Paper ID- 835

Proceedings of the 16th INDIACom; INDIACom-2022; IEEE Conference ID: 54597 2022 9th International Conference on "Computing for Sustainable Global Development", 23rd - 25th March 2022 Bharati Vidyapeeth's Institute of Computer Applications and Management (BVICAM), New Delhi (INDIA)

Performance Analysis of VGG-19 Deep Learning Model for COVID-19 Detection

Authors:

1. Sahithya Namani, MVSREC, Hyderabad
2. Lalita Snigdha Akkapeddi, MVSREC, Hyderabad
3. Saritha Bantu, Associate Professor, MVSREC Hyderabad

PRESENTATION SUMMARY

- Introduction
- Methodology
- Implementation
- Observations
- Results
- Conclusion
- Future Enhancements

INTRODUCTION

- The Novel Coronavirus, commonly known as COVID-19 is the disease that has bring the world to halt in the year 2020
- It's detection or prognosis plays a major role in the diagnosis of the patient
- The gold standard RT-PCR test is proven to be producing faulty results upto certain extent
- The highly accurate results provided by Chest CT Scans are helping the authorities to detect the virus even in the early stages in patients
- From the previous work, it is observed that the VGG19 has better performance with medical image data when compared to other deep learning models such as VGG-16, InceptionV3, DenseNet121 which showed overfitting in the initial epochs.
- In this study, we determined the best performing parameters for the VGG-19 transfer learning model to classify COVID-19 cases and normal cases. We experimented with the model against three parameters: activation function, loss function, and training batch size.

METHODOLOGY

- The following are the criteria on which the model was experimented with, and the performance evaluated:
  A. Activation Function
     a) Sigmoid Function
     b) Softmax Function
     c) Rectified Linear Unit(ReLU) Function
  B. Loss Function
     a) Categorical Cross-Entropy Function
     b) Binary Cross-Entropy Function
  C. Training Batch size

IMPLEMENTATION

- Our dataset contains the full original CT scans of 377 persons. There are 15589 and 48260 CT scan images belonging to 95 Covid-19 and 282 normal persons, respectively.
- Following are the steps for model implementation:
  A. Selection Of Transfer Learning Model
  B. Data Preprocessing
  C. Normalization
  D. Train And Test Split
  E. Building The Model
  F. Image Augmentation
  G. Training The Model
  H. Testing The Model

OBSERVATIONS

We used the following metrics as our evaluation criteria:

A. Classification Report
B. Accuracy and Loss plots
C. Confusion Matrix

OBSERVATIONS (Contd.)

1. Model with different activation functions:

Evaluation Criteria

A. CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.93	0.93	0.93	70
1	0.94	0.94	0.94	80
accuracy			0.93	150
macro avg	0.93	0.93	0.93	150
weighted avg	0.93	0.93	0.93	150

Classification report for VGG-19 model with Softmax activation function
function

	precision	recall	f1-score	support
0	0.74	0.96	0.83	70
1	0.95	0.70	0.81	80
accuracy			0.82	150
macro avg	0.84	0.83	0.82	150
weighted avg	0.85	0.82	0.82	150

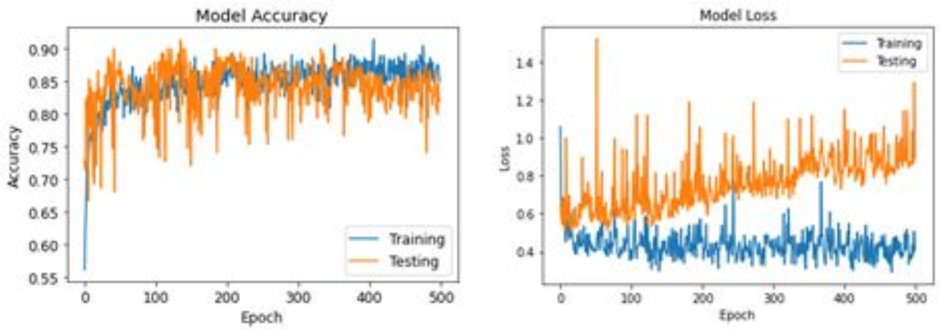
Classification report for VGG-19 model with Sigmoid activation

	precision	recall	f1-score	support
0	0.76	0.83	0.79	70
1	0.84	0.78	0.81	80
accuracy			0.80	150
macro avg	0.80	0.80	0.80	150
weighted avg	0.80	0.80	0.80	150

