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COVID-19 DETECTION USING QUANTUM COMPUTING

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ABSTRACT
Utilizing quantum mechanics, quantum computing generates giant strides in a way processing in order to tackle clear-cut problems. IBM developed quantum computers to deal with complex problems that even the most sophisticated supercomputers of today can't solve.
Covid-19 has taken over the globe, and it must be the predominant precedence at all levels. We can take precautions and help the infected because we have yet to defeat this virus. Continuous testing is one of the precautions. The goal of this research is to use machine learning advance technologies (like Quantum Computing) to abbreviate the time it clutches to test quantum computers.
We can achieve Covid-19(corona virus disease) detection in unfeigned I-B-M quantum processors and stimulators using the quantum transfer learning method. CT imaging has been recommended by many specialists as a diagnostic modus operandi for Corona virus disease. By rectifying a sample features set, we hope to conduct stratification of Covid-19 and wonted CT (Computer Tomography) images. Due to the better properties of Quantum Computers, this labour must be settled in a mite of the time and with greater accuracy than traditional computers.
KEYWORDS: Covid-19, Variational Quantum Circuit, Quantum Transfer Learnig

INTRODUCTION
Quantum computing uses quantum mechanics to build a huge leap ahead in processing in order to tackle specific problems. IBM developed quantum computers to deal with complex problems that even today's most advanced supercomputers can't or won't solve.
Covid-19 had taken the globe, and it also the paramount priority at all stages. Continuous testing is solitary of the backstop. The intent of this finding is to make use of machine learning to abridge the time it clutch to scrutinize quantum computers.
We have to bring off Covid2019 espial in unalloyed IBM quantum processors and stimulators using the quantum transfer learning method. CT imaging has been recommended by many specialists as a diagnostic technique for Covid-19. By processing a sample ascii file, we have classify Covid-2019 and normal CT images.
Due to the finer assets of Quantum or Quanta Computers, this chore must be fulfilled in, mite of the time and also with pronounced exactitude than conventional or personal computers. In

year 2019, Covid-19 made its occurrence in China. In just short time it became an epidemic, and later a pandemic. In today's time, we can immobile state that it is a major concern. WHO (World Health Organization) is quite concerned and has issued a number of precautions for us to follow in order to stay safe throughout this period-Strenuous testing is one of the guidelines. Because the virus's feature changes over time, tests may not always succeed in revealing the exact outcome.

CT scans are one thing we can always count on; they never lie. CT scans can successfully detect Covid-19 in people of all ages.

COVID-2019 is transferred through carriers or between people, as manifested by countless of contagions and rapid dissemination of the virus over the world, posing a severe challenge in controlling its spread. As a result, a variety of comprehensive preventative measures, such as social distancing, surely be administered at world level to cut the proliferate of infection. The disclosure of an result driving vaccine, though, this is the preponderance efficacious way to kill the virus and ultimately the pandemic. Experts and governments acknowledge that a vaccine wouldn't be made in 2-3 years, but it will be certainly developed in years to come. Therefore, until and unless a cure or vaccine is produced, an effective and immediate preventative technique must be implemented.

SARS-CoV-2 Overview

The virus that causes Corona-virus Disease 19 causes a respiratory illness (COVID-19). SARS-CoV-2 is really a corona-virus, that represents a ailment that be in to the corona-virus group. These virus can cause ailment in humans and certain animals. In 2k19, SARS-CoV-2 was found contaminate people for introductory time. The ailment (virus) is supposed to desseminate from individual to individual by droplets engender when a affected sole coughs/sneezes or speaks. It is most probably spreading by getting in contact with a virus-infected surface and one's lips, nose, or eyes. COVID-19 is being researched, as is the hindrance of SARS-CoV-2. Corona-virus 2nd is also known as appalling acute respiratory malady corona-virus 2nd. The virus like SARS-CoV-2 can easily be passed from person to person in our globalised environment, allowing it to spread quickly across all major lands.

The nucleic-acid-amplification test (NAAT) of the inhaling tract or blood samples is predicted to give positive results utilizing reverse transcription real-time fluorescence polymerase chain reaction (RT-PCR) to diagnose COVID-19. However, as consequences of truncated viral load in the expeditious stages, and sensitivity are limited and the detection rate, based on existing clinical experiences. As a result, incorrect findings are unavoidable. The computer-aided with machine learning algorithms system can speed up the diagnosis process owing to the cosmic number of debilitated patients, and excessive demand on healthcare staff.

