Deep Learning for COVID-19 prediction

Safa Bahri
National School of Engineering of Tunis
LTSIRS Laboratory, 1002, Tunis, Tunisia
Email: safa.bahri@enit.utm.tn

Moetez Kdayem
National School of Engineering of Sousse
Email: moetezkdayem@gmail.com

Nesrine Zoghlami
National School of Engineering of Tunis
LTSIRS Laboratory, 1002, Tunis, Tunisia
Email: nesrine.zoghlami@gmail.com

2020 4th International Conference on Advanced Systems and Emergent Technologies (IC_ASET) | 978-1-7281-6356-7/20/$31.00 ©2020 IEEE | DOI: 10.1109/IC_ASET49463.2020.9318297

Abstract—**From January 30, 2020, COVID-19 disease was announced by the World Health Organization (WHO) as a Public Health Emergency of International Concern (PHEIC). For that, many scientific researchers were interested in developing algorithms and models in order to mitigate the spread of this epidemic. Existing mathematical models including compartmental models such as SEIR, SIR, SIRQ and statistical models such as ARIMA, ARMA often fail to capture the dynamic of the propagation of an epidemic. Recently, artificial intelligence-based models have proven their effectiveness and accuracy in classification and prediction tasks. This paper aim to deploy a Recurrent Neural Network architecture called Long Short-Term Memory (LSTM) neural network for predicting the next COVID-19 recovered cases in USA, India and Italy for seven days ahead. The model' effectiveness is then evaluated on the basis of the Mean Absolute Percentage Error (MAPE) criterion. Experiments show that LSTM model is accurate with a minimal error that not exceed 3%.**

Keywords— Deep Learning, LSTM, Forecasting models, Time Series data

I. INTRODUCTION

From the beginning of December 2019, the worldwide is suffering from a global threat affecting the public health. This new COVID-19 pandemic, caused mainly by SARS-CoV-2, and firstly appeared in Wuhan province, have touched 213 countries and territories around the world. Up to September 28 (Fig. 1), 2020, more than 32.7 million cases have been announced, including 991 thousand of deaths [1]. The case fatality rate is, then, about 3.3%. In comparison with the two previous coronavirus outbreaks named Severe Acute Respiratory Syndrome (SARS-CoV) and Middle East Respiratory Syndrome (MERS-CoV), emerged in, Guangdong province and Saudi Arabia, respectively, COVID-19 outbreak is characterized with a higher prevalence and an increased virulence [2]. As for January 30, 2020, the World Health Organization declared this unforeseen outbreak as a Public Health Emergency of International Concern [3]. The major symptoms of this emerging virus are high fever, continuous and persisting cough, anosmia (loss of smell), ageusia (loss of taste), tiredness, myalgia and breathing difficulties [4]-[7]. Unfortunately, to date, there is neither a specific therapeutic treatment nor a vaccine-preventable COVID-19 disease. Many scientists and researchers are still trying to better understand the morphology and ultrastructure of this coronavirus in order to develop ways to control its spread [8]-[10]. However, many ongoing clinical trials are considered as efficient and potential in treating COVID-19 cases [11], [13]. Similar to previous outbreaks like Malaria [15], Ebola and influenza [12], artificial intelligence-based models were among accurate and efficient alternatives [14] to fight against this novel pandemic. Numerous scientific works are focusing on the development of sophisticated algorithms and models [16] for early diagnosis of the virus [17], development of drugs and vaccines [18], [19], tracing cases' close contacts [20] and forecasting the total future confirmed, recovered, deceased and negative COVID-19 cases [21]-[24]. In our paper, we are interested in developing an artificial intelligence model based on Deep Learning algorithms [23] for estimating the total future recovered cases allocated in three countries from three different continents (Asia, North America and Europe): India, USA and Italy. A Recurrent Neural Network architecture named Long Short-Term Memory (LSTM) was implemented and then evaluated with reference to the Mean Absolute Percentage Error (MAPE) measurement.

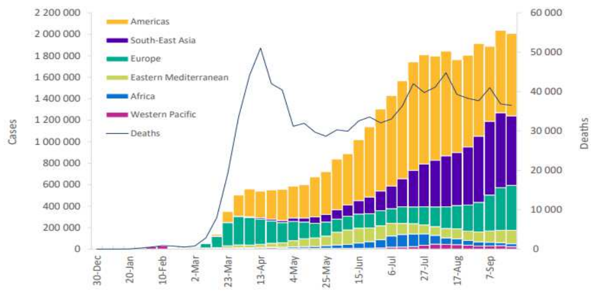

Fig. 1. Weekly number of infected inividuals from December 30 to September 27, 2020 [1]