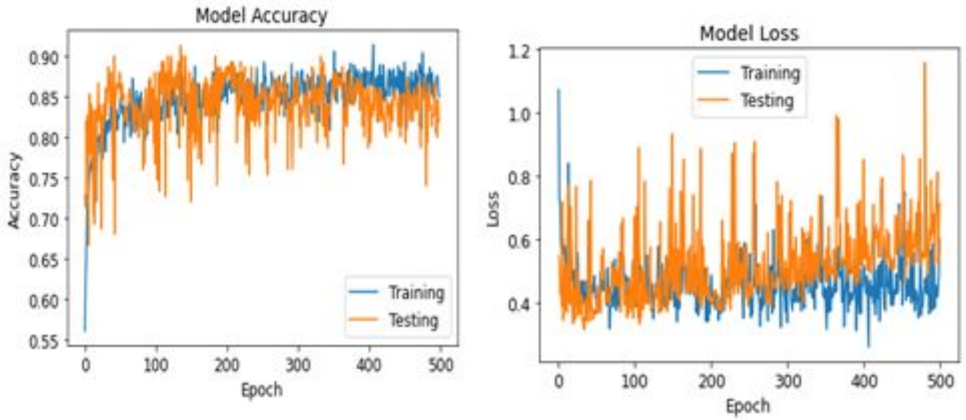
Classification report for VGG-19 model with ReLU activation function

OBSERVATIONS (Contd.)

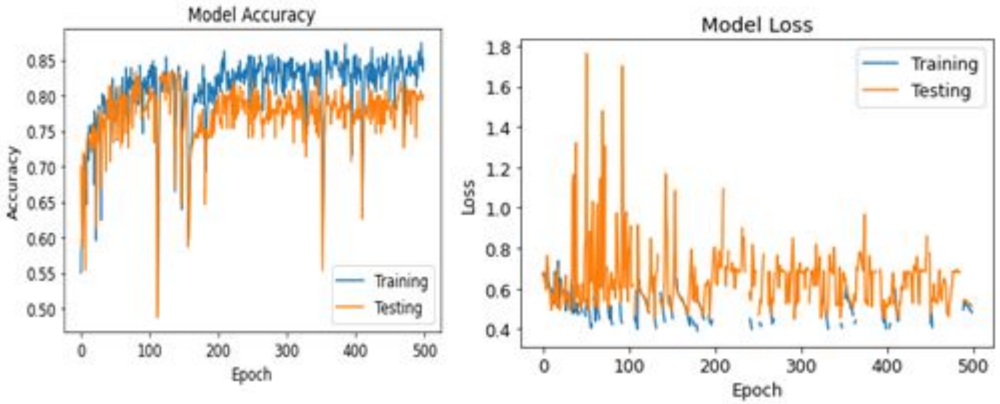
B. ACCURACY AND LOSS PLOTS



Accuracy and Loss Plots for VGG-19 model with Softmax activation function



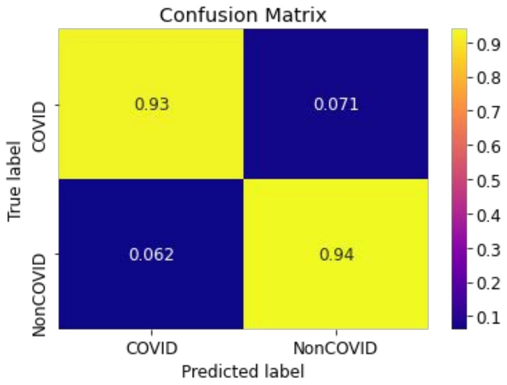
Accuracy and Loss Plots for VGG-19 model with Sigmoid activation function



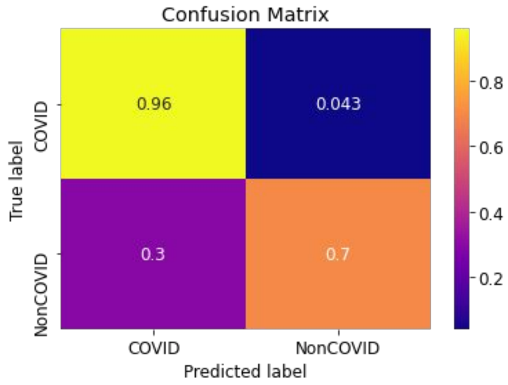
Accuracy and Loss Plots for VGG-19 model with ReLU activation function

OBSERVATIONS (Contd.)