METHODS

INCLUSION/EXCLUSION CRITERIA

Compositions were ponder in this findings if they mark any sort of Quantum computing or Detection of covid-19 and provided an examination of the minuscule appraisal or gauging of

the training's relatively long consequences. We only included publications that were written in English-language journals. Articles that used higher-order research methodology, such as meta-syntheses, or estimation that uses the experimental
methods, were given precedence under these criteria.

Observational research, qualitative investigations, editorial commentary, and articles, or book chapters are all unfasten from the perusal.

Quantum computers and simulations
In our research, we employ the following quantum computing simulators: Pennylane's default simulator1 is a noiseless simulator, whereas Qiskit-Aer simulator2 allows us to create capricious noise (sound) rates, and obstreperous Cirq-Mixed simulator3 is elucidate with four qubit cluster configurations. Furthermore, we used the following 5-qubit IBM Quantum Computers4 in our research: IBMQx2, IBMQ-London, and IBMQ-Rome are some of IBM's most popular products.

Transfer Learning
Transfer learning is a useful method for employing artificial neural networks to tackle muddles with little data[6]. If a hitherto tutored ANN is potent in decoding one problem, it can be utilized to tackle a different but similar problem with some extra training. Consider a problem-solving deep neural network that has been pre-trained with the data set. The deep neural network's completely linked layer is unfasten from the network. The webbing that results may be used to extract features.
A new network is introduced to the denouement of the aforementioned training network that may be utilized as the feature extractor. The new network was created by the feature extractor being retained network's weights constant.

DATASET
With the wide impact of COVID-19 (corona virus) virus, having access to unmediated CT images as well as medical information is scathing for steering clinical resolution, supplying evidences that helps us better acknowledge the virus's infection trends, and providing systematic designs for early assessment and quick medical interventions. To facilitate this universal scrimmage against COVID-19 (corona virus), one important tactic is to burgeon a thorough directory with unfettered concede to CT (Computed Tomography) scour and with the aloof manifestations. Many, as mentioned in the Associated Work section, databases for COVID-19 (corona virus) linked studies have devised and are obtainable to researchers, and data scientists. Although the COVIDx-CT dataset is clearly vast than numerous additional CT (Computed Tomography) sample sets utilised in the composition on COVID-19 (corona virus) testing, the narrow range of patient demographics is a potential disadvantages of using COVID-x CT for deep neural network learning. Because COVID-x CT data is gathered from the CNCB, only data from several Chinese provinces are offered, which means the manifestations of

COVID-19 (corona virus) seen in CT (Computed Tomography) imaging might be not applied on instances besides China. Deep neural networks would increase in diversity and depth as the number and patients became increasingly diverse, increasing their generalizability and relevance across a range of therapeutic settings around the world.

Previous researchers36 developed the COVID-x (dataset) CT-2A and COVID-x (dataset) (CT-2B) dataset by methodically processing and arranging CT-scans photos of patients utilising a range of CT scan equipments, process , and valid abilities. COVID-x (dataset) CT-2A contains of 194,922 CT scan images from 3,745 patients between the ages of 0 - 93 years . Here are multiples CT slides for every CT scan for each participants .

To identify COVID-19, we utilise CT slides as input photos, making the COVID-19 detection issue an image classification problem. The dimension of the CT images is 512x512 pixels. The following are the image input dataset for COVD-x and CT-2A:

According to Figure 1, in the dataset, the images of COVID-19 cases are intense between 40-70 age and showed a normal distribution. The images of normal cases are intense between 50-80 age and showed normal distribution. According to Figure 2, in the dataset, it can be observed that the number of male patients with COVID-19 is slightly higher than that of female patients.

