A Hybrid Method Based on Quantum-enhanced RNN and Data Integration for the Prediction of COVID-19 Outbreak

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Abstract

Due to the continuous spread of COVID-19 worldwide, it is urgent, especially in the data science era, to develop accurate data driven decision-aided method to early detect its outbreak. Currently, Deep Learning and especially Recurrent Neural Networks (RNN) are one of the promising methods to accurately predict COVID-19 outbreak. However, designing an accurate RNN is always a challenging task because RNN often require big data and computational cost. To overcome these challenges, we propose in this paper a novel method to predict daily COVID-19 positive cases that consists of two steps: 1) data integration where medical data and weather data are integrated to improve both data quantity and quality especially when we deal with countries with less facilities of collecting data and 2) quantum improvement where quantum and classical RNN are integrated to provide super-calculator for the prediction. Experiments on six countries from Africa (Tunisia, Algeria, Senegal, Cameron, Niger, and Nigeria) indicate two main results. First, through data integration, a correlation between medical and weather data is detected where we note a real impact of the weather on COVID-19 outbreak. Second, compared with classical RNN, quantum-enhanced RNN trained on augmented data achieved the best results in terms of accuracy as well as root mean square error (RMSE) and it required the lowest time for training. Thus, our main contributions are i) to enrich medical data by weather data to improve data quality and quantity and ii) to enhance RNN by quantum layers to accurately and speedily forecast COVID-19 outbreak. All implementations and datasets are available online to the scientific community at https://github.com/nasriAhmed/Master_Covid.git.

Keywords: Deep Learning, RNN, Quantum Neural Networks, Covid-19

1. Introduction

COVID-19 is a global pandemic which is persistently threatening public health worldwide. In order to fight against this pandemic and to better control it, predicting the probability of COVID-19 outbreak has been studied in recent years attracting the attention of practitioners and academicians alike especially in the data science era. In fact, healthcare analytics, in the data science era, are introduced to provide accurate techniques and tools to properly manage this big and complex data and to support decision making in healthcare

[1]. In this context, a significant development of deep learning techniques is recently noticed, dealing with their advantages to accurately predict COVID-19 outbreak [2]. In particular, recurrent neural networks (RNN) are promising and powerful deep learning solutions for forecasting the time-series COVID-19 data thanks to their internal memory that can remember the important features of the input sequential data and which allows them to accurately predict the future [3] and [4]. Although many researches on deep learning-based prediction and mainly RNN have been carried out, it still remains a hot research topic because of the following major issues. First, in order to be able to give performing results, RNN often require big data and huge numbers of training data. Thus, these solutions cannot allow an accurate prediction of COVID-19 outbreak when we deal with less facilities of collecting data and we do not have access to big data. Thus, a good quantity of data is a key prerequisite to improve COVID-19 outbreak prediction accuracy. But, how can we enrich data to increase the size of the dataset especially for countries with less facilities of collecting data?

Second, RNN often require huge computational cost to be able to be trained on the needed big data. In this context, recently, there is an increasing focus on quantum machine learning (QML) where quantum computing, the amalgamation of quantum physics and computer science, is finding a vital application in providing speedups for machine learning problems, critical in our 'big data' world [5]. Recent developments in quantum computing have led researchers to explore and to provide a more comprehensive framework for deep learning when compared to the classical computing [6]. QML supersedes classical machine learning by harnessing quantum effects for computational vantage providing polynomial and even exponential speedups for specific problems [7]. In fact, QML reduces the training time of deep learning [6]. So, our research question here is how can we improve the accuracy of classical deep learning models with quantum computing paradigm?

To address the above research questions, our salient contributions to improve the accuracy of COVID-19 outbreak prediction, in this paper, mainly focus on two dimensions: a data dimension and a functional dimension. 1) From a data dimension, we aim to increase the size of the dataset by investigating the enrichment of data where medical data (presenting daily COVID-19 confirmed, recovered and deaths cases) and weather data (presenting temperature and humidity) are integrated to improve both data quantity and quality especially when we deal with countries with less facilities of collecting data. 2) From a functional dimension, we aim to improve the accuracy and the convergence of predictive models by investigating the integration of classical and quantum RNN where quantum layers are added to enhance the accuracy and the rapidity of classical RNN.

