Incorporating an Intelligent System Based on a Quantum Algorithm into Predictive Analysis for Screening COVID-19 Patients

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Abstract: The work seeks to develop an expert prediction system based on artificial intelligence that can serve as a tool for healthcare professionals, as a diagnostic aid when estimating whether a patient with COVID will show rapid clinical improvement or whether they will be intubated. Such a system is important for hospital management in relation to the acquisition of materials, in addition to enabling early treatment of patients with COVID. The predictive analysis algorithm for screening COVID patients addressed was the Variational Quantum Classifier (VQC) and Deep Neural Networks (DNN). As a result, an accuracy of 90% was obtained for DNN and 96% for VQC.

1 INTRODUCTION

In the context of the pandemic of the new coronavirus or SARS-CoV-2, which causes the disease called COVID-19, the advance of technologies that allow precise information to be obtained and predictions to be made using computational methods, is already a practice adopted in some hospitals, particularly in intensive care units (ICUs).

The challenge of high cost continues to represent an obstacle to the implementation of dedicated data processing systems. Artificial intelligence (AI) techniques illustrate an example of what can be used to improve the hospital environment, proving useful in detecting alarms related to clinically significant vital signs and predicting clinical deterioration (Parreco et al., 2018).

COVID mainly targets the respiratory system, due to the affinity of the SARS-CoV-2 virus for mucosal cells and alveolar epithelial cells. In most cases, this syndrome is mild, but in some cases it develops into a serious condition. It can manifest as rapid pneumonia with acute respiratory failure, leading, in extreme situations, to death (Pessanha et al., 2021).

In general, it is recommended to use low-flow oxygen therapy devices, such as a nasal catheter and a non-rebreathing mask with a reservoir bag, to treat this hypoxemic condition, in order to minimize the dispersion of aerosols, since the disease is highly contagious through droplets containing the virus (Silva et al., 2020).

The appropriate use of non-invasive ventilation (NIV) in COVID-19 patients improves oxygenation, reduces the need for intubation and reduces mortality. Careful application of NIV is vital and must be aligned with the stages of the disease. In the ICU, various methods are used, including high-flow oxygen

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therapy, NIV and invasive mechanical ventilation, depending on severity (Wang et al., 2020) (Spadari and Gardenghi, 2020).

(Guérin et al., 2020) the prone positioning technique, known as the prone position, which has been used for years, is now recommended for sedated, mechanically ventilated patients taking neuromuscular blockers, especially those suffering from severe to moderate acute respiratory distress syndrome (ARDS).

In the context of the COVID-19 pandemic, a study carried out in China with a sample of 1,009 patients revealed that 41% of all patients required hospitalization, with more than 70% of cases considered serious requiring the administration of supplementary oxygen (Siemieniuk et al., 2018).

For Elharrar (Elharrar et al., 2020), only 63% of the total of 24 patients with hypoxemic respiratory failure with COVID19 were able to endure more than three hours in the prone position and oxygenation improved in only 25% of this sample.

Patients who remained in the prone position for three hours experienced an improvement in oxygenation, while those who did so for just one hour had unfavorable outcomes, including intubation (Elharrar et al., 2020).

Some studies explore the application of computational methods for monitoring and predictions based on hospital data. As an example, Meneses' study (Meneses, 2021) explores the use of machine learning algorithms, such as *Random Forest* and *Gradient Boost*, to predict ICU patient admission based on data from the first 24, 48 and 72 hours of hospitalization. Using data from a real hospital during the COVID-19 pandemic, Gradient Boost models showed the best performance metrics. For example, for data from the first 24 hours, Gradient Boost achieved AUROC of 92.7%, Accuracy of 61%, Sensitivity of 81.6%, Specificity of 86.1%, Accuracy of 85.1% and F1-Score of 69.9%. The study suggests that this approach can be an effective tool in predicting ICU admissions, helping with hospital management.

(Fabrizzio et al., 2023) proposes the development of a Web App using a decision tree model to estimate the risk of ICU admission for patients with COVID-19. Streamlit, created in Python, stratifies patients based on variables associated with Precision Nursing, assisting healthcare professionals in making clinical decisions. Despite the possible impact of vaccination on data, the Web App proved to be viable for presenting research results in an understandable way and supporting clinical decision-making.