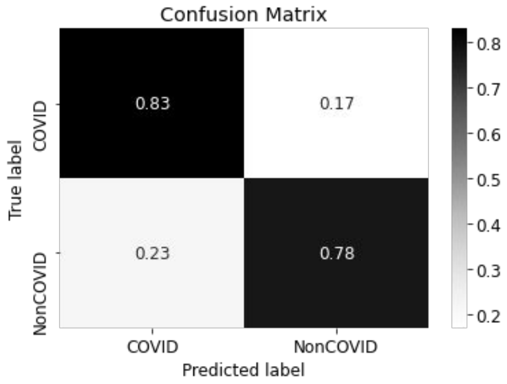
C. CONFUSION MATRIX



Confusion Matrix for VGG-19 model with Softmax activation function



Confusion Matrix for VGG-19 model with Sigmoid activation function



Confusion Matrix for VGG-19 model with ReLU activation function

OBSERVATIONS(Contd.)

Following are the metrics obtained using different activation functions:

Activation Function	Accuracy	Sensitivity	Specificity
SoftMax	93%	93.75%	92.98%
Sigmoid	82%	76.19%	94.21%
ReLU	80%	78.3%	82.11%

OBSERVATIONS(Contd.)

2. **Model With Different Loss Functions**

Evaluation Criteria:

A. **CLASSIFICATION REPORT**

	precision	recall	f1-score	support
0	0.93	0.93	0.93	70
1	0.94	0.94	0.94	80
accuracy			0.93	150
macro avg	0.93	0.93	0.93	150
weighted avg	0.93	0.93	0.93	150

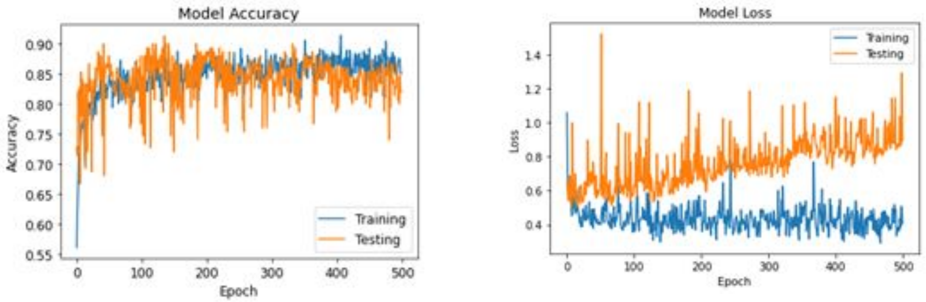
Classification report for VGG-19 model with Categorical Cross-Entropy loss function

	precision	recall	f1-score	support
0	0.76	0.83	0.79	70
1	0.84	0.78	0.81	80
accuracy			0.80	150
macro avg	0.80	0.80	0.80	150
weighted avg	0.80	0.80	0.80	150

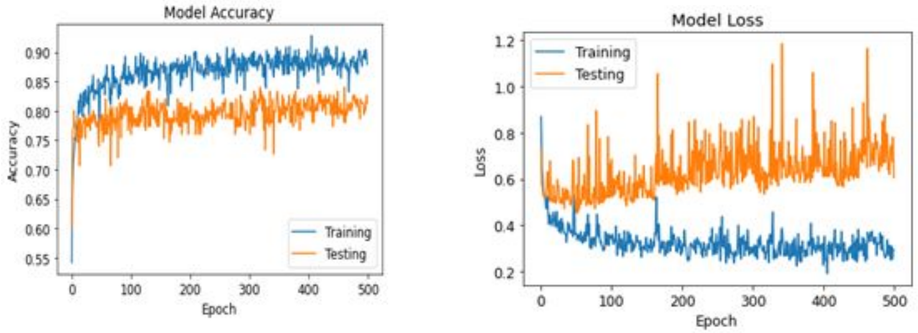
Classification report for VGG-19 model with Binary Cross-Entropy loss function

OBSERVATIONS(Contd.)

