameters). An independent t-test was utilized to compare the outcomes of the Resnet-50 and Squeezenet algorithms.

Result

The colon cancer identification using a Resnet-50 algorithm is able to locate the cancer and provide better performance rather than a Squeezenet.

Figure 1. displays a graph evaluation of the average accuracy variance among Resnet-50 and Squeezenet approaches. X-axis represents Resnet-50 and Squeezenet; Y-axis represents average accuracy 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-50 and Squeezenet approaches. X-axis represents Resnet-50 and squeezenet; Y-axis represents average losses observed from two different groups and it possesses a standard deviation of ±1SD.

Figure 3. shows the training process taken over sample images

Table 1. represents Accuracy of colon cancer detection for 30 samples using Resnet-50 and Squeezenet algorithm.

Table 2. shows The mean and standard deviation of the group and accuracy of the novel texture analysis are Resnet-50 and Squeezenet algorithms were 87.5060% and 0.30049, and 85.5433 and 0.28579, respectively. In comparison to the Resnet-50 approach, the Squeezenet technique had a lower standard error of 0.17997. Applying independent sample t-tests, there is a large discrepancy in accuracy between the two methods.
Table 3. the group and accuracy of the Resnet-50 and Squeezenet approach are compared. When utilizing independent sample t-tests to compare Resnet-50 and Squeezenet algorithms, there is a statistically significant difference. The accuracy of the Resnet-50 (87.5060 %) was the greatest, while the Squeezenet algorithm was the poorest (85.5433 %).

Discussion
A statistically significant difference (p= 0.05) was discovered between the Resnet-50 and Squeezenet classifier techniques using an independent sample t-test. The classification accuracy and precision rate of Resnet-50 approaches are higher than that of Squeezenet.(Toraman et al. 2019)) published a study that used Fourier Transform Infrared (FTIR) spectroscopic data to classify the chance of colon cancer. The authors retrieved numerous statistical features from the signals and then classified them using Support Vector Machine(SVM) and Artificial Neural Networks(ANN), achieving a classification accuracy of 95.71 percent (ANN). In 2019, a strategy for detecting lung cancer using CT scan pictures was reported (Mohan et al. 2021)(Toraman et al. 2019). For picture de-noising, they used bin smoothing normalization and picked features using the least repetition and Wolf heuristic feature selection processes. The authors used a Discrete Adaboost optimized ensemble learning generalized neural network (DAELYNN) and achieved above 99 percent classification accuracy, which is the most interesting aspect of this study.

In 2020, a lung cancer diagnosis approach based on nodule ROI-based feature learning with CNN will be described (Suresh and Mohan 2020). They used Generative Adversarial Networks (GANs) to create new CT scan images from the Lung Image Database Consortium (LIDC) and the Infectious Disease Research Institute (IDRI) databases to enhance the sample size. Using CNN-based classification algorithms, they were able to attain a maximum classification accuracy of 93.9 percent.

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

It is clear from the preceding statement that the Resnet-50 algorithm is a better option for predicting colon cancer and is more successful. From the above statement it is evident that the novel texture analysis Resnet-50 algorithm would be a better choice for predicting colon cancer and it is more effective. Based on the experimental results, the Resnet-50 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-50 model gives better accuracy 87.5% than the Squeezenet model 85.5%.

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-50 and Squeezenet algorithm.

Training Size	Epochs	Iterations	Accuracy (%)		Loss (%)	
			Squeezenet	Resnet-50	Squeezenet	Resnet-50
60:40	20	396	85.3	87.1	2.32	3.54
	40	605	85.5	87.24	2.23	3.35
	60	800	85.7	87.22	2.54	3.44
	80	1000	85.4	87.45	2.11	3.87
	100	1370	85.9	87.78	2.29	3.89
70:30	20	570	85.78	87.23	2.35	3.20
	40	780	85.90	87.17	2.88	3.10
	60	980	85.45	87.66	2.90	3.33
	80	1385	85.34	87.79	2.89	3.77
	100	2170	85.22	87.76	2.20	3.98
80:20	20	980	85.14	87.11	2.98	3.88
	40	1405	85.76	87.99	2.77	3.27
	60	1775	85.67	87.66	2.99	3.34
	80	2545	85.98	87.65	2.65	3.23
	100	3140	85.11	87.78	2.98	3.21

Table 2. The mean and standard deviation of the group and accuracy of the novel texture analysis are Resnet-50 and Squeezenet algorithms were 87.5060% and 0.30049, 85.5433% and 0.28579, respectively. In comparison to the Resnet-50 approach, the Squeezenet technique had a lower standard error of 0.78481. Applying independent sample t-tests, there is a large discrepancy in accuracy between the two methods.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	Resnet-50	15	87.5060	.30049	.07759
	Squeezenet	15	85.5433	.28579	.07481
Loss	Resnet-50	15	3.4933	.30215	.07802
	Squeezenet	15	2.6053	.32754	.08457

Table 3. The group and accuracy of the novel texture analysis of Resnet-50 and Squeezenet approach are compared. When utilizing independent sample t-tests to compare Resnet-50 and Squeezenet algorithms, there is a statistically significant difference. The accuracy of the Resnet-50 (87.5060%) was the greatest, while the Squeezenet algorithm was the poorest (85.5433 %).