Given the difficulties of treating respiratory failure in COVID-19 patients and their current high mortality rate, it is essential to develop software based on artificial intelligence to optimize this type of treatment. The system would be based on AI to apply scales and care flows objectively, learning from previous data to improve the effectiveness of procedures and thus improve care while reducing hospital costs.

This study presents a quantum computing algorithm for predictive analysis in the screening of COVID patients. This algorithm is based on the Variational Quantum Classifier (VQC). For comparison purposes, a widely recognized deep neural network (DNN) model was used.

The use of quantum computing is driven by improved artificial intelligence, faster processing of matrices and vectors and the joint properties of qubits.

Achieving the research objectives will allow patients to receive more effective treatment in cases of readmission for similar reasons, as well as benefiting new patients with similar profiles.

The article is carried out without any commercial or financial relationship that could be interpreted as a potential conflict of interest. It is divided into four sections: section 2 deals with the computational technique used in the work, while section 3 describes the results obtained and, finally, the conclusion.

2 METHODOLOGY

The representation of the process adopted can be seen in the flowchart 1. First there is the data input, then there are two architectures that can be used, flow 1 or flow 2. Flow 1 is characterised by the use of the DNN algorithm and flow 2 by the use of PCA followed by the VQC algorithm. Finally, the classification result is obtained.

2.1 Dataset

This project is based on the (Barros et al., 2022) dataset, which was developed from an observational, longitudinal and retrospective study of patients who were exposed to respiratory failure treatment at a reference hospital for the treatment of COVID-19 in Teresina-PI. Biometric data and monitoring signs were taken into account.

The dataset shows only patients with respiratory failure diagnosed with COVID-19 by the new SARS-CoV-2 coronavirus defined by molecular tests (PCR-RT).

The input elements that were part of the programme and data collection were: oxygenation control indices such as PaO2/FiO2, age, gender, address, pathological history, symptoms, monitoring data such

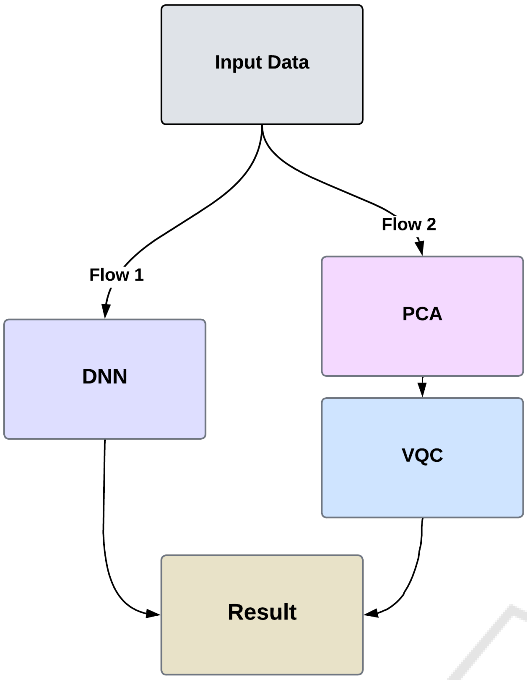

Figure 1: Flowchart of the process adopted in the study.

as: heart rate, respiratory rate, blood pressure, imaging reports, laboratory analysis data: lactate, platelets and INR, blood gas data, defined care procedures, average execution times and respective results.

The amount of data used in the proposed architecture is 476 patients, 70% for training and 30% for validation.

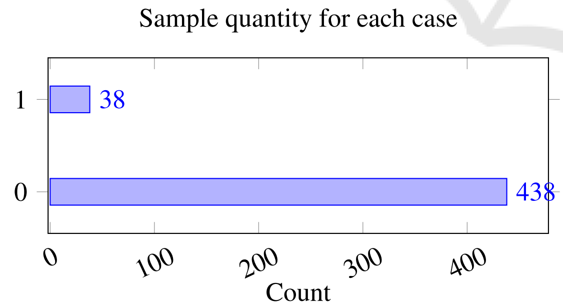

Figure 2: Quantity of samples.

Figure 2 shows the distribution of the number of samples in the dataset for different scenarios: 0 represents the cases in which there was clinical improvement without the need for intubation, while 1 indicates the patients who required intubation for treatment.

2.2 Deep Neural Networks

The DNN belongs to the Artificial Neural Network family (Passafaro et al., 2020). Figure 3 shows a representation.