B. ACCURACY AND LOSS PLOTS



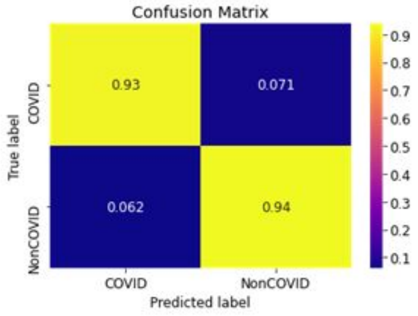
Accuracy and Loss Plots for VGG-19 model with Categorical Cross-Entropy loss function



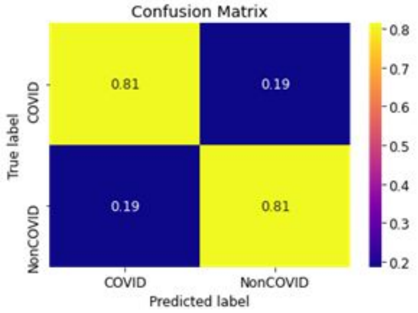
Accuracy and Loss Plots for VGG-19 model with Binary Cross-Entropy loss function

OBSERVATIONS(Contd.)

C. CONFUSION MATRIX



Confusion Matrix for VGG-19 model with Categorical Cross-Entropy loss function



Confusion Matrix for VGG-19 model with Binary Cross-Entropy loss function

OBSERVATIONS(Contd.)

Following are the metrics obtained using different loss functions:

Loss Function	Accuracy	Specificity	Sensitivity
Categorical cross-entropy	93%	93.75%	92.98%
Binary cross-entropy	81%	81%	81%

OBSERVATIONS (Contd.)

3. Model With Different Batch Sizes For Training:

Following are the metrics obtained using different batch size for training:

Batch Size	Accuracy	Sensitivity	Specificity
8	75%	68.75%	97.75%
16	81%	78.38%	85.4%
32	93%	93.75%	92.98%

RESULTS

After the analysis from the observations, we have found that the VGG-19 model with following parameters provides high performance:

- Activation function : Softmax
- Loss function : Categorical-cross entropy
- Training batch size : 32
- Accuracy achieved : 93%

	precision	recall	f1-score	support
0	0.93	0.93	0.93	70
1	0.94	0.94	0.94	80
accuracy			0.93	150
macro avg	0.93	0.93	0.93	150
weighted avg	0.93	0.93	0.93	150

Classification report for VGG-19 model with Categorical cross-entropy loss function, Softmax activation function, and training batch size 32

CONCLUSION

- Our project demonstrates the determination of COVID-19 in the used dataset and the best performing parameters of VGG-19 deep learning model for COVID-19 detection.
- Using the current limited and challenging COVID-19 datasets, VGG19 model could be used to develop suitable deep learning-based tools for COVID-19 detection.
- Initially while selecting the model, we found that both VGG16 and VGG19 classifiers provided good results within the experimental constraints of the small number of currently available COVID-19 medical images.
- But deeper networks generally struggle, while they will perform better when larger datasets are available which will reduce the impact of data quality variation. And we have chosen to utilize the VGG-19 model.

FUTURE ENHANCEMENTS

- Our future work will focus on improving the performance of the system
- Use the results produced by our model to extended the project to include the critical information about the spread of virus in the patient’s lungs i.e., predicting some important factors like CO-RADS level.
- Since the data is limited and not proportionate we intend to implement imbalance classification.
- Several other models can also be built on top of this model which in turn will be useful in detecting families of such viral diseases.
- The tool has potential to be utilized by radiologists when encompassed in a seamless workflow.