The outline of this paper is as follows. Section 2 presents RNN models that will be used in this research. Section 3investigates related research works to RNN based solutions of COVID-19 outbreak prediction. Section 4 illustrates our contributions to deal with a novel method for COVID-19 outbreak prediction based on quantum-enhanced RNN and data integration. These contributions are evaluated in section 5 by exposing our experimental settings and discussing the results. Finally, Section 6 concludes this research and presents some future works.

2. Background Knowledge of Recurrent Neural Networks

RNN, [8], are robust and powerful type of artificial neural networks that uses existing time-series data to predict the future data over a specified length of time such as the prediction of COVID-19 outbreak[4]. In fact, RNN are very promising deep learning techniques due to their internal memory that can remember the important features of the input sequential data which allows them to accurately predict the future. In RNN, the current state of the model is influenced by its previous states because the output of the previous timestamp as well as the current timestamp will be fed into the RNN cell.

However, simple RNN have shorter memory to remember the features as they can only recollect the recent information but cannot recollect the earlier information. In fact, due to vanishing gradients, it is very difficult to train RNN for long input sequences. Hence, Long short-term memory (LSTM), Gated recurrent unit (GRU) and Bidirectional LSTM (Bi-LSTM) provide improvements of simple RNN to overcome their drawbacks.

In fact, LSTM [9] have been proposed to overcome the problem of the vanishing and exploding gradients. The LSTM cell memory will be stored and converted from input to output in cell state. LSTM cell consists of the forget gate, input gate, output gate and update gates. The forget gate decides what to forget from the previous memory units, the input gate decides what to accept into the cell, the update gate updates the cell, and the output gate generates the new long-term memory. So, LSTM cell has an input sequence at a given time step, a long-term memory and a short-term memory to generate an output sequence at a given time step, a new long-term memory and a new short-term memory where the input gate decides which information must be transferred to the cell. Then, Bi-LSTM [10] are bidirectional LSTM where the learning algorithm with the original data is fed from beginning to the end as well as from end to beginning in time which allows the networks to have both backward and forward information about the sequence at every time step. Thus, in Bi-LSTM, inputs will be processed from past to future and from future to past so they are able to preserve information from both past and future. Furthermore, GRU [11] are considered as simplified and improved version of LSTM because they require less training time. In fact, the GRU cell operation is similar to LSTM cell operation but GRU cell requires one hidden state that merges the forget gate and the input gate into a single update gate. In addition, GRU combine the cell state and hidden state into one state. Thus, the number of GRU gates (update and reset gates) has been reduced compared to the total number of LSTM gates.

We will present in the next section existing works that are based on the use of RNN to predict COVID-19 outbreak.

3. Related Work

At present, the existing RNN deep learning-based solutions in the field of COVID-19 prediction can be classified as follows: classical or quantum solutions. As classical RNN solutions, [2], for example, proposed six RNN deep learning models that will be used later for COVID-19 time-series forecasting namely RNN, LSTM, Bi-LSTM, GRU, and VAE (variational autoencoder) where VAE achieved better forecasting accuracy in comparison to all other models. In [4], authors aim to forecast the trend of COVID-19 cases for 60 days in top-10 highly affected countries using RNN along with GRU and LSTM cells. In [3], autoregressive integrated moving average (ARIMA), support vector regression (SVR), LSTM and Bi-LSTM are assessed for time series prediction of confirmed cases, deaths and recoveries in ten major countries affected due to COVID-19 where Bi-LSTM generates lowest mean absolute error (MAE) and root mean square error (RMSE). The second class emphasizes attempts that used quantum computing to assist classical RNN based deep learning. For example, [7] presented two kinds of quantum neural networks: a Quantum Back propagation Multilayer Perceptron (QBMLP) which utilizes the superposition feature and complex numbers and a Continuous Variable Quantum Neural Network (CVQNN) that uses Gaussian and non-Gaussian gates to perform affine and non-linear transformations. In short, we found in recent studies that acceptable attention has been paid to integrate quantum computing in deep learning models, in particular quantum RNN to predict the outbreak of COVID-19. However, most of the existing models present a challenge in terms of efficiency and scalability because most of the models require massive data to be able to generate accurate results which increases models' complexity. Based on the above, we propose in this paper a hybrid method that investigates not only the integration of classical and quantum RNN but also the integration of data to predict daily COVID-19 confirmed cases more efficiently.