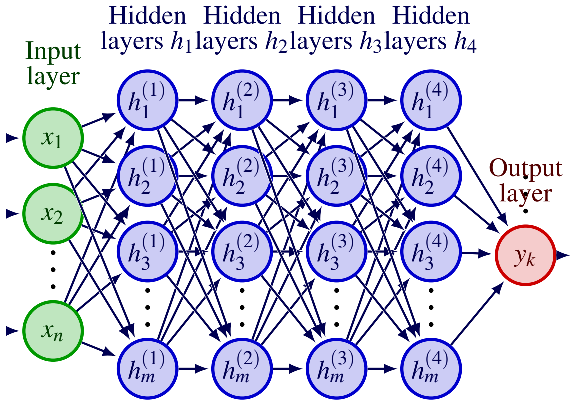

Figure 3: Schematic representation of DNN.

They are typically feed forward networks in which the data flows from the input layer to the output layer without backtracking and the connections between the layers are unidirectional and never touch a node again.

The outputs are obtained by supervised learning with data sets of some information based on ”what we want” by means of backpropagation.

The DNN architecture adopted in this work, as illustrated in Figure 3, is composed of the input layer, represented by the values $x_1, \ldots, x_n$, responsible for receiving the data without reducing resources. This layer has 90 variables, with $x_n = 90$.

Then, the information flow passes through four hidden layers $h_1, \ldots, h_4$. The first h_1 layer contains 16 units, while the second h_2 has 24 units, both using the ReLU activation function. To avoid *overfitting* problems, a Dropout layer is incorporated with a rate of $rate = 0.5$. Subsequently, two additional layers h_3 and h_4 are applied, each with 20 and 24 units, respectively.

The output layer y_k is composed of a sigmoid function that maps any real value to the range between 0 and 1 (Zaheer and Shaziya, 2018).

$$f(x) = sigmoide(x) = \frac{1}{1+e^{-x}} \tag{1}$$

As x becomes large and positive, e^{-x} approaches zero, and the fraction $\frac{1}{1+e^{-x}}$ approaches 1. Likewise, when x becomes large and negative, e^{-x} becomes large and the fraction approaches 0. The output $f(x)$ is the classification probability, which can have two values: The value ”0” corresponds to a patient who will improve clinically without the need for intubation and the value ”1” corresponds to a patient who will need to be intubated.

2.3 PCA

The visualisation of the PCA process adopted in the methodology, as shown in the flowchart 4, is characterised by data input, in which the dimension of the existing columns in the data set is reduced from 90 variables to 2 characteristics, which is the number of qubits used in this project. The technique used is known as probabilistic principal component analysis (PCA). More details on PCA can be found in the work by Tipping (Tipping and Bishop, 1999).

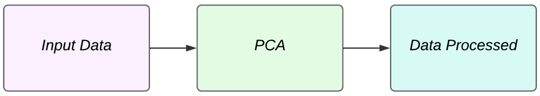

Figure 4: Flowchart for using PCA on data.

This technique synthesizes information efficiently, preparing the data for the proposed VQC quantum model. The goal is to improve model efficiency, explore relationships and patterns, and make the data structure easier to understand.

2.4 Variational Quantum Classifier

Variational circuits play a role in quantum machine learning similar to that of neural networks in classical machine learning (Schuld et al., 2020). The variational circuit used consists of three main parts, as shown in figure 5.

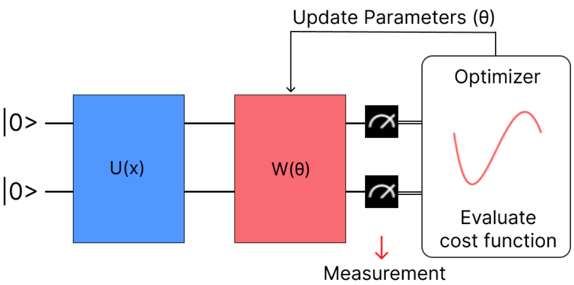

Figure 5: Schematic representation of the VQC.

The VQC consists of a $|0>^n$ state preparation phase, in which it encodes the x classical data into qubits, using the AngleEmbedding encoder, which encodes N features in the rotation angles of n qubits. The N represents the number of input features to be embedded, where $N \leq n$.

Before the x input data reaches the $U(x)$ coding block, this data is pre-processed using PCA to reduce the features, as illustrated in figure 4.

