OPEN ACCESS

J. Innovation Sciences and Sustainable Technologies, 2(4)(2022), 175 - 180.
https://doie.org/10.0213/JISST.2023200513

Technology & Innovation

Narayana 1.0: Emergence of New Information Based Technology for the Diagnosis of COVID-19 and the Related Support

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Received in final form on August 25, 2022

Abstract

Narayana 1.0 is a user-friendly technology that helps to diagnose the presence or absence of COVID-19 (SARS Coronavirus (SARS-CoV)) in humans. This technological tool will not insist on the presence of a subject but relies on the data related to the laboratory tests. Information and results of any/all of the following diagnostic tests, such as CT scan, Ultrasound, and Chest X-ray images, are the key inputs to this technology. This article purports to discuss a methodology that paves way for the creation of the technology Narayana 1.0. Notable features of this technology include, among others, very high accuracy with very little time for diagnosis, and an ability to outperform the less accurate reverse transcription polymerase chain reaction (RT-PCR). Narayana 1.0 may be deployed at airports, transit stations, auditoriums, conference venues, and private and public gatherings where large crowds are witnessed. Also, the current challenges in handling this pandemic are discussed in this exposition.

Keywords: Narayana 1.0, Technology, Support, SARS Corona virus, Cooperative and Supportive Deep Capsule Network.

1 Introduction

COVID-19 is a dangerous disease caused by the coronavirus of Severe Acute Respiratory Syndrome (SARS-CoV-2). COVID-19 has been classified as a global pandemic disease by the World Health Organization (WHO), resulting in a global health crisis that has had a major impact on our daily lives [1]. This virus is a single-stranded RNA virus that is more susceptible to mutation than DNA-based viruses and spreads more quickly than other viruses [2]. COVID-19 is rapidly affecting the world resulting in a large number of deaths all over the world. Despite the global undertaking to prevent the outbreak of this disease, thousands of

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cases still appear daily worldwide. Therefore, it is crucial for the early diagnosis of COVID-19, in order for the Governments to develop effective allocations of resources and break the chain of transmission. At this critical stage, the reverse transcription polymerase chain reaction (RT-PCR) [3] testing method is used for detecting COVID-19 cases, which is time-consuming and prone to a high false-negative rate [4]. In this context, computer tomography (CT) scans and X-rays have demonstrated different characteristics and increased sensitivity when compared with other diagnostic techniques, particularly the current gold standard method, the RT-PCR. However, a radiologist needs to analyze these images manually, which is time-consuming. There is a need for a rapid diagnostic tool for COVID-19 identification. The rapid tests provide aid for medical practitioners to avail quick and efficient examinations in identifying COVID-19. In this article, we discuss a methodology that paves way for the creation of the technology Narayana 1.0. Notable features of this technology include, among others, a very high accuracy with very little time for diagnosis and an ability to outperform the less accurate RT-PCR.

2 Issues and Challenges

The main thrust of this research is the design and development of a cooperative and supportive deep capsule neural network that determines the presence or absence of COVID-19 in individuals. Building a comprehensive collection of CT scans, Chest X-rays, and Ultrasound Images that are associated with clinical symptoms is a crucial step in combating the COVID-19 world over. Clinical information is vital for acquiring a deeper knowledge of virus infection patterns and for developing systemic models for effective diagnosis by rendering accurate classification. The following are the challenges in this study:

1. Determination of the number of layers in the proposed deep capsule network.

2. Allocation of the optimal percentage of data sets for training the network and also for testing the network.

3. Determination of the minimal time required for correctly classifying a record.

3 Network Architecture

This study develops a cooperative and supportive deep capsule neural network for the diagnosis of COVID-19-infected and non-infected cases to make a binary class classification of COVID-19 and non-COVID-19 cases. The concept of cooperative and supportive neural networks for the classification of data sets originally stems from the work of Sree Hari Rao and Raja Sekhara Rao [5]. The present research highlights this concept and enhances its utility to classify images that form the main core of Narayana 1.0.

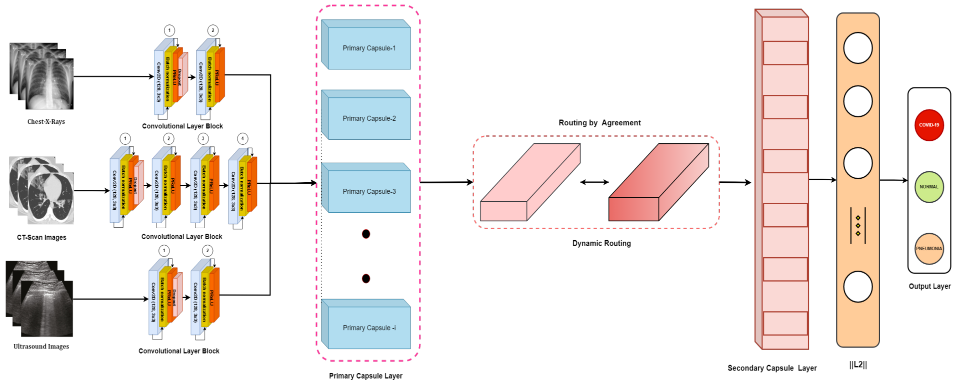

Figure 1: Cooperative and Supportive Deep Capsule Neural Network Architecture.

