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Modeling recurrence of COVID-19 and its variants using recurrent neural network

Jesufunbi Damilola Bolarinwa[1], Olufunke Rebecca Vincent[1], Dada Olaniyi Aborisade[1], Cecilia Ajowho Adenusi[2], Charles Okechukwu Ugwunna[1]
[1]Department of Computer Science, Federal University of Agriculture, Abeokuta, Nigeria
[2]Linux Professional Institute, Nigeria Master Affliate, Abeokuta, Nigeria

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ABSTRACT

Coronavirus disease 19 (COVID-19), a disease caused by severe acute respiratory syndrome-coronavirus-2 (SARS-CoV-2), began as the flu and gradually developed into a highly infectious global pandemic leading to the death of over 6 million people in about 200 countries of the world. Its pathogenic nature has qualified it as a deadly disease, causing moderate and severe respiratory difficulty in infected individuals with the ability to mutate into different variants of the first version. As a result, different government agencies and health institutions have sought solutions within and outside the clinical space. This paper models COVID-19 possible recurrence as variants and predicts that the subsequent waves will be more severe than the first wave. Long short-term memory network (LSTM) was used to predict the future occurrence of COVID-19 and forecast the virus's pattern. Machine evaluation was performed using precision, recall, F1-score, an area under the curve (AUC), and accuracy evaluation metrics. Datasets obtained were used to test the data. The collected characteristics were passed on to the system classification network, demonstrating the function's value based on the system's accuracy. The results showed that the COVID-19 variants have a higher disastrous effect within three months after the first wave.

Corresponding Author:

Jesufunbi Damilola Bolarinwa
Department of Computer Science, Faculty of Physical Science, Federal University of Agriculture
Alabata Street, 111101 Abeokuta, Nigeria
Email: damilolajesufunbi@gmail.com

1. INTRODUCTION

The coronavirus called COVID-19 began as the flu and gradually developed into a global pandemic that has taken many lives with millions of infected persons. Some studies have shown that the virus has a particular pattern and that these patterns are dependent on the epidemic's complex transmission [1]-[3]. To find and assess certain infectious diseases, various methods were used to study epidemic rises under some conditions such as weather, region, and spread of the virus over time [4]-[6]. In December 2020, the United Kingdom (UK) and the Republic of South Africa authorities announced a version referred to as Corona VOC202012/01 and 501Y.V2. Another variant was then announced in Tanzania which was killing more people than the first variant that broke out in China. It is unclear how and when Corona VOC202012/01 emerged [7]. Corona VOC202012/01 was found from routine sampling and genomic testing. Tentative epidemiological, modeling, phylogenetic, and clinical findings suggest that transmissibility has been enhanced by Corona VOC202012/01. Preliminary research also revealed no difference in the incidence or frequency of diseases or reinfection among variant cases relative to other Corona VOC202012/01 [8]-[10].

The UK Corona VOC202012/01 has the phylogenetic analysis of South Africa's 501Y.V2 mutation, which revealed that South Africa's 501Y.V2 were distinct types. The new variants have essentially displaced SARS-CoV-2 viruses. Testing indicated that the variants were associated with a higher viral load resulting in higher transmissibility capacity. However, there was no firm evidence of more severe diseases related to the variants [8]. COVID-19 data are time sequences and sequential models have been widely supported to cope with their dynamic existence. In addition, the long short-term memory of recurrent neural networks was suggested as an appropriate tool for its analysis [11]. The reported study aimed to classify confirmed cases, mortality, and recovered cases of COVID-19 variants and construct a COVID-19 predictor to determine future patterns [12]. The analysis is based on a dataset of cases identified and reported up to 15 December 2020 for seven African countries. Many researchers have forecast the current coronavirus distribution, but the virus is a data collection of real-time series, which are complex. Therefore, sequential networks, statistical, and epidemiological models are good recommendations for its analysis [13], [14]. According to researchers, low specific humidity has been discovered to be a critical component in influenza laboratory transmission and the onset of seasonal influenza in the United States.

