Applications of Neural Network Models in Kaggle Competitions

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Abstract

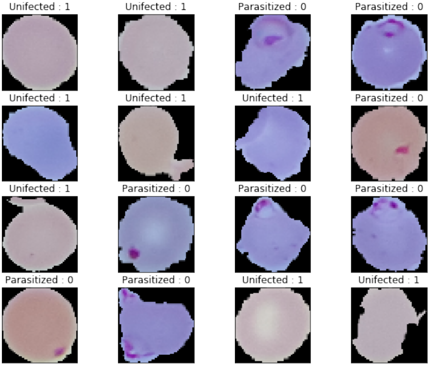
Neural networks are a collection of precise rules which is used in recognizing patterns in data generated from various real life applications such as medicine etc.

Aims

- To understand and implement neural network models on certain medical image datasets via the Kaggle platform
- Classify these images and analyze the performance of the models
- Hyperparameter tuning and comparison of optimizers
- Reduces the workload and misdiagnosis of such diseases by medical practitioners

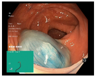
Kaggle Datasets

Figure: Cells from the Pre-processed Malaria Dataset

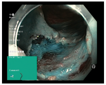


Kaggle Datasets

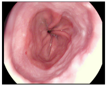
Figure: Endoscope images of the 8 classes from the Kvasir dataset



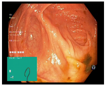
(a) dyedlifted-polyps



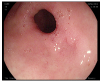
(b) dyed-resection-margins



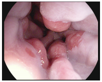
(c) esophagitis



(d) normal-cecum

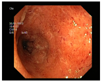


(e) normal-pylorus



(f) normal-z-line

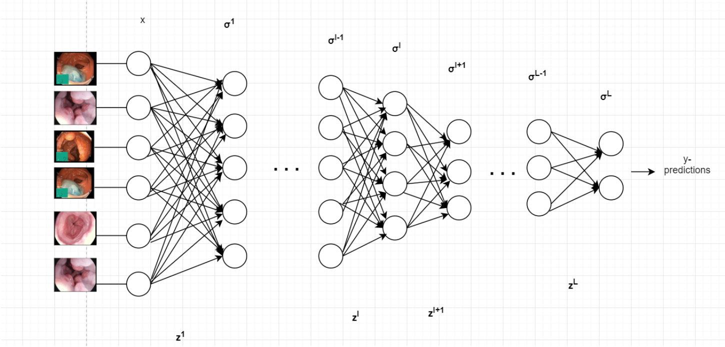
(g) polyps



(h) ulcerative-colitis

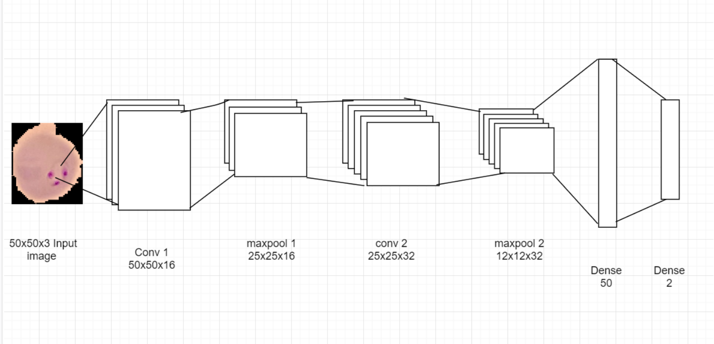
Topology Of Neural Network Models

The Fully Connected Neural Network (FCN) is usually comprised of three (3) basic layers namely: the input layer, the hidden layers and the output layers.



Topology Of Neural Network Models

A standard architecture of the Convolutional Neural Network (CNN) is comprised of the convolutional layers with a nonlinear activation function, the pooling layers and the fully connected layers.



Topology Of Neural Network Models

- Parameters with activation:

$$\sigma_i^{[l]} = \sigma^l(z_i^{[l]}) = \sigma^l\left(\sum_i (w_i^{[l]})^T \cdot x_i^{[l-1]} + b_i^{[l]}\right),$$

- where the activation can be:

$$ReLU, \ \sigma(z_i) = max(0, z_i),$$

$$Softmax, \ \sigma_i(z_i) = \frac{\exp^{-z_i}}{\sum_j \exp^{-z_j}}.$$

- Loss function:

$$\mathfrak{L} = -\frac{1}{m}\sum_{i=1}^{m} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i).$$

