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The application of fast CapsNet computer vision in detecting Covid-19

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Abstract: The COVID-19 pandemic outbreak, also named as SARS COV-2 had created havoc around the world. With global death reaching 357,432 as of 28 May 2020, had created fear, disruption and economic collapse, with many countries are officially in recession. The speedy detection of this disease is important for stopping the spread of disease and provide treatment to the infected people. Artificial Intelligence (AI) can be used to detect, predict, analyse and help in the decision-making process to control this infectious disease. This paper had used the deep learning technique in image processing for detecting COVID-19 in patients. This paper has proposed using computer vision image techniques to reduce the time required to obtain the result. But due to some of the shortcoming of Capsule Neural Network and Convolution Neural Networks for prediction the article had considers ResNet-50 and AlexNet architectures. For data analysis, the paper uses free data obtained from across the world mainly China, Europe and America using a site such as coronavirus worldmeter. After analyzing four architecture, this paper recommends the use of 2D fast CapsNet to detect the COVID-19. This research paper will set the ground for further practical application.

Keywords: COVID-19; Deep Learning; Pandemic;COVID-19; Capsule Neural Network; Convolution Neural Networks (CNN); computer vision techniques.

1. Introduction

The use of deep learning techniques in image processing with an aim of increasing precision of correctly detecting presence of COVID-19 in the body has received increased attention from the artificial intelligence community. The use of computer vision imaging techniques will not only increase precision but also reduce the overall time required to obtain the COVID-19 results. Despite the numerous attempts to mass test the population, testing has not met the minimum number of people to be tested in the majority of the countries where COVID-19 spread has been on rise. This paper aims at increasing the precision of computer vision by assessing precision of using Capsule Neural Network (CapsNet) to address the main disadvantages of using Convolution Neural Networks (CNN) in detecting COVID-19, with an aim of determining the most effective architecture to use in detecting COVID-19 using computer vision techniques. This paper explores how deep learning techniques can be used to improve the accuracy of the tests currently being used to detect presence of COVID-19 in a body.

2. Literature review

Coronavirus disease 2019 (COVID-19) is an infectious disease caused by a newly discovered virus[1]. The World Health Organization has declared that COVID-19 is a pandemic and has now become a global crisis. In the coming of COVID-19 pandemic since December 2019, health experts, policy creators and governments have been battling to make an important decision under uncertainty. Precise and expedient recognition of the COVID-19 contamination is basic to distinguish, make a better decision and provide quicker treatment to the patients to save their lives. Time to react to the pandemic is additionally important in halting the epidemic in order to decrease its harm to people [2]. In addition, uncertainties due to data and testing available are the largest obstacle to obtain an accurate forecasting and the future behaviors of the epidemic. Figure 1. Shows countries affected by COVID-19 as of May 27, 2020.