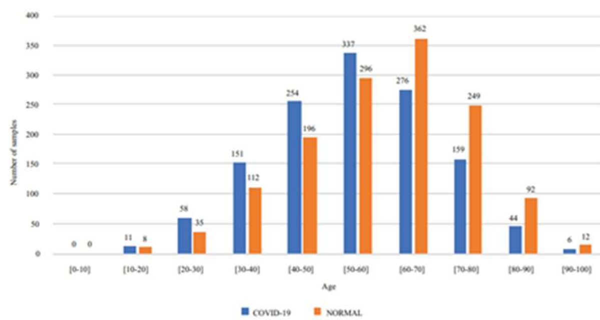

Figure 1.1 Data distribution in terms of age

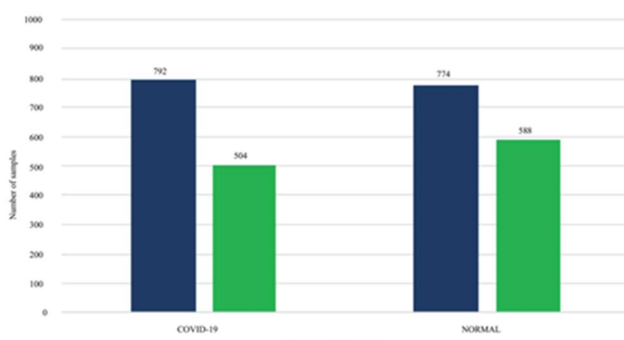

Figure 1.2 Data distribution in terms of gender

“China National center for Bio-information” (China) 32 (CNCB) “Intramural Targeted Anti-COVID-19 (ITAC) Program by the National Institutes of Health” (countries unknown)40 Iran's Negin Radiology Medical Center41:

COVID-x (dataset) CT-2B appended weak validation (Mos-Med) from the “Research and Practical Clinical center of Diagnostics and Telemedicine Technologies, Department of Health

Care of Moscow" (Russian Federation)45 to the COVID-x CT-2A dataset. The goal of developing this test dataset is to see whether adding weak validation (i.e., findings obtained without employing RT-PCR training data would increase the precision. This evaluation can assist to enhance the dataset's breadth and variety. We used COVID-x (dataset) CT-2A for COVID-19 validation in this finding due to the openness of the data and the comparison with earlier functioning models.

Three different types of CT scans are represented in the relevant cases from the COVID-x CT-2A dataset in Figure: SARS-CoV-2-infected novel corona-virus pneumonia (NCP), typical controls, and common pneumonia (CP). We made some adjustments to database photographs in order to make our models simpler. We employed an automated cropping method to eliminate the backdrop and standardise the field to the body region since the possible contrast in the images' backgrounds might lead to biases in the models (as

shown by the red frames in Fig. 1). We detected ground glass opacity (GGO), bronchial consolidation, and even the occurrence of white pneumonia in CP groups by examining various kinds.

Although, because the graphic distinctions among those infected with regular pneumonia and those exposed to the virus with SARS-CoV-2 are so nuanced, even radiologists may have trouble differentiating the virus.

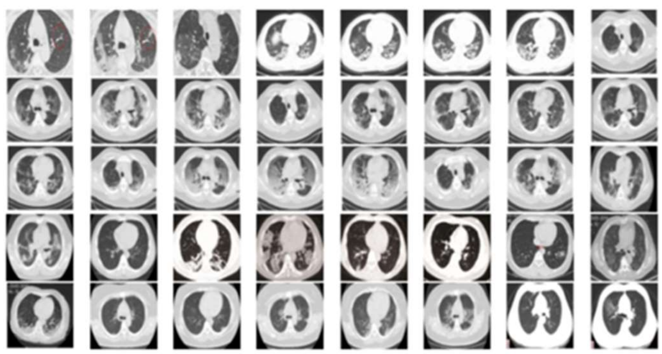

Figure 2.1 Positive COVID-19 CT Scan Images

Figure 2.2 Negative COVID-19 CT Scan Images

Limitations

The approach that we chose for this investigation has the following drawbacks. Because the bulk of published studies of education and training in low- and middle-income countries did not match the criteria for a more rigorous systematic review or meta-analysis, an integrated review of the literature was chosen. Integrative reviews have a key flaw in that they can be skewed by the inclusion of non-peer-reviewed data or low-quality studies. With the exception of original publications that expressly discussed quality, the inclusion of articles representing a spectrum of rigour in their research design limits the degree of confidence that can be placed on the authors' interpretations (such as systematic reviews). There was no attempt to reanalyse or integrate original data in this review.

Discussion

Manual feature extraction may not yield an effective feature vector because feature engineering is susceptible to and subjective to human bias. Instead, a Convolutional Neural Network (CNN)-based application obtains an efficient feature vector because CNN-based applications automatically extract properties such as differences, density, colour, and shape, and most studies have shown a considerable boost in performance. The amount of data needed for CNNs to be effective is critical, but this issue has

been solved via transfer learning. A 512-dimensional feature vector is produced in our study using ResNet18, a pre-trained network. The feature vector is then encoded into the quantum variational circuit.