4. Method

The novelty of this research is to propose a hybrid method of daily COVID-19 cases prediction that can be used as a decision support tool for forecasting COVID-19 epidemic trends worldwide. This method consists of two main steps. The first step is based on the integration of medical and weather data to enrich data and to improve both its quantity and quality. The second step is based on the integration of classical and quantum neural networks to improve the accuracy and the rapidity of the prediction.

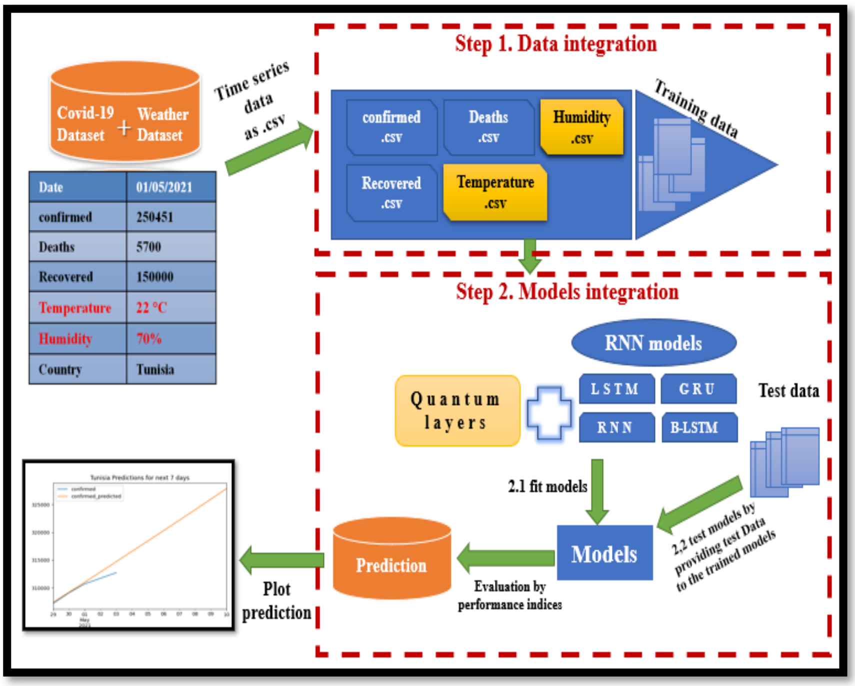

Figure 1 Pipeline of the proposed method.

4.1. Step 1: Data Integration

In this step, we deal with the data acquisition and integration, as well as how these data are processed in order to proceed to the training step of predictive models. In fact, in this first step, we address the fusion of different sources of information toward solving the problem of small and insufficient data. For data acquisition and integration, we are using two sources of data (medical data and weather data). Medical data to be used in this work are administrative medical data that have been acquired from[1]. These data include COVID-19 confirmed cases (CC) as well as the death cases (DC) and the recovered cases (RC) daily numbers across the world starting from January 22, 2020 until November 30, 2021. These data represent time series COVID-19 cases datasets worldwide where rows represent countries and columns represent cases number for each country. From these data, including time series datasets and global situation reports, we only extract the data of 6 countries from Africa that are Tunisia, Algeria, Senegal, Cameron, Niger, and Nigeria. We also study the ongoing COVID-19 outbreak for Tunisia using the time series data provided by the official sources the Tunisian National Observatory of New and Emerging Diseases2 that represent official data published by the Tunisian ministry of the public health. Then, in order to augment the dimensionality of the dataset, we have also decided to enrich the features space by considering weather data, we combined the medical data with the weather data to discover possible dependencies between them which allows us to explore the impact of weather on COVID-19 outbreak. In fact, we have retrieved daily weather data from3 for all days in the period of study. The weather features that are considered are temperature (T in Celsius degrees) and humidity (H). The values of these variables for the studied days and locations were used to extend the dataset of medical data. Thus, after fusing data, we obtain for each country an initial dataset, that we call dataset 0, which represents a time series dataset characterized by 5 features i.e. CC, DC, RC, T and H. In fact, this dataset can be considered as a sequence of vectors, X(t), where X represents COVID-19 confirmed cases, death cases, recovered cases, temperature and humidity and t represents elapsed time i.e. the studied period (days) where x varies continuously with t.

