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The analysis of image classification for automatic COVID-19 detection on chest CT-scanning images using CNN algorithms

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ABSTRACT
Our project focuses on early detection of COVID-19 using a classification method. Detecting COVID-19 at an early stage is crucial in reducing mortality rates. While computed tomography (CT) images have been studied for COVID-19 detection, magnetic resonance imaging (MRI) could also be a viable imaging technique. However, to the best of our knowledge, no detection methods have been developed for MR images. In our paper, we propose a COVID-19 detection method based on deep learning specifically for thoracic MR images. Our method utilizes parameter optimization, spatial three-channel input construction, and transfer learning to design a faster R-convolution neural network (CNN) that can accurately locate COVID-19 regions.

Keywords: **- Image** Classification, Covid – 19, CNN, CT Scanning, Data O.

I. INTRODUCTION

The first step in studying any new biological entity involves classifying it in relation to other known organisms. This process, which involves classification and naming, is known as taxonomy and is a crucial aspect of biological research. In December 2019, Chinese health authorities reported an outbreak of pneumonia cases in Wuhan, China, with an unknown cause. On January 9th, 2020, the China CDC identified a new coronavirus as the cause of these cases. The virus was also found to be capable of human-to-human transmission, as reported by Chinese health authorities. The Coal Classification of Viruses and the taxonomy of the Coronaviridae family were defined by the CSG. After assessing the novelty of the human pathogen based on phylogeny, taxonomy, and established practices, it was officially classified. In the study, ResNet18, ResNet50, ResNet101, VGG16, and VGG19 were the CNN models utilized. The deep characteristics model (ResNet50) and SVM with linear kernel function achieved the highest accuracy score of 94.7% among all results obtained from the testing conducted in the study.

The results of the ResNet50 model's retuning and the end-to-end training of the Developed CNN model were 92.6% and 91.6%, respectively. As the number of COVID-19 X-Ray image samples is limited, transfer learning (TL) is considered the standard method for accurately classifying disease data to develop automated diagnosis models. In this regard, networks are capable of acquiring knowledge from pre-trained networks on large-scale image datasets or other data-rich sources.

Previous reviews have covered most of the research on machine learning, deep learning, and medical imaging related to COVID-19 these reviews have analysed the research and drawn conclusions to encourage further studies in the field. The reviews have also identified challenges that future researchers should address in order to achieve better results and build more efficient models.

II. RELATED WORK

The use of AI to aid in the management of COVID-19 is crucial. Manual diagnosis of X-Ray image involves a considerable amount of manual labour and time. To alleviate the workload of radiologists, computer-aided diagnostic tools have been developed utilizing deep learning or machine learning technology. These tools have demonstrated the potential to increase diagnostic efficiency and relieve the pressure on radiologists. Several studies that have been published recently have suggested that COVID-19 usually exhibits GGO or lesions in CT images. With the rapid spread of COVID-19, medical resources have become inadequate in many regions. According to the studies, transfer learning enables the network to extract essential features associated with the diagnosis of COVID-19. In fact, several studies have implemented this concept to quickly create a dependable tool that assists medical professionals in diagnosing COVID-19. Due to the extensive popularity of convolution neural networks, many studies have utilized these architectures to identify lungs affected by COVID-19 in X-Ray image images. When the World Health Organization (WHO) announced the rapid spread of the aggressive COVID-19 virus, the scientific community put forth great efforts to propose a solution for the early diagnosis of the virus. Early detection of COVID-19 can help control the spread of the disease. Real-time molecular methods are used to analyze a sample taken from the nose/mouth and pharyngeal swab, targeting the viral genes that are most expressed during the infection. This analysis can only be conducted in highly specialized laboratories designated by health authorities and takes an average of 2 to 6 hours to produce results. Another category of tests, known as antigen swabbing, have lower sensitivity and specificity than the previous molecular tests.