Previous studies have analyzed COVID-19 using artificial intelligence and machine learning techniques. Multilayer perceptron (MLP) and adaptive network-based fuzzy inference method (ANFIS) were used to determine the complicated behavior [15] of variance and forecast the spread of COVID-19. Reported cases were projected with the number of infected persons using a hybrid of support vector regression (SVR) and autoregressive integrated moving average (ARIMA) [16]. A radial base function (RBF) SVR model was also used to predict regular, recovered, and death cases [17], [18]. Another research used developed SVR and random forest (RF) ensemble predictors to predict patient numbers before being hospitalized [19], [20]. The deep learning algorithm demonstrated a vital role in studying and predicting enormous outbreak data patterns and helped prevent coronavirus's high spread in early exploitation [21]. Based on the research that has been carried out by different researchers, in this study, long short-term memory network (LSTM) is being proposed as an analyzing tool for COVID-19 due to its time-series nature. LSTM is a deep learning model with the capability of handling long-term dependencies. In machine learning, complicated problems are usually solved by gathering necessary data to give excellent output [22]-[25]. The rest of this paper is organized as follows, section 2 gives an insight into the method, section 3 shows the result gotten and section 4 gives a full discussion and conclusion.

2. METHOD

LSTM network is composed of memory blocks connected by layers to build more complex recurrent networks. The block contained in the network contains an intelligent component that makes it more desirable than a classic neuron and memory chain. In LSTM, there is also a modular chain and memory block mainly designed to store data longer. In addition, LSTMs contain modules that are linked together, more complex structures for repeated modules, and three different multiplicative units called 'gates.' With LSTM, long-term dependencies are possible, just as there is the tendency for long-time information recovery to provide excellent solutions to complex sequence problems. The proposed LSTM is made to recall every bit of knowledge over time to predict time series with the capability to identify and recognize previous input. It could be used to transfer intermediate information, with internal and external reference to feedback, while they can encode the time context. For the fact that feedback can both be internal and external, LSTM could learn patterns from records and generalize and forecast future virus cases. Hence, information is moved easily through the cells without any change.

It should be noted that LSTM learns more easily from long-term dependence. The gates of input, forget, and feeds input flows into the constant error carious (CEC) cell, process information, and output streams to the rest of the networks by the cells. Algorithm 1 depicts using LSTM for predicting the reoccurrence of COVID-19.

Algorithm 1. An LSTM recurrent neural network for COVID-19 variants' analysis

Input:	$\chi=(X_1,\ X_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ X_n)$
Output:	*Reoccurrence Prediction (RP)*
Parameters:	$(\mathcal{W}_i \mathcal{U}_i \mathcal{B}_i \mathcal{W}_c \mathcal{U}_c \mathcal{B}_c \mathcal{W}_f \mathcal{U}_f \mathcal{B}_f \mathcal{W}_\sigma \mathcal{U}_\sigma \mathcal{B}_\sigma)$
Process:	
Step 1:	*Initialize* $\mathcal{B}_\sigma\ \mathcal{C}_\sigma = \overline{0}$
Step 2:	*For* $t = 1 \ldots\ldots\ldots\ldots.,\ 360$ *do*
Step 3:	*Calculate* $F_t\ (I_t = \sigma\ (X_t\ W_{xi} + H_{t-1}\ W_{t-1} + \mathcal{B}_\sigma)\ (\mathcal{O}_t = \sigma\ (\mathcal{X}_t \mathcal{W}_{x\sigma} + \mathcal{H}_{t-1} + \mathcal{W}_{h\sigma})\ (\mathcal{C}_t = \mathcal{F}_t\ \theta\ \mathcal{C}_{t-1} + \mathcal{I}_t\ \theta \bar{\mathcal{C}}_t))$
Step 4:	*Update cell state* $\mathcal{C}_t\ (\mathcal{H}_t = \mathcal{O}_t \odot \tan h\ (\mathcal{C}_t))$
Step 5:	*Calculate* $\mathcal{C}_t\ (\mathcal{R}_t = \sigma\ (\mathcal{X}_t * \mathcal{U}_r + \mathcal{H}_{t-1} * \mathcal{W}_r)\ (\mathcal{U}_t = \sigma\ (\mathcal{X}_t * \mathcal{U}_u + \mathcal{H}_{t-1} * \mathcal{W}_1$
Step 6:	*End for*
Step 7:	*Reoccurrence prediction*
Step 8:	*End.*