Topology Of Neural Network Models

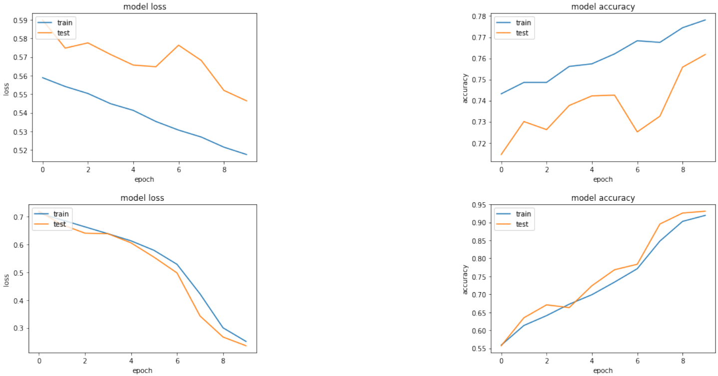
- Parameter update via backpropagation:

$$z_i = z_i - \eta \Delta_i z_i.$$

- Regularization:

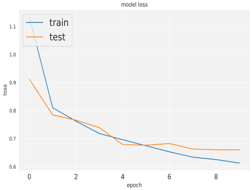
$$\mathfrak{L}_{L1} = \mathfrak{L} + \lambda \sum_{i=0}^{m} |z_i|, \qquad \lambda,\ z_i \text{ are the parameters}.$$

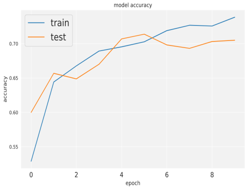
Results: Analysis of Models for Malaria Samples

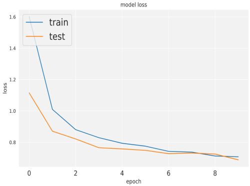


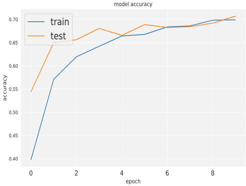
The FCN had an accuracy of 77.81% with loss 0.5176 on the train set and accuracy of 76.18% with loss 0.5464 on the test set. The CNN had an accuracy of 91.94% with loss 0.2511 on the train set and accuracy of 93.11% with loss 0.2356 on the test set.

Results: Analysis of Models for Kvasir Samples









The FCN had an accuracy of 73.84% with loss 0.6130 on the train set and accuracy of 70.50% with loss 0.6602 on the test set. The CNN had an accuracy of 71.08% with loss 0.6942 on the train set and accuracy of 70.06% with loss 0.6975 on the test set.

Results: Analysis of Models

Table: Confusion Matrix and Classification Report for Malaria

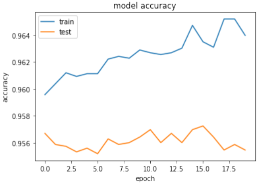
Malaria Classes	0. Parasitized	1. Uninfected	recall	total
0. Parasitized	2470	264	0.90	2734
1. Uninfected	116	2662	0.96	2778
Precision	0.96	0.91	-	-
f1-score	0.93	0.93	-	-
total	2586	2926	-	5512

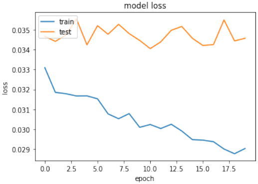
Results: Analysis of Models

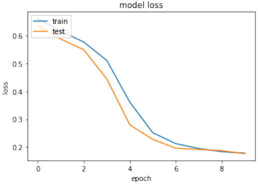
Table: Confusion Matrix and Classification Report for Kvasir dataset

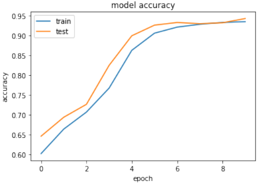
Endoscopic Classes	0.	1.	2.	3.	4.	5.	6.	7.	recall	total
0. Dyed-lifted polyps	105	80	0	1	0	0	13	0	0.53	199
1. Dyed-resection margins	53	130	0	0	0	0	5	1	0.69	189
2. Esophagitis	0	1	108	0	6	82	0	0	0.55	197
3. Normal Cecum	0	0	0	180	0	0	17	7	0.88	204
4. Normal Pylorus	0	0	1	0	195	5	2	0	0.96	203
5. Normal Z-line	0	0	25	0	22	174	0	1	0.78	222
6. Polyps	2	0	0	29	6	0	125	22	0.68	184
7. Ulcerative colitis	1	1	0	30	3	0	53	114	0.56	202
Precision	0.65	0.61	0.81	0.75	0.84	0.67	0.58	0.79	-	-
f1-score	0.58	0.65	0.65	0.81	0.90	0.72	0.63	0.66	-	-
total	161	212	134	240	232	261	215	145	-	1600

Results: Hyperparameter Tuning And Optimizer Analysis



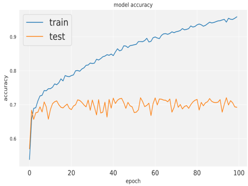






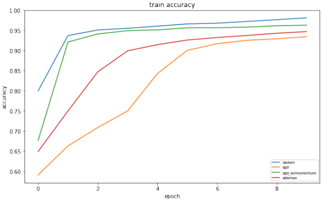
Model an accuracy of 96.43% with loss 0.0290 on the train set and accuracy of 95.58% with loss 0.0351 on the test set. Model with regularization had an accuracy of 93.48% with loss 0.2149 on the train set and accuracy of 93.65% with loss 0.2135 on the test set.

