

A Project Report
on
**COVID-19 detection on IBM quantum computer
with classical-quantum transfer learning**

*Submitted in partial fulfillment of the
requirement for the award of the degree of*

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CANDIDATE'S DECLARATION

I/We hereby certify that the work which is being presented in the thesis/project/dissertation, entitled “**COVID-19 detection on IBM quantum computer with classical-quantum transfer learning**” in partial fulfillment of the requirements for the award of the Bachelors of Technology submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of September 2021 to December 2021, under the supervision of Dr. M Arvindhan (Professor), Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering, Galgotias University, Greater Noida

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

Ritik katiyar, 19SCSE1180025

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Dr. M.
Arvindhan

CERTIFICATE

The Final Thesis/Project/ Dissertation Viva-Voce examination of Ritik katiyar, 19SCSE1180025 has been held on _____ and his/her work is recommended for the award of Bachelors of Technology.

Signature of Examiner(s)

Signature of Supervisor(s)

Signature of Project Coordinator

Signature of Dean

Date: December, 2021 Place: Greater Noida

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Contents

Title	Page No.
Candidates Declaration	2
Acknowledgement	3
Contents	4
Acronyms	5
Abstract	6
Chapter 1 Introduction	7
Chapter 2 Literature Survey/Project Design	9
Chapter 3 Functionality/Working of Project	11
Chapter 4 Results and Discussion	14
Chapter 5 Conclusion and Future Scope	16
Reference	17
Publication/Copyright/Product	20

Acronyms

B.Tech.	Bachelor of Technology
M.Tech.	Master of Technology
BCA	Bachelor of Computer Applications
MCA	Master of Computer Applications
B.Sc. (CS)	Bachelor of Science in Computer Science
M.Sc. (CS)	Master of Science in Computer Science
SCSE	School of Computing Science and Engineering

ABSTRACT:-

COVID-19 detection using quantum computer is very important in order to diagnose the coronavirus pandemic. It is usually performed by analyzing the presence of COVID-19 in a patient. This study shows that it is possible to detect COVID-19 from CT images with a high accuracy using a quantum transfer learning method. It was performed in real computers with different hardware configurations. By using a small number of data sets, we were able to obtain positive and negative classifications of COVID-19 in classical computers and quantum computers. Our results show that machine learning can be achieved in a very short time with a small quantum processor. Due to the properties of quantum, it is believed that computers with small data sets outperform those with large ones.

CHAPTER :-1

INTRODUCTION

The coronavirus outbreak (COVID-19), which began in China in December 2019, quickly expanded over the world, prompting the World Health Organization (WHO) to declare it a pandemic. During the pandemic, being able to diagnose COVID-19 in an infected patient is critical.

The nucleic acid amplification test (NAAT) of the respiratory tract or blood samples is predicted to give positive results utilising reverse transcription real-time fluorescence polymerase chain reaction (RT-PCR) to diagnose COVID-19. However, due to the low viral load in the early stages, the detection rate and sensitivity are limited, based on existing clinical experiences. As a result, incorrect findings are unavoidable. Furthermore, it can only produce positive or bad outcomes. The infection's severity and progression cannot be tracked. After taking the test sample from the patient, it may take 1 day or more to determine the test result. The test results are negative in a patient with suspected COVID-19, but if abnormalities are discovered in the CT imaging results, the patient should be isolated and treated as soon as possible. Because computerised tomography (CT), which provides both fast and accurate data, has a prognostic role in the early diagnosis of COVID-19, this is critical to aid clinician decision-making for quick isolation and proper patient therapy. The benefit of CT imaging in the diagnosis of COVID-19 is clear. As a result, specialists recommend CT imaging as the primary diagnostic tool for COVID-19. The computer-aided with machine learning algorithms system can speed up the diagnosis process due to the large number of infected patients and the excessive demand on healthcare staff.