1 https://github.com/CSSEGISandData/COVID-19/

2 http://onmne.tn/fr/index.ph

3 https://www.meteoblue.com/en/weather/historyclimate/weatherarchive/

For data preparation, it is helpful to precise here that in this work, COVID-19 outbreak prediction will be approached as data supervised learning problem where the input is X(t) and the output represent the trend for the next week. In particular, we will be based on historical data to predict future data. In this context, we have to know how many steps we need to predict the daily confirmed cases for the seven following day. To do so, we have used the sliding window method to determine the size of the window that accumulates the historical time series data to predict next days. In the process of sliding window, we have tested various values of window size (2, 3, 5, 7) and the window size 3 reached the less error approximation. Thus, we segmented our data to this optimum size where each 3 days' historical data will be used for the prediction of next seven days COVID-19 confirmed cases.

4.2. Step2: Models' Integration

In this step, we aim to enhance the accuracy of classical RNN models (simple RNN, LSTM, GRU and Bi-LSTM) by combining them with quantum learning. In fact, Quantum Neural Networks (QNN) are computational neural network models based on the principles of quantum mechanics such as superposition, entanglement, and interference to perform rapid calculations. Our motivation to use QNN in our research is their ability to achieve better effective results and to train faster compared with classical feed forward networks [12]. Otherwise, according to [7], QNN are still somewhat unexplored in terms of their applicability to eclectic and pragmatic problems. Thus, in this step, we aim to improve the accuracy and the rapidity of the predictive models by investigating the integration of classical and quantum RNN where quantum layers are added to enhance the accuracy of classical RNN. In fact, we first construct 4 classical RNN Models (LSTM, B-LSTM, GRU and Simple RNN) that individually predict the epidemic trend of COVID-19. Then, these algorithms were combined with Quantum Neural Networks (QNN), from which we obtain a hybrid model (RNN + QNN). These models were developed in python using PennyLane which is a Python 3 software framework for optimization and machine learning of quantum and hybrid quantum-classical computations and simulations were performed on Graphical Processing Units (GPUs) of the Google COLAB cloud computing platform. It is helpful to indicate here that in order to verify the generalization capacity of the proposed method and to avoid the overfitting of the different models, we are based on the classical cross validation approach by splitting the available data into two sets (80% for the training set and 20% for the test set).

5. Results

In order to validate the proposed predictive method for forecasting COVID-19 outbreak, we have chosen six African countries (Tunisia, Algeria, Senegal, Cameron, Niger and Nigeria) that are generally with less facilities to collecting complete and reliable data and that are implicated in our healthcare project coordinated by the Pasteur International Network association to fight COVID-19 (see Acknowledgement section).

Furthermore, the performance of models is measured by the root mean square error (RMSE) which is commonly used in other fields as well as in the prediction of the spread of infectious diseases and the accuracy that identifies the overall efficiency of the models. We also considered the time of models training as a comparison criterion to evaluate the impact of QNN integration. Experimental results of training the classical RNN (LSTM, Bi-LSTM, GRU and Simple RNN algorithms) on medical data for the selected countries are summarized in Table 1. The evaluation of these models is based on the accuracy (Acc), RMSE and time (in seconds) of models training (Time) using the time series of selected countries. Then, to evaluate the enrichment of data (integration of medical and weather data), and in order to facilitate data acquisition, we conducted our experiments on one case study i.e. Tunisia where weather data are obtained from[4].