- E.J. Lefkowitz and D.M. Dempsey[1] Says The serological tests highlight the presence of antibodies against the virus and tests reveal that there has been exposure to the virus; but only in a few cases can they detect that an infection is in progress. In the current state of scientists development, serological tests cannot replacemolecular tests based on the identification of viral RNA.
- Abbas.M and M.Abdelsamea[2] The lungs are the two organs responsible for supplying oxygen to the body and for the elimination of carbon dioxide from the blood, or the gaseous exchanges between air and blood. Located in the thoracic cavity, they are surrounded by a serious membrane, the pleura, which is essential for the performance of their functions. The lungs are separated by a space between the spine and the sternum, the includes the heart, esophagus, trachea, bronchi, thymus and great vessels.
- As Per A. Borakati,[3] Instruction was In recent times, the attention for the diagnosis of infection is focusing on imaging tests. Chest X-ray (CXR) and computed tomography (CT) are the most popular imaging techniques for diagnosing COVID-19 disease. The historical conception of diagnostic imaging systems has been fully explored through several approaches ranging from automation engineering to deep learning.
- C.Schaefer-Prokop[4] says The accuracy of the classification was used to evaluate the performance of the proposed methods .The dataset used in this work is a collection of chest X-Ray image images that were (and still are) gathered by researchers from different countries, with the specific purpose of creating a publicly available database for COVID-related research. Compared performances of several CNNs, presenting a test accuracy of 99.48% obtained byDenseNet121.
- D.Dong,Z.Tang and S.Wang[5] Instruction was The ViT's capability to connect local patches of information on a single image and build up the picture context has led the Vision Transformer to often surpass its convolutional competitors. Thus, many other works have deployed the Vision Transformer for COVID detection.
- A.M.Ismael and A.engur [6] authors developed a small-sized CNN architecture due to pertained CNN models being known to present difficulties in practical applications. A 12-class chest X-ray image dataset was used by the authors, with an 86% accuracy score reported in their testing. Proposed a deep-learning-based approach for the detection of tuberculosis. In their approach, the authors developed a novel CNN model that used chest X-ray images as input, and transfer learning.
- Katsamenis, E. Protopapadakis [7] The pandemic brought forth by the coronavirus disease 2019 (COVID-19) not only sustains a devastating response on the well-being and health of the worldwide population but also demands a high rate of monitoring so that it does not extend on its destructive path. A vital aspect of the battle against COVID-19 is the efficient examination of the patients, which can help the infected receive quick treatment and immediate.

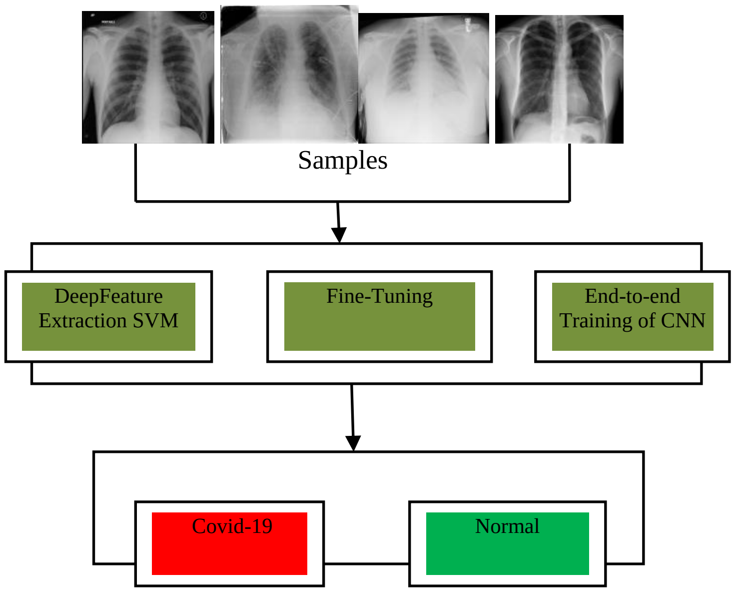

Fig.1 Illustration of Proposed Methodology for Covid-19 Detection

III. METHODOLOGY

Convolutional Neural Networks (CNNs) have demonstrated their remarkable capabilities in image classification. The underlying idea is to employ Convolution layers with a soft ax function to the input. Although CNNs are powerful, they face certain challenges, such as the inability to preserve information about the composition and location of septic elements within an image and to transmit such information to the next layers. To overcome this limitation, various architectures have been developed and proposed in recent years. Among them, Transformers have attracted significant attention, particularly in NLP applications. This work focuses on the Vision Transformer (ViT), which is likely the most well-known version of the Transformer architecture for image classification.

The input images are partitioned into patches, and the linear projection of attended patches is embedded to maintain positional information. The embedded patches are then arranged in a sequence and inputted to the Encoder, which utilizes the multi-head attention approach to extract information, patterns, and relationships among image patches.

The outputs are finally sent to a Multi-Layer Perception for classification. To better understand the similarities and differences between CNNs and ViT, a brief overview of the architectures of three of the most important and widely used Convolutional Networks will be presented. InceptionV3 began as a module for GoogleNet, with the goal of enabling deeper networks without significantly increasing the number of parameters.