Deep learning is used to solve a variety of real-world challenges, including autonomous vehicles, natural language processing, computer vision, and biological analysis. Deep learning requires a vast amount of data to operate well. Access to medical data, on the other hand, frequently necessitates specific approval, therefore it is not always possible. As a result, medical data sets are tiny in size. When the data set is small, generative adversarial networks or transfer learning can be utilised to augment the data. Quantum machine learning, on the other hand, can improve machine learning performance and efficiency by utilising quantum features such as entanglement and superposition . The superposition is the simultaneous evaluation of all potential states of a qubit state. The two-qubit states are entangled with one other if they are interconnected and this relationship holds even at infinite distance. This idea is defined as the instantaneous effect of any operation done in one qubit on the other qubit.

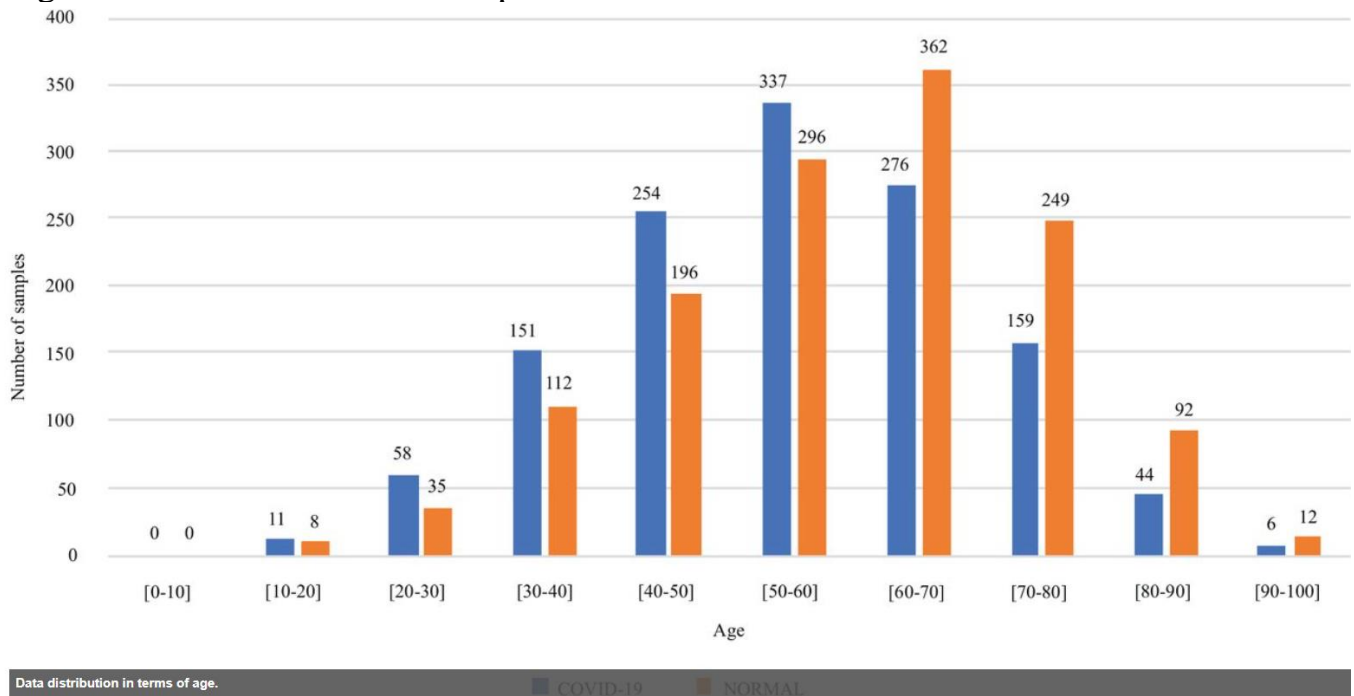
Chapter-2

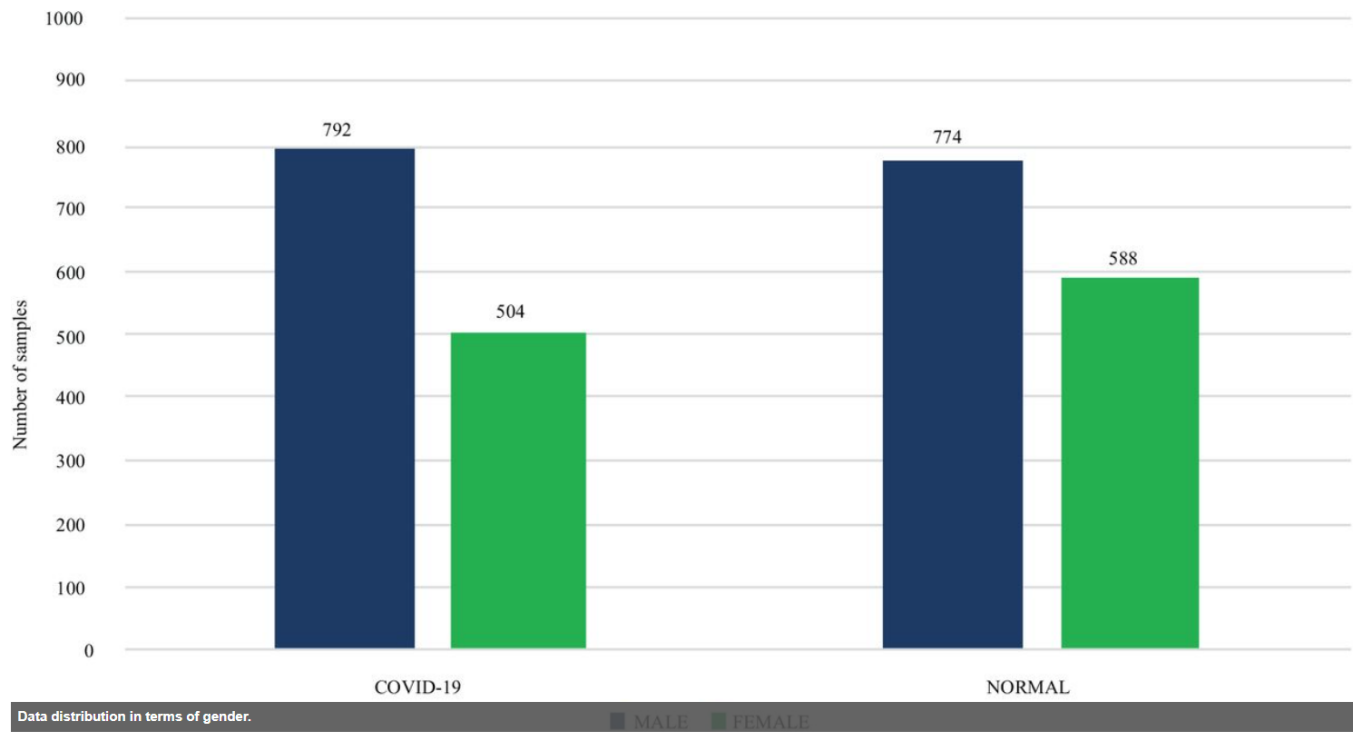
Literature Survey/Project Design

Chapter-3

Functionality/Working of Project