[4] https://www.meteoblue.com/en/weather/historyclimate/weatherarchive/tunis_tunisia_2464470?fcstlength=1y&year=2020&month=1

Table 1: Results of classical RNN trained on medical data

	Classical RNN (trained on medical Data)					
	LSTM			Bi-LSTM		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	31.109	22.05	0.95	2795.511	35.70	0.89
Algeria	92.82	21.15	0.92	1279.835	37.61	0.79
Senegal	16.947	23.80	0.97	426.451	33.68	0.77
Cameroon	64.126	22.94	0.96	431.653	33.46	0.77
Niger	21.713	24.03	0.9	80.62	36.21	0.70
Nigeria	44.617	23.12	0.9	756.857	30.04	0.75
	GRU			Simple RNN		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	61.57	24.65	0.93	587.759	22.86	0.91
Algeria	51.140	28.44	0.91	1177.323	22.79	0.82
Senegal	23.639	22.79	0.95	274.746	21.65	0.86
Cameroon	38.860	23.60	0.93	226.314	22.73	0.88
Niger	13.634	28.16	0.91	23.28	21.00	0.92
Nigeria	39.257	24.05	0.92	498.083	20.88	0.84

Table 2: Results of classical RNN with medical and weather data

	Classical RNN trained on integrated data					
	LSTM			Bi-LSTM		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	28.156	22.21	0.99	280.62	29,01	0.98
	GRU			Simple RNN		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	31,024	22,09	0.99	187.759	22,98	0.97

Next, experimental results of the integration of models (classical RNN and QNN) trained on medical data for the six selected countries are summarized in Table 3.

Table 3: Results of integrated models (Classical RNN + QNN) trained on medical Data

	Integrated models trained on medical Data					
	LSTM			Bi-LSTM		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	36.46	15.51	1.00	795.543	26.10	0.92
Algeria	72.62	16.85	0.99	579.750	32.54	0.89
Senegal	14.547	16.84	1	336.491	24.58	0;88
Cameroon	64.126	17.14	0.99	231.053	27.16	0.80
Niger	21.713	19.03	1	79.962	30.01	0.82
Nigeria	24.517	18.12	0.99	706.107	24.44	0.85
	GRU			Simple RNN		
	RMSE	Time(s)	Acc	RMSE	Time(s)	Acc
Tunisia	40.907	16.05	1	347.749	17.06	0.99
Algeria	50.740	23.24	0.96	977.393	19.19	0.88
Senegal	33.249	19.19	1	124.706	18.07	0.90
Cameroon	32.560	18.60	1	126.304	18.23	0.92
Niger	23.604	22.66	0.97	25.288	18.33	0.94
Nigeria	39.257	20.95	0.99	478.183	17.75	0.88

In this last part, we will evaluate integrated models (quantum data with classical RNN) that are trained on integrated data (medical with and weather data). In table 4, we show experimental results of Tunisia case study.

Table 4: Results of integrated models (Classical RNN + QNN) trained on integrated data

	Integrated models trained on integrated data					
	LSTM			Bi-LSTM		
	RMSE	Time(s)	Accuracy	RMSE	Time(s)	Accuracy
Tunisia	22.006	16.21	0.99	210.34	26,77	0.99
	GRU			Simple RNN		
	RMSE	Time(s)	Accuracy	RMSE	Time(s)	Accuracy
Tunisia	27,924	16,09	0.99	77.159	16,98	0.99