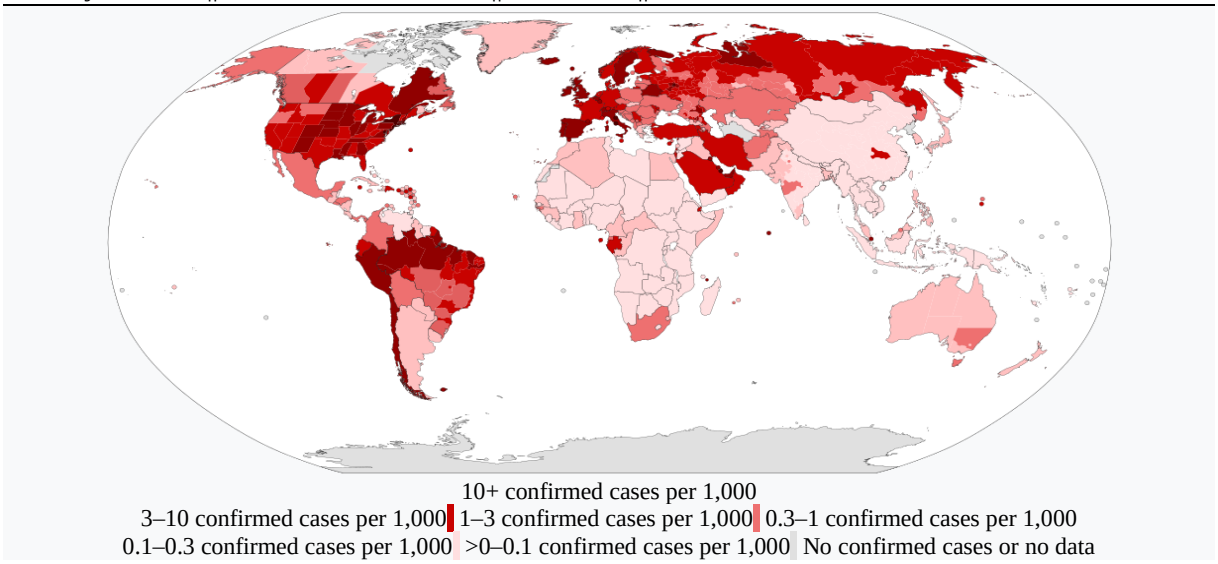


Figure.1 Heat Map of the COVID-19 verified number of infected per capita as of 27 May 2020 (Coronavirus worldmeter)

As we can see in Figure 1. that some section of the map shows no confirm case or no data. This represent a typical problem of deep learning in data science, over limited or incomplete data available in the early stages of the epidemic. Numerous machine learning including deep learning algorithm are developed over the last decades dealing with various health-related problems [3]. The field of machine learning and artificial intelligence has continued to be applied in many fields ranging from medicine, agriculture and also the automotive industry. As lots of COVID-19 data set is collected from multiple sources globally. Big Data as an emerging technologyin health industry provides faster, accurate data analysis for high volume data in today's technology-driven world [4]. Most of this data need to be stored in the Cloud computing for storage and processing. Cloud computing provides scalability, flexibility and processing powered required for such large dataset[5]. COVID-19 is therefore not a unique case where solutions based on artificial intelligence is being used. It is important to understand the value, applicability and usability of such an approach in order to fight against COVID-19. With proliferation of such approaches need to minimise the economic cost, loss of human lives and societal cost caused by this infectious disease.Therefore, given that COVID-19 mainly affects the lungs, machine learning algorithms used in the past to detect lung cancer are now being modified to detect COVID-19 with the same precision.

Previously, enough data was not present to train deep learning algorithms, however with the increased COVID-19 cases across Asia, Europe and the Americas it is now possible to train deep learning algorithms capable of detecting similar patterns notable on the COVID-19 patients' lung scans. As mentioned earlier, majority of the deep learning algorithms being used were previously used to detect Lung Cancer but has since then been modified to detect Covid-19 based on the fact that COVID-19 affects the lungs of an individual[6].In the next section the paper will outline the methodology used followed by the analysis and findings section. The study will then proceed with the discussion section and lastly conclude with areas for further study.

3. Methodology

To test the effectiveness of using Capsule Network over using CNN to detect COVID-19 in a potential patient, the article considers ResNet-50 and AlexNet architectures. The two architectures are compared with Capsule Network in terms of precision levels, error rates, number of parameters and the overall time taken to train the different models [7]. Notably, Capsule Network is slow and takes more computation power[8]. Therefore, a new architecture is aimed to increase the speed of Capsule Network is used, Fast Capsule Network. The Fast Capsule Network mitigates the disadvantages of using Capsule Network using dynamic routing. All the architectures are trained using both 2D and 3D versions.

3.1 CapsNets Architecture

This paper uses modified convolution neural network (CNN) to classify obtained images. In the modification, convolution neural networks (CNN) use the CapsNets Architecture. CapsNets address the shortcomings of CNN by being able to recognize an image in its 3D view despite the images' position during the training of the model. Hence the CapsNets are able to detect the presence of particular infections associated

with COVID-19 infections in the lungs. This mainly has an advantage given that presence of the infections on the lungs is not uniform for all patients. To achieve this CapsNets uses an example of a face to face recognition to route image information from one layer to another[9] .