In this study, a time series, the linear model is built using recurrence neural networks (RNNs) and LSTM blocks. Memory blocks, a key element of LSTM networks, are created to combat fading gradients through long-term memorization of network properties. Memory blocks in the LSTM architecture resemble differential storage systems in digital computers. With the aid of the activation sigmoid function, gates in LSTM process the data, and the output ranges from 0 to 1. To transfer only positive values to the next gates to get an outcome. The (1) here more details about LSTM,

$$Z_t = \sigma(Q_f.[P_t - 1, X_t]) + O_f, \tag{1}$$

where the weight matrix and the bias of the forgotten direction are collectively P, Z, and O, and the sigmoid function is σ,

$$I_t = \sigma(W_c[P_t - 1, X_t]) + O_I, \tag{2}$$

where I_t is the function of the input gate while σ is the output gate and

$$c_t = \tanh(W_c[P_t - 1, X_t]) + O_c, \tag{3}$$

determines the component that makes it output from the current cell state (Schmidhuber and Hoch Reiter 1997). Figure 1 shows the architecture model used in this study.

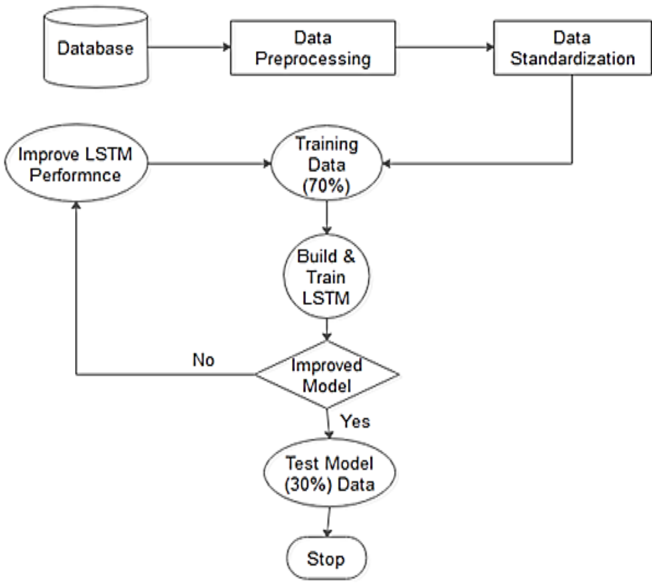


Figure 1. Proposed LSTM model

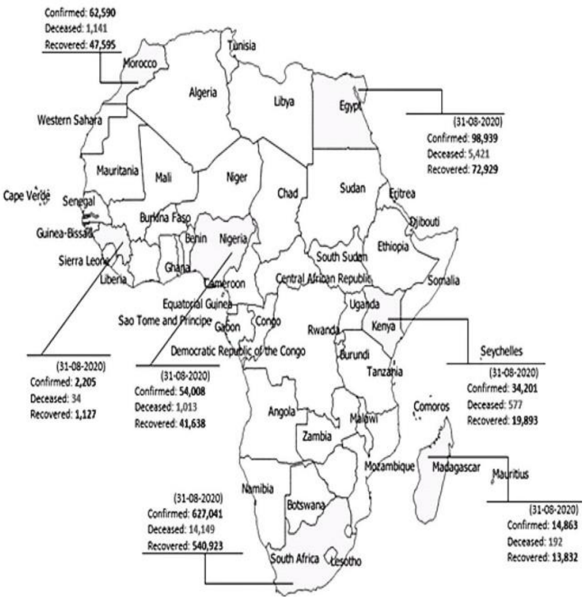
Data was collected from Africa center for diseases and Nigeria center for diseases and were stored on the system, which served as the database. The data was then retrieved from the database and was preprocessed by cleaning and checking for null values, and information not needed was then discarded. The data standardization came into play by checking for 0 s and 1 s, strings, and the character in the data since they were raw data from the websites mentioned. The data was divided into two: training and testing data. The training data took 70% and the testing data took 30%. LSTM was applied to the training data to measure the model's performance and accuracy, and the result was generated. The model was then retrained by hyper-turning the data when the LSTM performance was low due to a system factor or error in the data. If the model performed well in the first trial, it then proceeds to test the model by using the remaining 30% of the data. The system performance is being measured by using evaluation metrics.