The section of the network responsible for image classification utilizes the information extracted and processed by the Transformer heads. To better understand the similarities and differences between CNNs and ViT, this article will briefly discuss three of the most relevant and popular Convolutional Networks. InceptionV3 was originally created as a module for Google Net to enable deeper networks without significantly increasing the number of parameters. To reduce dimensionality, 1*1 convolution blocks were introduced. These blocks also serve as rectified linear activators, giving them a dual purpose. The fundamental concept behind this approach is based on the assumption that cross-channel correlation and spatial correlation can be separately mapped. The idea is to use 11 convolution to map cross-channel correlations and apply 33 convolutions to map spatial correlations later. This approach has been shown to perform slightly better than InceptionV3.

IV. EXPERIMENTS SETUP AND TESTS

The initial stage of the process involved training and testing the three aforementioned CNNs using the chest X-Ray image dataset. Transfer learning was utilized to train the networks by preserving and freezing network weights obtained from previous training sessions on septic datasets, using weights acquired from the ImageNet21k database. Afterward, only a few of the top layer weights were designated as trainable, as the chosen architectures varied in terms of the number of trainable layers. The reduced number of unfrozen layer weights were then trained and tested on the chest X-Ray image database.

The retuning process for the Vision Transformer differs significantly from that of CNNs. Unlike CNNs, all of the weights in ViT are subtly modeled during the process and no layers are frozen. The fine-tuning method helped to significantly reduce the overall amount of time and computational resources required for training and testing all convolution networks.

The retuning process was initiated at different layers for each CNN architecture. Specifically, for InceptionV3, it was set at layer 308 out of 311 total layers, while for Exception it was set at layer 128 out of 132 total layers. For ResNet50, it was set at layer 172 out of 175 total layers. The dataset was divided into three parts, with 70% used for training, 10% for validation, and 20% for testing. The same split was maintained for all models.

TABLE 1:

PERFORMANCE COMPARISON BETWEEN VISION TRANSFORMER

In Table 2, We have given the Precision, Recal, F1-

Network Architecture	Test Accracy
Inception V3	0.7936
Xception	0.8362
ResNet50	0.8558
ViT	0.9930

Score Value of our Algorithm.

TABLE 2:
PRECISION, RECALL AND F1-SCORE FOR VISION TRANSFORMER

	Precision	Recal	F1-Scorer	Support
COVID (Class:0)	0.97	0.94	0.96	353
Lung Opacity (Class:1)	0.87	0.93	0.90	602
Normal (Class:2)	0.95	0.92	0.94	1019
Viral Pneumonia (Class:3)	0.96	0.98	0.97	135

V. EXISTING METHOD

1. *CT Lung image Classification using*

- Construct concentric multilevel partition .
- Incorporate intensity, texture, and gradient information
- Image patch feature description
- Contextual latent semantic analysis-based classifier

2. *Draw Backs:-*

- Difficult to get accurate results
- Not applicable for multiple images for cancer detection in a short time

Medical resonance images may contain noise due to operator performance, which can result in significant inaccuracies in classification.