Given an encoded feature vector $U(x)$, the layer structure of the variational circuit represented by block $W(\theta)$ maps the vector and applies different angular rotations. Optionally, it includes some entanglement gates between them.

The θ parameters of this circuit are then trained in a classical optimisation cycle using the Adam optimiser. For more details on the optimiser, we suggest reading (Kingma and Ba, 2017).

The output information is obtained by performing a measurement with an observable operator in the base Z, which will be applied to a subset or all of the qubits, thus obtaining a classical bit string $z \in \{0,1\}^n$. The string is then mapped by a cost function C, given by the equation 2. The real labels are compared with the circuit labels $\{-1,1\}$, where -1 corresponds to the patient with clinical improvement without the need for intubation and 1 to the patient who will need to be intubated. The optimiser is then used to optimise the circuit. And the results of the measurements tell the classic optimiser how to adjust the θ parameters, as shown in figure 5.

$$C(\theta) = \sum_k f_k(Tr[O_k U(\theta)\rho_k U^\dagger(\theta)]) \tag{2}$$

3 RESULTS

This section presents the results obtained in each development flow of this article. A comparison is presented based on the accuracy of the implemented pretrained neural networks, as detailed in table 1. This metric is critical, demonstrating the comprehensive accuracy of the model.

Table 1: Accuracy comparison table between DNN and VQC.

Models	Accuracy
DNN	90%
VQC	96%

The red line in figure 6 shows the evolution of accuracy over the seasons, with the value before the second season reaching approximately 90% and remaining stable. The green line, meanwhile, shows the losses, demonstrating the model’s consistency.

Figure 7 shows that accuracy reached a higher value after the ninth season and was increasing. The green line representing losses showed lower values from the eighth season onwards than in figure 6.

Analysing figure 7, it can be seen that the quantum algorithm adjusted to the data fed into it and was able to maintain the training efficiently without any change considered substantial in the results over the epochs.

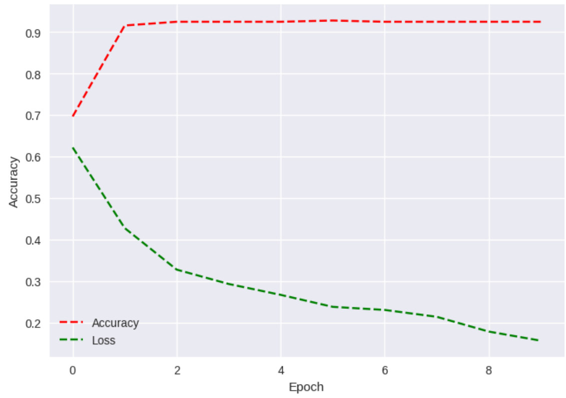

Figure 6: DNN accuracy and loss graph.

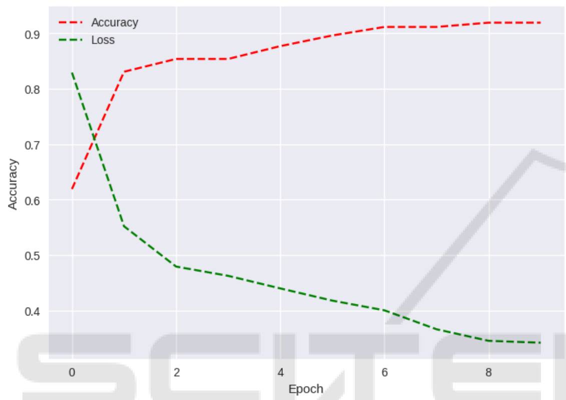

Figure 7: VQC accuracy and loss graph.

4 CONCLUSION

Thus, considering that the process of managing respiratory failure is made up of a series of interconnected diagnostic and therapeutic events with different specificities, it is suggested that a system be developed with a view to progressively standardising care through AI, in order to increase assertiveness and, consequently, reduce hospital costs.

The study had two limiting factors, namely the high number of variables analysed (90) and the small number of patients.

Two artificial intelligence techniques were used, DNN and VQC, with learning strategies. Based on the results, the study showed that the quantum computing algorithm (VQC) was able to predict different types of data with a reduction in the errors to be processed and, therefore, the possibility of carrying out the prediction and classification process with greater precision.

Accuracy can be better observed in the table 1. It can be seen that the VQC method is more accurate than DNN, with accuracy results of 96% and 90% respectively.

Future activities include testing other algorithms and even developing an application for use by society.

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