6. Discussion and Threats of Validity

Recently, deep learning models and especially recurrent neural networks demonstrated important improvements when handling and forecasting time-series data. In addition, parallel computing is a promising solution for building efficient deep learning models. In this study, we proposed a generic and accurate data-driven method for forecasting COVID-19 epidemic outbreak by integrating multi- source data and enhancing classical RNN (simple RNN, LSTM, Bi-LSTM and GRU) with QNN. This proposal is unique as regards bringing together integration of data and integration of models. The proposed predictive method is validated on four experimental scenarios. In the first and second experimental setup, we respectively evaluated classical RNN trained on only medical data for the six countries and then trained on integrated data (medical and weather data) for Tunisia case study. Then, in the third and fourth experimental setup, we respectively evaluated the enhancement of classical RNN with QNN trained on only medical data for the six countries and then trained on integrated data for Tunisia case study. Experimental results of the first experimental setup illustrated in Table 1 show that classical LSTM and GRU trained on medical data globally outperformed Bi-LSTM and Simple RNN in terms of accuracy and RMSE. Then, experimental results of the training of classical RNN on integrated data shown in Table2 demonstrated that data integration can indeed improve the prediction performance by reducing the RMSE error for all models. In fact, for Tunisia, LSTM, GRU, Simple RNN and Bi-LSTM respectively generate 0.95, 0.93, 0.91 and 0.89 when trained on medical data, then when they are trained on integrated data, their accuracy has been respectively improved to 0.99, 0.99, 0.98 and 0.97. Furthermore, through the third experimental setup that concerns the integration of models trained on medical data, experimental results of the six chosen countries illustrated in Table 3 show that, compared with results of classical RNN trained on medical data of Table 1, quantum enhanced RNN improve the prediction performance by generating highest accuracy and lowest RMSE and they need lowest time cost. Finally, in the fourth experimental setup, experiment results of Tunisia case study illustrated in Table 4, indicate that, compared with results of classical RNN in Table 2, quantum-enhanced RNN trained on integrated data achieved the best results in terms of accuracy as well as RMSE and they required the lowest time for training. The accuracy is 0.99 for all models and the time of training is reduced (classical LSTM, GRU, Simple RNN and Bi-LSTM respectively need 22.21, 22.09, 22.98 and 29.01 seconds however quantum enhanced LSTM, GRU, Simple RNN and Bi-LSTM respectively need 16.21, 16.09, 26.77 and 16,98 seconds to be trained).

In a nutshell, on the basis of demonstrated robustness and enhanced prediction accuracy, quantum enhanced RNN trained on integrated data can be exploited as an effective healthcare decision support tool to better control and predict COVID-19 outbreak. Thus, we also highlight the correlation between the spread of the epidemic and the weather as the consideration of meteorological data has improved the performance of predictive models.

With regard to threats of validity of this study, we assume, at this stage, that our research findings might have some threats of validity, and we try to self-assess them here in order to denote the trustworthiness of our experimental results, to what extent they are correct and not biased by our subjective point of view. In addition, we treat these potential threats according to the classification proposed in [13]. Concerning the construct validity, we assume that the provided measures could be biased regarding the researchers' expected results. However, RMSE has been used in this study, to evaluate the performance of the proposed predictive models, which is usually and commonly used in the prediction of epidemic diseases spreading [14]. Concerning the external validity, there might be some threats regarding the generalization of our proposed method. To overcome this issue, this method has been validated on six different countries which can provide more consistent feedback about the relevance of our results and their dependency on the used data.

7. Conclusion and Future Works

In this study, we proposed a generic and accurate COVID-19 outbreak predictive method that is based on the integration of data (combination of medial and weather data) and the and integration of models (classical RNN and QNN) where quantum integration has shown its potentials in improving RNN models in terms of solution quality and computational cost. The main outcomes of this research are i) to enrich medical data by weather data to improve data quality and quantity where a correlation between them is demonstrated and ii) to enhance RNN by quantum layers to accurately forecast COVID-19 outbreak. In terms of future works, we aim to enrich data from other sources such as social data. We aim equally to test the combination of quantum RNN with other deep learning models like convolutional neural networks within an ensemble learning framework such as in [15] in order to take advantage of their complementarity in the prediction of COVID-19 outbreak.

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