Models	Accuracy%	Precision%	Recall%	F1-Score%	Specificity%
Classical Model	0.909 ± 0.011	0.926 ± 0.010	0.890 ± 0.012	0.908 ± 0.011	0.929 ± 0.010
PennyLane without U	0.909 ± 0.011	0.926 ± 0.010	0.890 ± 0.012	0.908 ± 0.011	0.929 ± 0.010
PennyLane with U	1.000 ± 0.000	1.000 ± 0.000	1.000 ± 0.000	1.000 ± 0.000	1.000 ± 0.000
Qiskit-Noise Simulator	0.977 ± 0.006	0.969 ± 0.007	0.984 ± 0.005	0.976 ± 0.006	0.971 ± 0.006
Cirq-Mixed Simulator	0.956 ± 0.008	0.970 ± 0.006	0.940 ± 0.009	0.951 ± 0.008	0.971 ± 0.006
IBMQx2	0.959 ± 0.008	0.971 ± 0.006	0.946 ± 0.009	0.958 ± 0.008	0.972 ± 0.006
IBMQ-London	0.966 ± 0.007	0.971 ± 0.006	0.959 ± 0.008	0.965 ± 0.007	0.972 ± 0.006
IBMQ-Rome	0.969 ± 0.007	0.974 ± 0.006	0.963 ± 0.007	0.969 ± 0.007	0.976 ± 0.006

Table 1. Accuracy of Model

Result

In regards of COVID-19 susceptibility (98.7%), positive predictive value (98.5%), selectivity (99.5%), but also negative predictive value (99.5%), the BiT-M model centered on transfer learning surpassed the competitors (99.5 percent). (99.6% of the time). Our proposed method outperforms previous work because it enables the model to acquire more generic information because it is pre-trained on a bigger out-of-domain dataset. From a clinical standpoint, high sensitivity guarantees that patients with COVID-19 infection receive few false negatives, resulting in missed diagnoses, and high PPV ensures that patients with COVID-19 infection receive few false positives, putting an unneeded strain on the health-care system.

The high sensitivity and NPV of our Bit-M algorithm assures that COVID-19 negative results are real negatives in the great majority of instances, guaranteeing that results obtained for COVID-19 negative individuals are reliable and dependable. The task of handling false positives or rather false negatives is just the same; for instance, we cannot afford to mistake a COVID-19 positive person for a COVID-19 negative patient because the individual may bring it back to the society, hoping he or she is devoid of COVID-19, likely to result in public transmission. When we mistakenly diagnose too many COVID-19 negatives as positives, it puts a strain on the healthcare system and raises alarm among the population. If a negative

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individual is diagnosed as positive, it may cause psychological stress.
In the results and discussion sections, selected papers that best illustrate common findings and outcomes (effects) of Quantum Computing are examined; the corresponding tables included all of the articles studied and grouped for that topic, and each article is only featured once. In the debate, important information from field of quantum computing is cited.

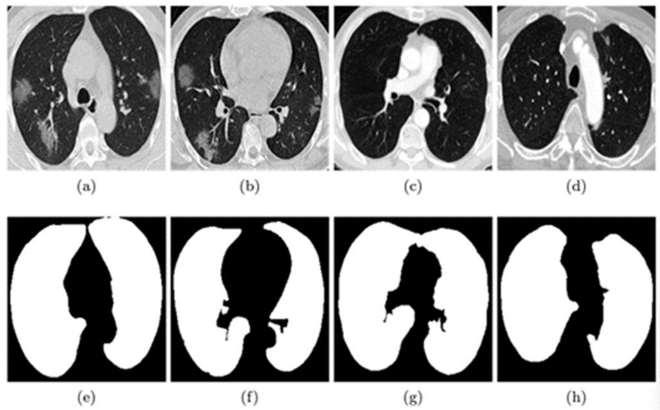

Figure 3.1 The samples and obtained mask images by using ConvLSTMU-Net model. a, b, c and d are sample images. e, f, g and h are mask images.