3.2 Fast Capsule Network

Consistent Dynamic Routing- A Capsule Computation is hence an architecture that groups neurons into a capsule[10]. The capsule is responsible for the capture of the hazy patches associated with the infection of COVID-19 despite the location of the patches on the lungs[11]. This procedure is however computationally costly and does not scale well to high-dimensional data, like 3D CT scans with a high pixel count. In CapsNetsi-th capsule in a lower layer and j-th capsule is encoded in next higher layer. To complete the prediction vectors, parent capsule that agree the most with their prediction receive information from lower-level capsule after computing. The mechanism of parent capsules receiving the output of the child capsule is termed as dynamic routing[12]. No new information flowing between the two capsules if cij=o, whereas if cij=1, all the information from lower i capsules will be sent to next level j capsule. The paper proposes continuous dynamics Routing mechanism for tackling this issue. In particular applying all the capsules in the PrimaryCaps layer which corresponds to the same pixels k hence having the coefficients with the same routing. By reducing the number of routing operation, it is expected to dramatically increase the efficiency of network. Constraint can be enforced in many possible ways as shown in equation.

$$c_{ij} = c_{kj}, \forall i, k \in S = \{i, k \mid loc(i) = loc(k)$$

Each child capsule can freely vote to parent capsule. Where the loc () function converts the capsule index to its pixel location.This will dramatically reduce the number of routing coefficients.

Coefficients Routing- When the network parameters are being learned the CapsNet applies additional regularization to prevent over fitting. This is possible as a reconstruction loss is added hence prompting the digital capsules to store as much input information as possible. This is achieved by feeding the final capsules with 16D outputs to a neural network with three layers of feed-forwards [9].

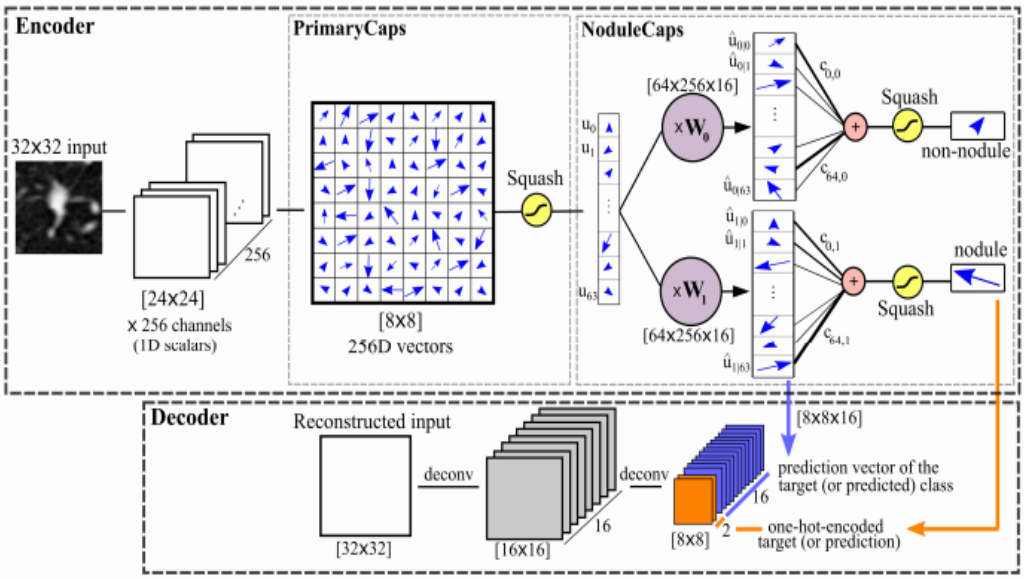
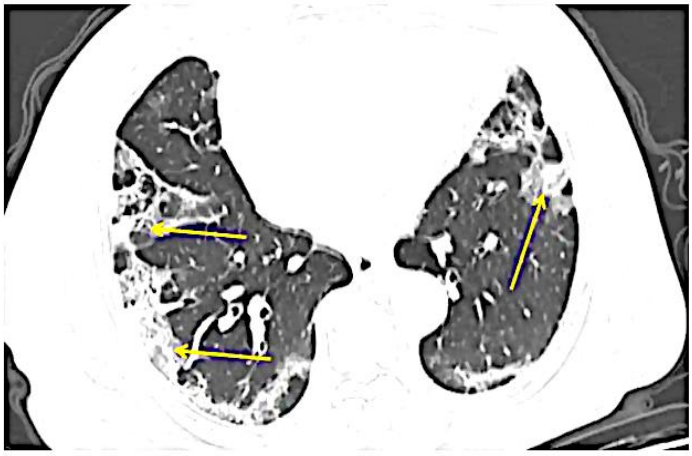