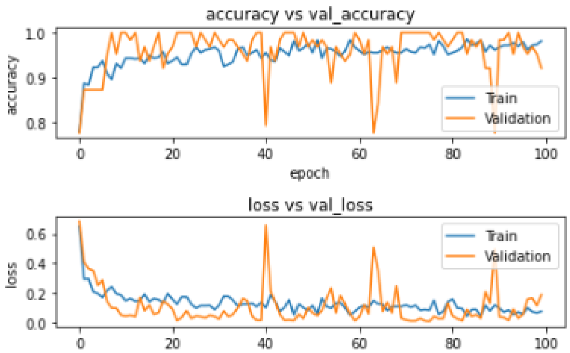

Fig 3. Finding-tuning of ResNet50 Model for Covid-19 Classification

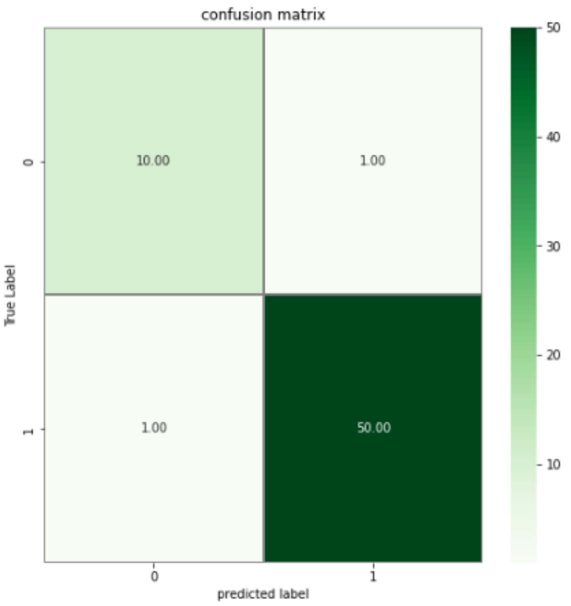

Fig 4. Confusion Matrix Obained by Find-tuning Resnet50 Model

Layer(type)	Output Shape
Resnet50(Functional)	(None, 2048)
Flatten (Flatten)	(None, 2048)
batch_normalization (Batch Normalization)	(None, 2048)
dense(Dense)	(None, 2048)
batch_normalization_1 (BatchN ormalization)	(None, 2048)
dense_1(Dense)	(None, 1024)
batch_normalization_2 (BatchN ormalization)	(None, 1024)
dense_2(Dense)	(None, 2)

Total Params:29,904,770
Trainable Params:6,306,818
Non-trainable Params:23,597,952

VI. CONCLUSION

In this study, three deep CNN methods were tested for detecting COVID-19 using chest X-Ray image images. These included transfer learning approaches, deep feature extraction, and fine-tuning, as well as an end-to-end trained new CNN model. The deep features extracted were classified using an SVM classifier with various kernel functions. Additionally, eight common local descriptors were examined, and the results of the study led to the following conclusions

- The Cubic kernel function generally outperformed all other kernels in deep feature classification.
- The ResNet50 CNN model exhibited superior results compared to the other pre-trained CNN models. When it comes to end-to-end training, deep CNN models outperformed shallow networks.
- The local feature descriptor extraction was outperformed by the deep learning approaches, especially the deep features and SVM classifier. It was found that fine-tuning and end-to-end training require significantly more time compared to deep feature extraction and local feature descriptor extraction.

REFERENCES

1) E. J. Lefkowitz, D. M. Dempsey, R.C. Hendrickson, R.J.Orton, S.G. Siddell, and D. B. Smith, ``Virus taxonomy: The database of the international committee on taxonomy of viruses (ICTV),'' Nucleic Acids Res., vol. 46, no. D1, pp. D708_D717, Jan. 2018, doi: 10.1093/NAR/GKX932
2) Abbas, M.M. Abdelsamea, and M.M. Gaber, ``Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network,'' Int. J. Speech Technol., vol. 51, no. 2, pp. 854_864, Sep. 2020, doi: 10.1007/S10489-020-01829-7.
3) A.Borakati, A. Perera,J. Johnson, and T.Sood, ``Diagnostic accuracy of X-ray versus CT in COVID-19: A propensity-matched database study,'' BMJ Open, vol. 10, no. 11, Nov. 2020, Art. no. e042946, doi: 10.1136/bmjopen-2020-042946.
4) C. Schaefer-Prokop and M. Prokop, ``Chest radiography in COVID-19: No role in asymptomatic and oligosymptomatic disease,'' Radiology, vol. 298,

no. 3, pp. E156_E157, Mar. 2021, doi: 10.1148/radiol.2020204038.

5) D. Dong, Z. Tang, S. Wang, H. Hui, L. Gong, Y. Lu, Z. Xue, H. Liao, F. Chen, F.Yang, R. Jin, K.Wang, Z. Liu, J.Wei,W. Mu, H. Zhang, J. Jiang, J. Tian, and H. Li, ``The role of imaging in the detection and management of COVID-19: A review," IEEE Rev. Biomed. Eng., vol. 14,pp.16_29, 2021, doi: 10.1109/RBME.2020.2990959.
6) A.M.Ismael and A.engur, ``Deep learning approaches for COVID- 19 detection based on chest X-ray images," Expert Syst. Appl., vol. 164, Feb. 2021, Art. no. 114054, doi: 10.1016/j.eswa.2020.114054.
7) I. Katsamenis, E. Protopapadakis, A. Voulodimos, A. Doulamis, and N. Doulamis, ``Transfer learning for COVID-19 pneumonia detection and classi_cation in chest X-ray images," in Proc. 24th Pan- Hellenic Conf. Informat., Nov. 2020, pp. 170_174, doi: 10.1145/3437120. 3437300.
8) Shazia, T. Z. Xuan, J. H. Chuah, J. Usman, P. Qian, and K. W. Lai, A comparative study of multiple neural network for detection of COVID- 19 on chest X-ray," EURASIP J. Adv. Signal Process., vol. 2021, no. 1,p. 50, Dec. 2021, doi: 10.1186/s13634-021-007551.