Figure 1 illustrates a step-by-step process of proposing a customized deep capsule neural network involving three separate networks of the same nature created to achieve greater efficiency, which is akin to the architecture advocated by Geoffrey Hinton et al. [6] for image classification. This study uses a deep capsule neural network with a modified routing algorithm for the classification of COVID-19 infected and non-infected cases with the same public datasets of CT scans, Chest X-rays, and point of care ultrasound (POCUS) images of COVID-19 positive and negative samples. The deep capsule neural network is made up of three blocks, which are shown in Figure 1: i) the convolution block, ii) the capsule network block, and iii) the loss function. More details on the design and development of this network, the modelling efforts, and the results of a wide variety of experiments with these networks are presented in [7].

4 Datasets

The above networks take the images as input and upon due processing return data sets as tuples with key attributes for the purpose of classification with a high level of accuracy. The details are as follows: Due to the pandemic nature of COVID-19, access to first-hand CT scans and clinical information is vital for supplying information to obtain a deeper knowledge of virus infection patterns and develop systemic models for fast diagnosis and effective treatment interference. Building a comprehensive collection of CT scans and associated clinical symptoms is a critical step in combating COVID-19 internationally. Some datasets are created and made available for COVID-19-related researchers, doctors, and data scientists. In this research, three publicly available COVID-19 datasets are used to find the efficiency of the proposed model. The first one is an open-source SARS-CoV2 dataset [8], which consists of a total of 1252 CT scan images for COVID-19 positive cases and 1229 negative images are made publicly accessible. These datasets are gathered from real-time patients in hospitals in Sao Paulo, Brazil. The second is a Chest X-ray dataset which includes a total of 2905 chest X-ray images that are publicly available in the GitHub repository [9]. The third is a POCUS (point of care ultrasound) data set [10],that includes 64 videos taken from various sources consisting a total of 2149 images. A glimpse of the data records developed from all types of datasets fulfilling the challenges mentioned above may be found in the following table.

S.No.	Input	No. of Layers	Train set	Test set	% Test Accuracy	Time taken for diagnosis
1	Lung X-ray	2	2324 (80 % of TR)	581 (20% of TR)	94.66	506 seconds
2	Lung CT Scan	4	1984 (80 % of TR)	497 (20% of TR)	94.63	154 seconds
3	Lung Ultrasound	2	1719 (80 % of TR)	430 (20% of TR)	99.53	308 seconds

Table 1: A vista of data records.
In Table 1 above TR represents the total number of records.

S.No.	Benchmarks	Achievements
1	Subject's presence - not required	Reduces transmission risk
2	Information required	Lung X-Ray/CT Scan/ Ultrasound Images
3	Diagnosis	More reliable
4	Time required	Almost instantaneous No delays
5	Detection Accuracy	High level
6	Comparability	More accurate than RT-PCR
7	Usefulness	Airports, transit stations, auditoriums, conference venues, and private and public gatherings

Table 2: Highlights of Narayana 1.0.

5 Results and Technology Support

The main achievable from the emergence of Narayana 1.0 are presented in Table 2 above.
It should be noted that the essential features of Narayana 1.0 include, among others, a very high accuracy with very little time consumption for diagnosis, and an ability to outperform the less accurate reverse transcription polymerase chain reaction (RT-PCR). Nayana 1.0 may be deployed at airports, transit stations, auditoriums, conference venues, and private and public gatherings where large crowds are witnessed. It is important to observe that all experiments have been performed on a machine having the following configuration: The proposed model is trained and tested on Windows operating system with Intel ® Core (TM) i7-9700F CPU @ 3.00GHz processor, 16 GB Ram, a CUDA-enabled Nvidia ® GeForce RTX 2080 SUPER Graphic cards. While performing the experiments we noticed that simultaneously many tasks have been handled by the processors of the machine. Appreciably the time required to test an individual with Narayana 1.0, utilizing any form of the data sets ranges between 2.002 minutes to 8.25 minutes which is significantly lower than the time required for performing RT-PCR. Here we surmise that if a dedicated machine of similar or higher configuration is utilized, the new technology Narayana 1.0 may render an almost instantaneous and accurate diagnosis for the presence or absence of COVID-19. Evidently, this feature makes Narayana 1.0 a desirable destination for the determination of COVID-19 and its innumerable variants.

6 Conclusions

This research focuses on the current priorities in providing clinical diagnostic care to COVID patients in a pandemic setting. The study aims to detect and classify COVID-19 cases by understanding the parasite's temporal and recurring transformations in the host. To improve clinical care through interventions relating to digital clinical decision-support systems, we set out to establish an artificial intelligence framework for clinical decision-making in COVID management to control these diseases in human beings. Also, the techniques developed will help handle large databases of individual records and obtain effective and timely diagnoses in a real-time environment, which indeed is a real big challenge.

Acknowledgements The research of the first author (VSHR) is supported by the Foundation for Scientific Research and Technological Innovation (FSRTI)- A Constituent Division of Sri Vadrevu Seshagiri Rao Memorial Charitable Trust, Hyderabad-500102, India.

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