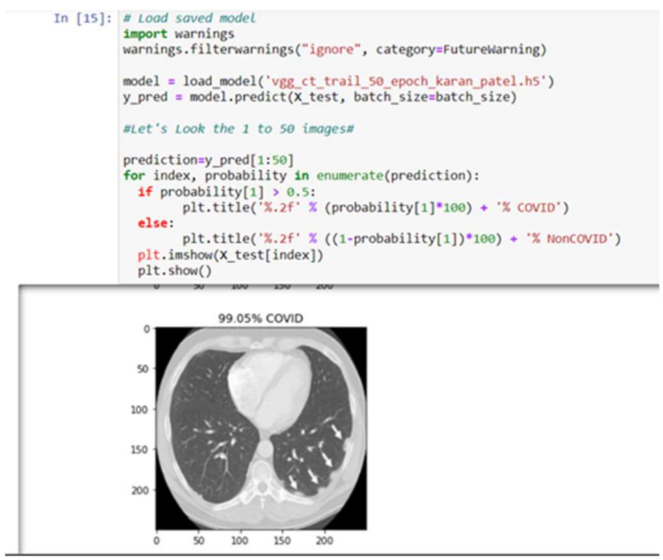

Figure 3.2 COVID Positive Image

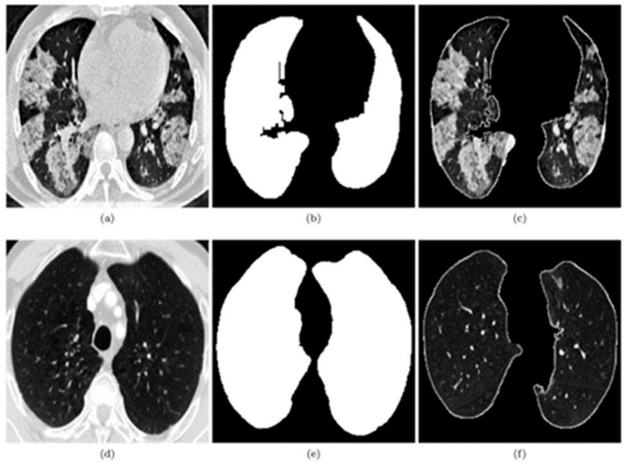

Figure 3.3 The sample images after applying graph-cut image processing. a, d are Sample images. b, e are mask images. c, f are region of interest images.

Experimental Evaluation:

The accuracy rate indicates how many of all test data were accurately identified and calculated.

$$\textbf{Accuracy}=\frac{T_p+T_N}{T_p+T_N+F_P+F_N} \qquad \textbf{(1)}$$

Precision is defined as the ratio of correctly predicted COVID-19 instances divided by the number of cases accurately predicted.

$$\textbf{Precision}=\frac{T_p}{T_p+F_P} \qquad \textbf{(2)}$$

The recall is defined as the percentage of correctly categorised labels in actually positive patients and is computed as follows.

$$\textbf{Recall}=\frac{T_p}{T_p+F_N} \qquad \textbf{(3)}$$

There is a trade-off between recall and precision, which are two key criteria. When you need to cope with this trade-off and find a balance between them, F1 Score is a good option.

$$\textbf{F1}=2*\frac{Recall*Precision}{Recall+Precision} \qquad \textbf{(4)}$$

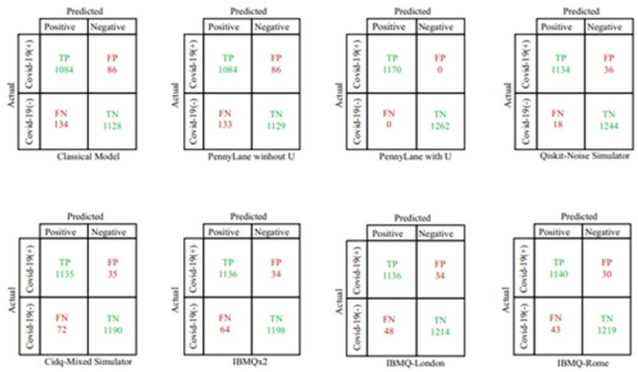

Figure 4. Comparision of obtained Values

Conclusion

Quantum computing has been and will remain a significant contribution towards technology and has helped in various projects including the one “detection of covid-19" using CT scans images. COVID-19 symptoms vary from patient to patient, making proper diagnosis difficult. COVID-19, like many other viral chest illnesses, has a set of symptoms that patients experience. As a result, clinicians confront a significant issue in diagnosing questionable cases before to completing the PCR, i.e., making a preliminary judgement on whether or not to proceed with further procedures. This gives the doctor reason to be unsure about the disease's diagnosis. As a result, this study aims to aid clinicians in making an accurate COVID-19 diagnosis by evaluating patient symptoms as well as CT imaging results to distinguish those from four other prevalent viral chest infections in an unclear setting.

As we understand more about the virus's behaviour and properties, potential research opportunities for COVID-19 studies are numerous and varied. The WHO has included more COVID-19 symptoms by the stage we finished our research.

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