The data collection we used in our study was generated by merging datasets from free source databases. The data was cleaned up and a new dataset was formed. The final collection contains 2658 lung CT images, 1296 COVID-19 images, and 1362 Normal CT images. The data set took 3-4 months to collect. The COVID-19 discoveries in the dataset's photos show a variety of patterns. Furthermore, the majority of the photographs in the data set were approved by doctors and belong to patients from China, Italy, and Spain. Figure 1 and Figure 2 show the age and gender distributions of the CT images of patients in the data set, respectively. The photos in the data collection are from patients aged 10 to 100. According to Figure 1, the images of COVID-19 instances in the dataset are concentrated between 40 and 70 years old and have a normal distribution. Between the ages of 50 and 80, the photographs of typical cases are vivid and exhibit a normal distribution. Figure 2 shows that the number of male patients with COVID-19 is slightly larger than the number of female patients in the dataset.





Quantum computers and simulators

PennyLane default simulator¹, which is a noiseless simulator, Qiskit-Aer simulator², which we may construct with any noise rates, and noisy Cirq-Mixed simulator³, which is defined with 4 qubit cluster configurations, are the quantum computing simulators we utilise in our research. In addition, we used IBMQx2 , IBMQ-London and IBMQ-Rome as near-term 5-qubit IBM Quantum Computers⁴ with varying qubit connections and noise rates in our research .