3. RESULTS AND DISCUSSION

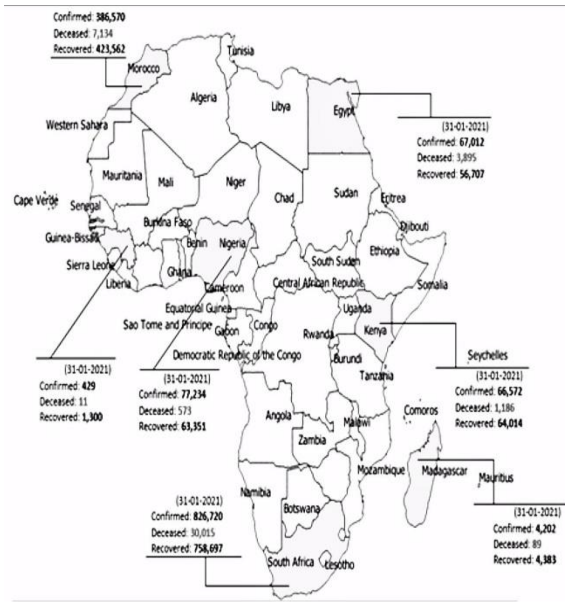
The data set was trained and modeled using the Python library and other necessary editor tools. The APIs for the recurrent neural network which is LSTM construct the existing model configuration. The dependent data structure was described and mapped to the current learning sequence by the model to forecast the number of reported cases in any given country. Using the models, the data structure change view shows country by the country daily occurrence of COVID-19 data history. This model's hyper-parameter tuning is performed rigorously. The dataset used for the study was gathered from six African countries via the center for diseases control. Other criteria considered in the dataset are the average number of female infections to the number of males infected. In addition, the age range for each individual will help make a good prediction. The training set is supplied to the LSTM network as a vector. Goals are compared to these metrics, and the weights used to modify the procedure are changed. The sample signals are subsequently transmitted online, where the aim values are determined using the weighted data. The map of Africa is represented in Figure 2, and the countries considered in the study are colored in yellow. Table 1 shows the data collected, and the data for each of the African countries selected are represented in Figures 2(a) and (b). The areas indicated shows the most affected countries in the African continent, and they are the countries selected for the study. Figure 2(a) shows the first wave of COVID-19 while Figure 2(b) shows the second wave of COVID-19, and Table 1 shows the total number of cases recorded, death, and recovered persons.

Table 1. Summary of the data collected for the training and testing of the model

Countries	Date	Cases	Recovered	Death 1
Nigeria	3 March- 15 July	34,259	13,466	760
Egypt	15 February-15 July	84,843	24,433	4,067
South Africa	6 March-15 July	311,049	13,495	4,453
Kenya	14 March-15 July	11,252	2,905	209
Morocco	3 March-15July	16,262	1,229	212
Madagascar	22 March-15 July	5,605	2,388	43



(a)



(b)

Figure 2. Map of the African continent, indicating with arrows the observation area for this study (a) first wave of COVID-19 and (b) second wave of COVID-19

The table summarizes the data collected for each country for the first wave of COVID-19 from the date it was first recorded in the countries. From the table, South Africa and Egypt have a high number of infected people and also a high number of fatalities than Nigeria follows. Since the data recorded was divided into 70% and 30% for the model's training and testing, March to May data recorded is used for the model's training, while June and July data is used for the (30%) testing. The high increase in cases can be linked to the stated countries' population, environment and human negligence or ignorance of health rules, also the regenerating of the virus in a more complicated genome in Table 2. The 2nd wave of the virus has a high tendency of infecting more population than the first wave, also it fights against the vaccination injected in the ody in some cases. The 0's and 1's used in the table represents the 'high' and 'very high'of each of the virus variant for each country. Table 3 show the results of some sample on the duration of recovery.

Table 2. First wave and second wave of COVID-19

Country	First Wave	Second Wave	Mortality	
			First Wave	Second Wave
Nigeria	0	1	0	1
South-Africa	1	1	1	0
Egypt	1	1	1	0
Kenya	1	0	1	0
Morocco	1	0	0	1
Madagascar	0	1	1	0

Table 3. Recovery rate and mortality rate recorded by the end of the first and second wave of COVID-19

Samples	Confirm Cases	Death	Recovery	Recovery Rate	Mortality Rate
3006	779	4	372	47.7635	0.513479
2542	745	6	340	45.6376	0.805360
2068	684	5	431	63.0117	0.730994
3058	661	6	143	20.0985	0.734214
1809	675	7	230	34.0741	1.03704
2504	667	12	274	41.0795	1.7991
2987	663	4	166	25.0377	0.603318
2523	661	19	137	20.7262	2.87443
2047	649	9	276	42.3720	1.36675
2032	627	12	397	63.3174	1.91366
2935	594	7	209	35.1852	1.17845
2207	587	14	344	58.6031	2.36601
2079	573	4	129	22.5131	0.69808
1953	566	8	395	69.788	1.41343
4205	561	17	344	61.3191	3.0303
2460	501	8	201	40.1198	1.59661
2140	490	7	382	77.9592	1.42857
7397	490	31	274	55.9164	6.32653
2539	452	8	229	50.6637	1.76901