REFERENCES

[1] Ansari, M., Singh, D.K. Monitoring social distancing through human detection for preventing/reducing COVID spread. Int. j. inf. tecnol. 13, 1255–1264 (2021). https://doi.org/10.1007/s41870-021- 00658-2

[2] Khanday, A.M.U.D., Rabani, S.T., Khan, Q.R. et al. Machine learning based approaches for detecting COVID-19 using clinical text data. Int. j. inf. tecnol. 12, 731–739 (2020). https://doi.org/10.1007/s41870-020-00495-9

[3] J. Liu, Z. Zhang, L. Zu, H. Wang and Y. Zhong, "Intelligent Detection for CT Image of COVID-19 using Deep Learning," 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), 2020, pp. 76- 81, doi: 10.1109/CISP-BMEI51763.2020.9263690.

[4] Lisboa Bastos M, Tavaziva G, Abidi S K, Campbell J R, Haraoui L, Johnston J C et al. Diagnostic accuracy of serological tests for covid19: systematic review and meta-analysis BMJ 2020; 370 :m2516 doi:10.1136/bmj.m2516

[5] A. K. Abdar, S. M. Sadjadi, H. Soltanian-Zadeh, A. Bashirgonbadi and M. Naghibi, "Automatic Detection of Coronavirus (COVID-19) from Chest CT Images using VGG16- Based Deep-Learning," 2020 27th National and 5th International Iranian Conference on Biomedical Engineering (ICBME), 2020, pp. 212-216, doi: 10.1109/ICBME51989.2020.9319326

[6] C. Nwankpa, W. Ijomah, A. Gachagan and S. Marshall, "Activation Functions: Comparison of trends in Practice and Research for Deep Learning", arXiv.org, 2021. arXiv:1811.03378 [cs.LG]

[7] M. Rahimzadeh, A. Attar and S. Sakhaei, "A fully automated deep learning-based network for detecting COVID-19 from a new and large lung CT scan dataset", Biomedical Signal Processing and Control, vol. 68, p. 102588, 2021. doi: 10.1016/j.bspc.2021.102588

[8] B.Saritha, S.V. Ramana Narra Manaswini, Rama Priyanka D.Hiranmayi, K.Eswaran,,"Classification of Liver Data using a New Algorithm", International Journal of Engineering Technology Science and Research, IJETSR, ISSN 2394 – 3386 , September 2017, Volume 4, Issue 9.

REFERENCES(Contd.)

[9] M. J. Horry et al., "COVID-19 Detection Through Transfer Learning Using Multimodal Imaging Data," in IEEE Access, vol. 8, pp. 149808-149824, 2020. https://doi.org/10.1109/ACCESS.2020.3016780

[10] K. He, X. Zhang, S. Ren, and J. Sun, “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification,” arXiv, 2015. arXiv:1811.03378 [cs.LG]

[11] A. Maas, A. Hannun, and A. Ng, “Rectifier Nonlinearities Improve Neural Network Acoustic Models,” in International Conference on Machine Learning (icml), 2013.

[12] U. Niyaz, A. S. Sambyal and Devanand, "Advances in Deep Learning Techniques for Medical Image Analysis," 2018 Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC), 2018, pp. 271-277, doi: 10.1109/PDGC.2018.8745790

[13] “A novel approach using Machine Learning Algorithm on healthy liver”, B. Saritha , K.Eswaran, Design Engineering ISSN: 0011-9342 | Year 2021, Issue: 8 | Pages: 7020- 7032

[14] C. Kavya Reddy, G. Gayatri Likhita, D. Hiranmayi, B.Saritha, K.Eswaran, “Classification of Diseased Plants using Separation of Points by Planes” , www.ijetsr.com ,Volume 4, Issue 9 September 2017, ISSN 2394 – 3386

[15] Zhang Z, Bi Q, Fang S, Wei L, Wang X, He J, Wu Y, Liu X, Gao W, Zhang R, Gong W, Su Q, Azman AS, Lessler J, Zou X. Insight into the practical performance of RT-PCR testing for SARS-CoV-2 using serological data: a cohort study. Lancet Microbe. 2021 Feb;2(2):e79- e87. doi: 10.1016/S2666-5247(20)30200-7. Epub 2021 Jan 19. PMID: 33495759; PMCID: PMC7816573.

[16] Kulkarni, T.R., Dushyanth, N.D. Performance evaluation of deep learning models in detection of different types of arrhythmia using photo plethysmography signals. Int. j. inf. tecnol. 13, 2209–2214 (2021). https://doi.org/10.1007/s41870-021-00795-8