Figure 2: Fast Capsule Network Representations [10]

Through neural network architecture, the images are analysed one by one and similar features of the image are then identified, mostly the capsule architecture will be identifying hefty patches on the lungs as shown in Figure 2. The images were detected by the model through assigning each characteristic of COVID-19 on the image a target which is then used to check whether new patients' lungs have any characteristics of the noted targets. The over sensitivity to labels with noise is the main drawback of using cross entropy loss. To mitigate this drawback, smoothing of labels and augmentation of data through ideas like CutMix were applied. The fitted CNN network used on the 3000 datasets was trained on 2,500 images and the accuracy of the model tested on the remaining 500 images.

4. Results

The World Health Organization (WHO) updates dataset daily based on global situation reports. The paper uses free data obtained from across the world mainly China, Europe and America. The data is pre labeled lung CT scans as shown in figure 3. The CT scans of the lungs used are labeled whether the CT scan belonged to a male or female, level of infection, age and lastly whether the patient had any lung related disease. For this study however, penitents CT scans with other types of lung complications are removed from the dataset. A total of 3000 images were collected for this study with 60 % (N = 1800) while the rest, 40 % (N = 1200).



▲ Respiratory physician John Wilson explains the range of Covid-19 impacts. This image shows a CT scan from a man with Covid-19. Pneumonia caused by the new severe acute respiratory coronavirus 2 can show up as distinctive hazy patches on the outer edges of the lungs, indicated by arrows. Photograph: AP

Figure 3: CT scan of Covid-19 patient

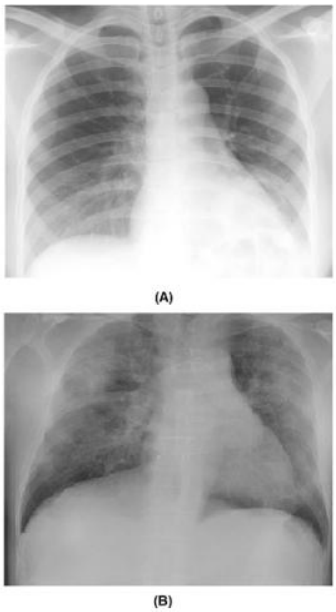


Figure 4 (A) COVID19 infection is negative and (B) COVID-19 viral infection from the dataset

From figure 4 it is clear that detecting hefty patches caused by COVID-19 is challenging given that the infected lung is almost similar to an uninfected one. This is the main reason why the detection of COVID-19 is extremely hard even for humans to identify. The study uses both 2D and 3D layers on three well known architectures; Fast Capsule Network, ResNet-50 and AlexNet. ResNet-50 and AlexNet are used as benchmarks on the fitted Fast Capsule Network.

4.1 Findings

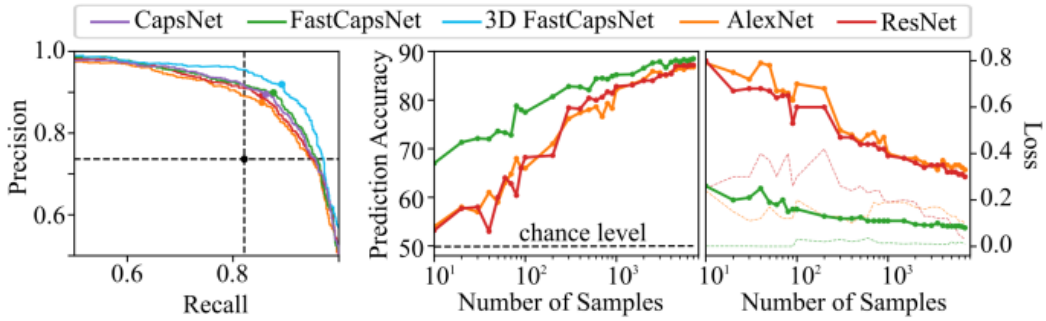


Figure 5. Comparisons of the Results [10]