		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	.684	18.210	28	.000	1.96267	.10778	1.74189	2.84345
	Equal variances not assumed			18.210	27.96	.000	1.96267	.10778	1.74188	2.84346
Loss	Equal variances assumed	.422	.521	16.409	28	.000	1.88800	.11506	1.65231	2.12369
	Equal variances not assumed			16.409	27.82	.000	1.88800	.11506	1.65224	2.12376

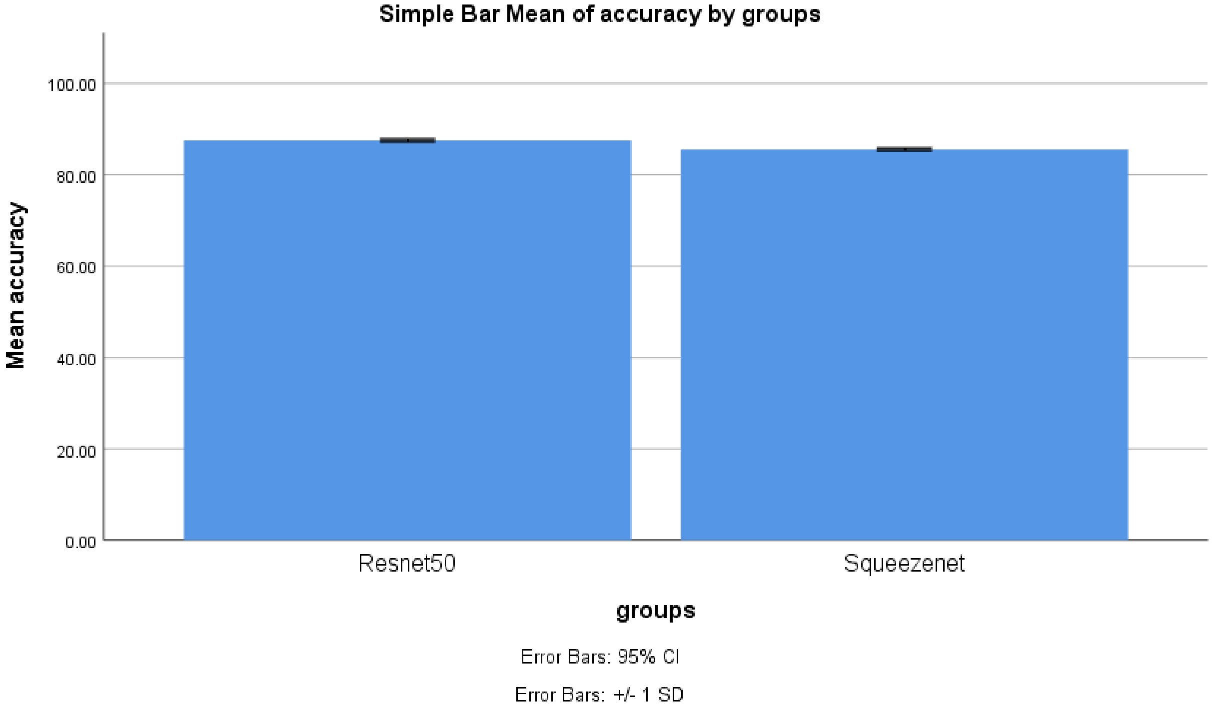

Figure 1. It displays a graph evaluation of the average accuracy variance among Resnet-50 and Squeezenet approaches. X-axis represents Resnet-50 and Squeezenet; Y-axis represents average accuracy observed from two different groups and it possesses a standard deviation of ±1SD.