Results: Hyperparameter Tuning And Optimizer Analysis

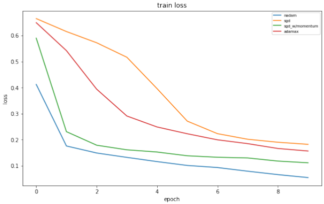


Model at 100 epoch an accuracy of 95.28% for the train with accuracy of 69.85% for the test and with regularization had an accuracy of 93.40% for the train with accuracy of 71.00% for the test. Model at 300 epoch had an accuracy of 99.98% for the train with accuracy of 69.90% for the test and with regularization had an accuracy of 99.92% for the train with accuracy of 72.69% for the test.

Results: Hyperparameter Tuning And Optimizer Analysis



(a) Accuracy graph

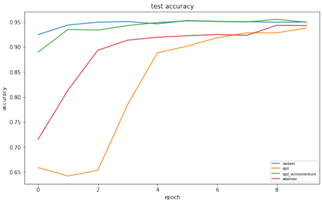


(b) Loss graph

Figure: Further Optimizer Comparison Loss and Accuracy for the malaria Dataset Model on the Test samples

train	MAcc	Mloss
Nadam	98.10%	0.0545
SGD	93.44%	0.1820
Adamax	94.69%	0.1563
SGDmom	96.29%	0.1112

Results: Hyperparameter Tuning And Optimizer Analysis



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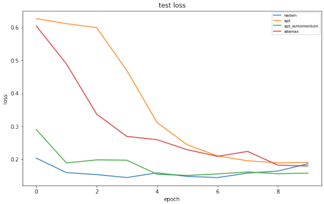
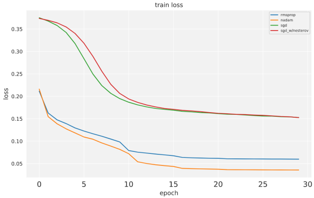


(b) Loss graph

Figure: Further Optimizer Comparison Loss and Accuracy for the Malaria Dataset Model on the Test samples

test	MAcc	Mloss
Nadam	94.99%	0.1861
SGD	93.80%	0.1900
Adamax	92.70%	0.1794
SGDmom	94.96%	0.1577

Results: Hyperparameter Tuning And Optimization Algorithms Analysis



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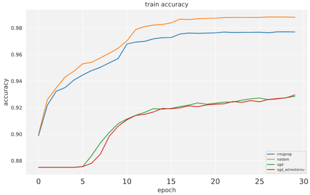
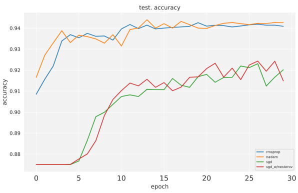


(b) Loss graph

Figure: Further Optimizer Comparison Loss and Accuracy for the Kvasir Dataset Model on the Test samples

train	KAcc	Kloss
Nadam	98.80%	0.0358
SGD	92.95%	0.1527
RMSprop	97.70%	0.0599
SGDnest	92.95%	0.1526

Results: Hyperparameter Tuning And Optimization Algorithms Analysis



(a) Accuracy graph

(b) Loss graph

Figure: Further Optimizer Comparison Loss and Accuracy for the Kvasir Dataset Model on the Test samples

test	KAcc	Kloss
Nadam	94.26%	0.1648
SGD	92.02%	0.1658
RMSprop	94.09%	0.1368
SGDnest	91.49%	0.1696

Conclusion

- Although the FCN is a good classifier, they are not good feature extractors but the CNN best quality is identifying and extracting the features from the images during training as seen in the malaria samples.
- For datasets with less samples, the choice of the hyperparameter or optimizer can help improve the performance of the network.
- A deeper CNN model with a combination of the best observable hyperparameters showed significant improvement with an accuracy of 94.99% on the malaria dataset and accuracy of 94.26% on the kvasir dataset for the CNN model.

Conclusion

- This suggest that in training more complex and deeper networks the adaptive methods still have a lot of improvements to be made in order to improve its generalization on the test samples.
- Also, further future work can be carried out by analyzing how higher order optimization algorithms can affect the performance of deep learning models on the medical imaging datasets.

References

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