Figure 5 represents the results obtained for the CapsNet, FastCapsNet, 3D FastCapsNet, AlexNet and ResNet. The difference between CapsNet and FastCapsNet is the speed which was improved by changing the routing mechanism. From the results it is clear that increasing the speed of CapsNet did not affect the accuracy of the algorithm. In the case of using 2D layers when modeling, FastCapsNet outperformed CapsNet by a small margin, 0.27 while in the case of the 3D FastCapsNet outperformed the 2D CapsNet by 2.13. Overall the best precision rate was achieved by the 3D FastCapsNet with a precision of 92 %. Automated software had the least accuracy levels at 74 %, this reveals that using building training models from scratch outperformed the automated software designed for general computer vision. Notably, using 3D for COVID-19 detection outperformed 2D in all the cases. Therefore,AlexNet and ResNet-50 architectures outperformed 2D FastCapsNet. This hints that, to increase the accuracy of a model in computer vision, 3D performs better than 2D.

Further analysis of the obtained results reveals interesting fact about the differences of using 3D and 2D, with the exception of AlexNet architecture the other architectures used have difference in terms of number of parameters. 2D and 3D AlexNet architecture difference in the number of parameters used is only 0.2 M with 3D AlexNet architecture having more parameters. Given that using 3D AlexNet architecture improves the accuracy of the AlexNet architecture by 2.96 % is a clear indication that AlexNet architecture uses less computing power to improve the accuracy of detecting COVID-19 cases.

For ResNet-50 architecture the difference between the number of parameters used in the case of 3D and 2D is significantly huge, 25 million more parameters were used when a 3D model was used. Increasing the number of parameters by approximately 25 million increased the accuracy of detecting COVID-19 by 2.1 %. Comparing the number of parameters added in the case of ResNet-50 architecture andAlexNet architecture shows that the AlexNet was able to increase the accuracy levels by increasing a smaller number of parameters. Comparison between 2D and 3D FastCapsNet reveal that 3D architecture had 53 M parameters while 2D had 6 M parameters, the accuracy levels however increased by 2 %. This shows that increasing the number of parameters for FastCapsNet had a slight effect on the accuracy levels but tremendous effects on the computing power required. Notably, the number of parameters used in a 2D CapsNet was higher than 2D FastCapsNets by 1.5 m while 1.5 M even though 2D FastCapsNets had higher accuracy levels compared to the 2D CapsNet, a difference of 0.27 %.

Among all the models used, 2D FastCapsNet was the fastest with a record 6 seconds while 3D ResNet-50 took the longest time 350 seconds. Notably, all the 2D versions took less than 20 seconds with 2D CapsNet taking the longest time of 19 seconds. Findings from the all the 3D versions indicate that 3D AlexNet took the shortest time per epoc, 177 seconds while 3D FastCapsNet took 320 seconds.

5. Conclusions

Analysis of thefour different architectures are used in this paper; FastCapsNet, CapsNet, ResNet-50 and AlexNet indicate that even though FastCapsNet had the highest accuracy levels, FastCapsNet have had the lowest error rate. Notably, FastCapsNet was outdone by 3D AlexNet in terms of speed and number of parameters. Considering that 3D AlexNet uses smaller number of parameters, indicates that the users with less computing power should opt for 3D AlexNet due to speed and the computation power. Additionally, the findings also revealed that 2D FastCapsNet used the least number of parameters and the also took the least time hence indicating that 2D FastCapsNet used less computation power compared to all the other deep learning algorithms fitted on the data. Therefore, users who cannot access 3D version, should use 2D FastCapsNet for

most accurate results with the least error rate. This paper recommends the use of 2D FastCapsNet to detect the COVID-19 given the small number of parameters needed and overall time taken to train the model.

6. Further research

Given the spread of the COVID-19 across the world and currently the expected wide spread across the developing world. It is important that the tests for disease be done with less time and more precision at lower cost. However, results from the analysis reveal that the CapsNets consume more computational power hence take more time. Changing the routing mechanism increased the seed of the CapsNets while maintaining the accuracy. This shows that higher accuracy levels can be achieved while the at the same time improving the speed. Hence further research on computer vision should be based on increasing the accuracy while also increasing the speed of achieving the results. This paper suggests further research on the area by pursuing CapsNet using unsupervised learning methods given that this paper covers only supervised learning of the CapsNets. Based on the findings from the study, the paper also suggests that research on 2D FastCapsNet should be done with an aim of increasing the accuracy levels for this deep learning technique. Increasing the accuracy levels should however not increase the computation power and overall time taken to train the model.

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