Chapter-4

Results and Discussion

The accuracy, precision, recall, f1-score, and specificity of the models in this work are all quantified using metrics like accuracy (see Eq 1), precision (see Eq 2), recall (see Eq 3), f1-score (see Eq 4) and specificity (see Eq 5)[36].

The number of positive samples correctly estimated is TP, the number of false predicted samples is FP, the number of correctly estimated negative samples is TN, and the number of false predicted negative samples is FN. The terms accuracy, precision, recall, and f1-score are defined as follows in this context. The number of positive samples correctly estimated is TP, the number of false predicted samples is FP, the number of correctly estimated negative samples is TN, and the number of false predicted negative samples is FN. Accuracy, precision, recall, f1-score, and specificity are defined as follows in this context.

- The accuracy rate is an indication of how many of all test data correctly classified and calculated as follows.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (1)$$

- Precision is the ratio of how many of the COVID-19 cases correctly predicted and calculated as follows.

$$Precision = \frac{T_P}{T_P + F_P} \quad (2)$$

- The percentage of correctly classified labels in truly positive patients is defined as the recall and is calculated as follows.

$$Recall = \frac{T_P}{T_P + F_N} \quad (3)$$

- Recall and precision are two important metrics, and there is a trade-off between them. F1 Score is a good choice when you want to deal with this trade-off and seek a balance between them.

$$F1 = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (4)$$

- Specificity is defined as the proportion of true negatives (T_N), which got predicted as the negative (or true negative). In other words specificity is how many Normal(healthy) cases are correctly predicted and calculated as follows.

$$Specificity = \frac{T_N}{T_N + F_N} \quad (5)$$

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1084	FP 86
	Covid-19(-)	FN 134	TN 1128

Classical Model

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1084	FP 86
	Covid-19(-)	FN 133	TN 1129

PennyLane winhout U

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1170	FP 0
	Covid-19(-)	FN 0	TN 1262

PennyLane with U

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1134	FP 36
	Covid-19(-)	FN 18	TN 1244

Qiskit-Noise Simulator

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1135	FP 35
	Covid-19(-)	FN 72	TN 1190

Confusion matrix values of classical model and hybrid quantum model.

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1136	FP 34
	Covid-19(-)	FN 64	TN 1198

IBMQx2

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1136	FP 34
	Covid-19(-)	FN 48	TN 1214

IBMQ-London

		Predicted	
		Positive	Negative
Actual	Covid-19(+)	TP 1140	FP 30
	Covid-19(-)	FN 43	TN 1219

IBMQ-Rome

Chapter 4

Conclusion and Future Work

CONCLUSION

Machine learning, which in classical computers requires a lot of computing resources and takes a long time, can be done in quantum computers in a fraction of the time and with a lot less quantum resources. Although the quantum processors offered by IBM on the cloud take a long time to complete since the processes are queued, it is apparent that quantum machines outperform traditional computers in terms of performance and speed.

According to the findings, machine learning algorithms that require more processing and time in terms of resources and time can be completed in a relatively short amount of time utilising only four qubits in quantum computers. Considering the COVID-19 and Normal classification results on the quantum simulator and quantum real processors according to accuracy, precision, recall, f1-score, and specificity (for quantum simulators respectively 95 percent -100 percent, 96 percent -100 percent, 95 percent -100 percent, 95 percent -100 percent, 93 percent -100 percent and for quantum real processors respectively 95 percent -100 percent, 95 percent -100 percent, 95 percent -100 percent, 95 percent -100 (90 percent , 93 percent , 89 percent , 91 percent , 93 percent respectively). Furthermore, based on the results in Table 1, we can conclude that the U circuit that we use when encoding the classical data causes the performance results to improve.

We can conclude that quantum computers are favourable in tiny datasets and well classified according to their machine learning performance because of superposition and entanglement, which are superior features of quantum computers. It is obvious that these results will be superior both in terms of accuracy and time if the data is collected as quantum and the noise rates in the quantum processors are kept to a minimal.

FUTURE WORK

In the current time this is totally a new research field many research are still going on and we are contributing more of it. In this project we have used the open source databases and combining the datasets.

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Publication

Proof of acceptance:-