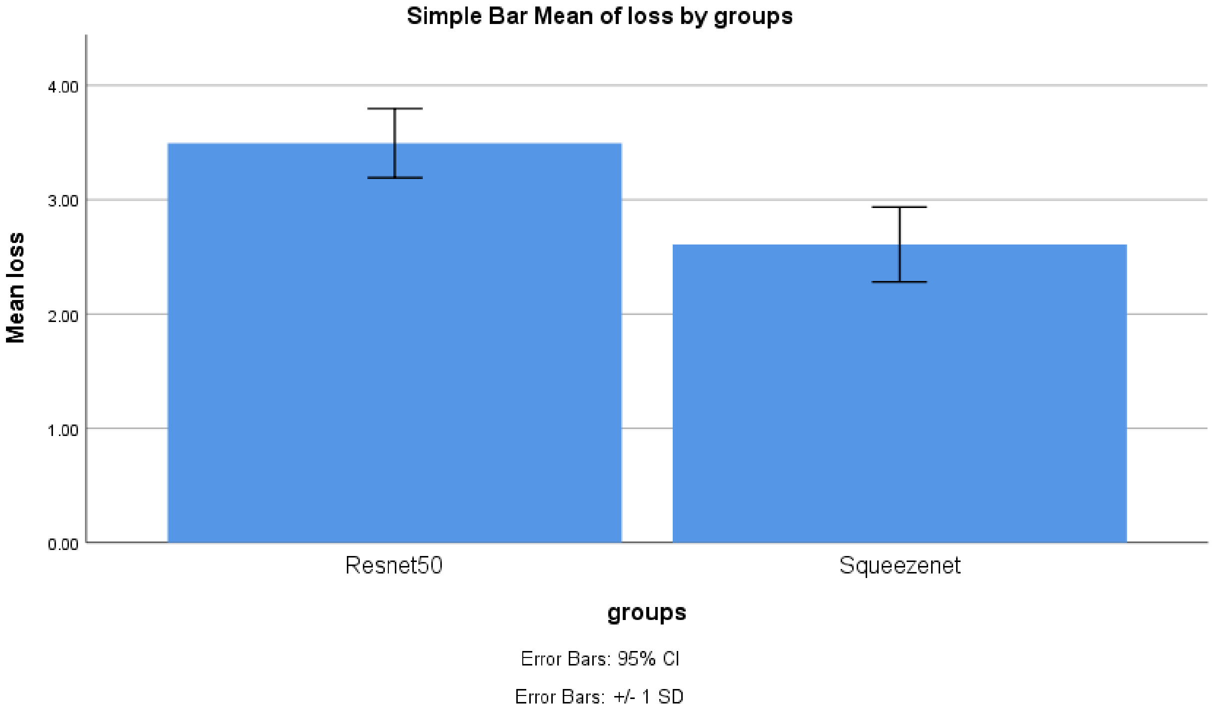

Figure 2. It displays a graph evaluation of the average accuracy and loss variance among Resnet-50 and Squeezenet approaches. X-axis represents Resnet-50 and Squeezenet; Y-axis represents average losses observed from two different groups and it possesses a standard deviation of ±1SD.

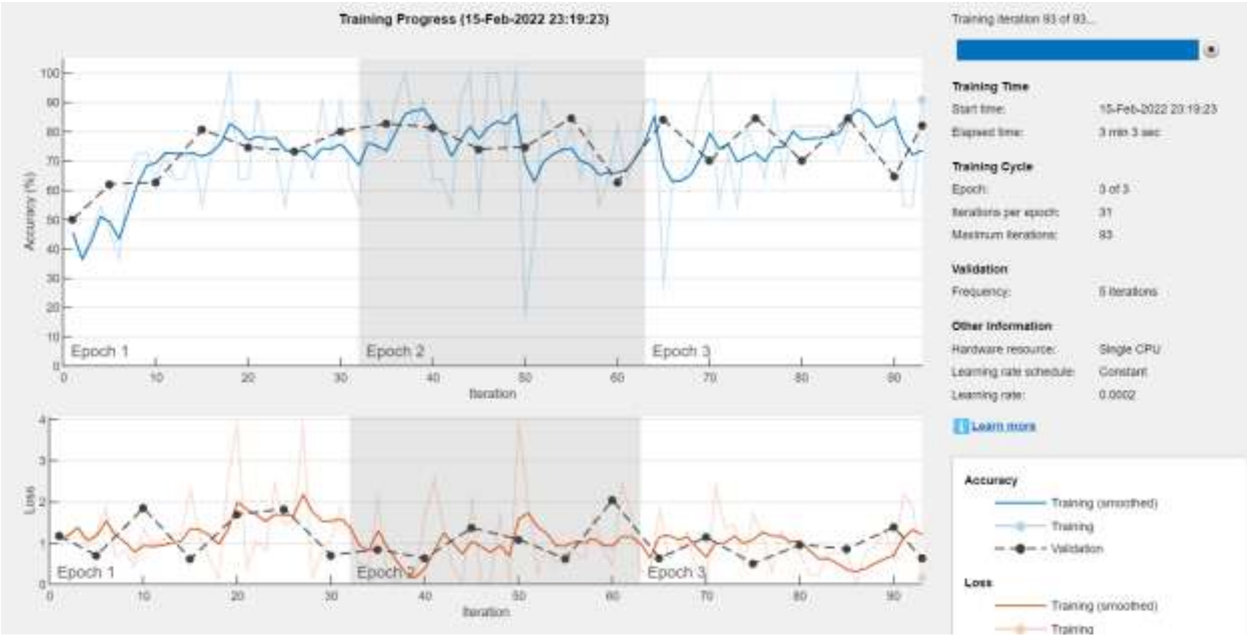

Figure 3. Training process taken over sample images