4. CONCLUSION

Since the outbreak of the COVID-19 pandemic, its discussion has dominated the global space, and solutions to its continued occurrence have been sought within and outside clinical parlance. This is important for health and government agencies to return their citizens to normal life activities after months of lockdowns. This paper used an RNN combined with LSTM to train, model, and predict the possible rise in COVID-19 occurrences. Using the LSTM-based model, it was possible to predict the virus prolonging at certain points with minimal prediction error, increased learning capacity, and higher precision. COVID-19 data curves from six African countries, Nigeria, South Africa, Egypt, Kenya, Morocco, and Madagascar were used as input data for the proposed RNN LSTM model.

In contrast, the dataset retrieved from the center for disease control was used to test the developed model. The developed predictive model is observed to be capable of capturing past data properties of time variants and related trends and forecasting the COVID-19 trend. It provides an effective means to aggregate the number of future cases of COVID-19 infections. This could serve as an alternate model for estimating the number of weather-based incidents that can be used to forecast such a pandemic's economic implications. It could also serve as a solid basis for a more accurate LSTM-based model in the nearest future for predicting the future occurrence of this form of the pandemic. The developed model could also be adapted to predict future cases of interest like fatality and morbidity. The model is expected to be adopted by relevant authorities in making informed decisions on prevention measures and policies. The forecast results would help to provide and organize adequate medical facilities and ensure that people's economic activities are not unnecessarily jeopardized for a long time.

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BIOGRAPHIES OF AUTHORS

Jesufunbi Damilola Bolarinwa is a postgraduate student in the Department of Computer Science at the Federal University of Agriculture Abeokuta, Ogun State Nigeria. Working as an IT Researcher at Africa Digital Economy Forum. Also, a Data Scientist, a member of the National Association of Computer Science Students (NACOSS). A member of the internet communication network society. She has three publications currently. She can be contacted at email: damilolajesufunbi@gmail.com.

Prof. Olufunke Rebecca Vincent is a Professor of Artificial Intelligence. She obtained a Ph.D. degree in Computer Science in 2010 after completing her fieldwork with the computational intelligence group, Clausthal University of Technology, Germany. She did a Post-Doctoral Fellowship in Germany in 2014. She is a Fellow of the Nigeria Computer Society and a member of IEEE. She can be contacted at email: Vincent.rebecca@funaab.edu.ng.

Dada Olaniyi Aborisade received Bachelor of Science (B.Sc.) degree from University of Agriculture, Abeokuta, Nigeria in Mathematical Sciences (Computer Science option) in year 2000, Masters (M.Sc) in Degree of the University of Ibadan, Nigeria in 2007. He undertook part of his Ph.D research benchwork at Hochschule Furtwangen University, (HFU) Germany between 2015 and 2016, and completed Ph.D in Computer Science in 2017 at the Federal University of Agriculture, Abeokuta, Nigeria. He is a Lecturer in the Department of Computer Science, College of Physical Sciences, Federal University of Agriculture Abeokuta (FUNAAB), Nigeria. He is a member of both local and international professional bodies. His research interests include cloud security, digital forensics, and using artificial intelligence. He can be contacted at email: aborisadeda@funaab.edu.ng.

Cecilia Ajowho Adenusi a postgraduate student of the Department of computer science at the Federal University of Agriculture, Abeokuta, Ogun State, Nigeria. I currently work at Linux professional institute, Nigeria master affiliate as the head of training at the institute. I am also a data scientist that does play with a lot of data and algorithms. I love researching, investing, and meeting people. She can be contacted at email: ceceresearch@gmail.com.

Charles Okechukwu Ugwunna is a researcher and lecturer with over 15 years of experience. He bagged his B.Sc. and M.Sc. from the University of Uyo and Nnamdi Azikiwe University respectively and is currently a Ph.D. candidate. He works at the Federal University of Agriculture in Abeokuta as an assistant lecturer. He presently coordinates the departmental part-time program. Data communication, network security, data science, simulation, and modeling are some of his scholarly interests (agent-based and epidemic modeling) program. He can be contacted by email: ugwunnaco@funaab.edu.ng.