II. RELEATED WORKS

Over the past decade, novel digital technologies have played a key role in solving key healthcare sector issues, including disease prevention. Effectively, [25] highlighted the numerous opportunities delivered by these sophisticated technologies like connected diagnostic devices, machine learning, mobile applications and social media in epidemiological surveillance, contact tracing, COVID-19 forecasting models, decline in global transmission rate. Our paper was interested in establishing a data-driven model for estimating the future number of recovered cases. This model will be useful for healthcare administrators in the management of available resources. In a research paper proposed by [26], an Auto-Regressive Integrated Moving Average (ARIMA) model was conducted for assessing the incidence pattern by estimating the basic reproduction number (R_0) of the COVID-19 epidemic. A statistical analysis was then handled in order to evaluate trends in the epidemic and to highlight the existing epidemiological status related to each region in order to identify efficient policies and strategies to fight against COVID-19 disease in numerous countries. Similarly, [27] evaluated two statistical approaches called Holt-Winters time series exponential smoothing and Autoregression Integrated Moving Average (ARIMA) in forecasting future confirmed and deceased cases in terms of accuracy. Experiments showed that ARIMA model was the best in the estimation of future confirmed and deceased cases with, respectively, 99.8% and 99.3% of accuracy. Recently, several studies have been interested in using Artificial Intelligence-based models due to their ability and efficacity in capturing the dynamics of spreading of infectious diseases [28]. Three machine learning based models named Non-linear Auto-Regressive Neural Network (NARNN), ARIMA, and LSTM, were implemented aiming to foresee the total number of cases in COVID-19 infection disseminated in 8 countries (Finland, Belgium, France, Switzerland, Turkey, United Kingdom, Germany, Denmark). With a Symmetric Mean Absolute Percentage Error (SMAPE) ranging that not exceed 3%, LSTM was the best approach [21]. Also, according to [22], LSTM Recurrent Neural Network was accurate in predicting, for 30 days ahead, the total future number of positive, recovered and deaths cases.

From this relevant state-of-the-art, we can confirm that in almost of cases, artificial intelligence models outperformed other forecasting models by giving the most accurate estimations of confirmed, recovered or deceased cases. In our paper, we aim to implement LSTM-RNN to forecast the total number of recovered cases in India, USA and Italy.

III. METHOD

For the purpose of getting accurate predictions of the future COVID-19 recovered cases, six steps are performed (Fig. 2):

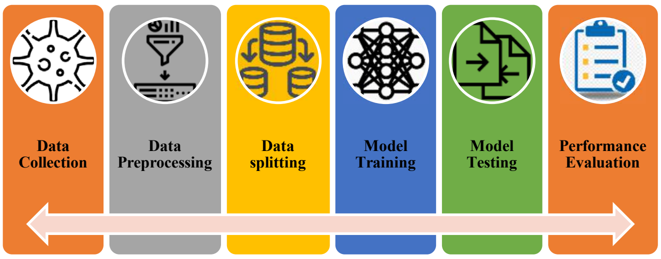

Fig. 2. Proposed process from data collection to perfomance evalution

1) Data Collection

In our paper, we choose to extract public clinical and demographical datasets relative to COVID-19 disease. These datasets will be well described in the next section.

2) Data Pre-processing

In order to avoid bias during model training and testing, we must transform data into the same scale. According to [51], Long Short-Term Memory model is very sensitive to normalization, mainly for capturing time series data. Then, in our case, we select to use a MinMaxScaler for data scaling. The scaling function is defined as:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X represents the data entries, X_{scaled} is the normalized data entries and X_{min}, X_{max} are the minimum and maximum values of data entries, respectively.

3) Data splitting

In our paper, we choose to divise input data into two sets: training and testing. 80% of data entries will be allocated for training and for the rest, it will be assigned for testing purpose.

4) Model Training and Testing

A. Artificial Neural Network

An interesting definition of ANN (Fig. 3) was given by [29]: "*A computational mechanism able to acquire, represent and compute from one multivariate space of information to another, given a set of data representing that mapping*". To begin, the first Artificial Neural Networks were invented, on 1958, by an American psychologist active in artificial intelligence field, named « Frank Rosenblatt » [30]. They were inspired by biological neurons in human brain and designed to recognize patterns [31], [32]. Generally, they are mainly represented by three interlinked layers (input, hidden and output layer) through predefined activation functions (sigmoid, linear, hyperbolic tangent, ReLU…). Each layer is composed by a highly number of interlinked perceptrons (artificial neuron) [35]. For the input layer, it allows to bring input data to the network for further processing. As for output layer, it is in charge of giving results or output data that can be discrete (classification) or continuous (regression). And for the hidden layer, it is considered as the intermediate layer between the two layers. It links the output data to the input data through connections [34], [35]. Adding more and more hidden layers to this simple artificial neural network allows a deep architecture. Artificial Neural Network (ANN) is considered as an advantageous Deep Learning Algorithm for classification or prediction tasks. For instance, [33] used ANN for diabetic classification and yielded an accuracy of 87.3%. As well, an intelligent ANN based healthcare decision support system with 100% of accuracy, was developed by [34] for supporting practitioners within the early diagnosis of Parkinson disease.

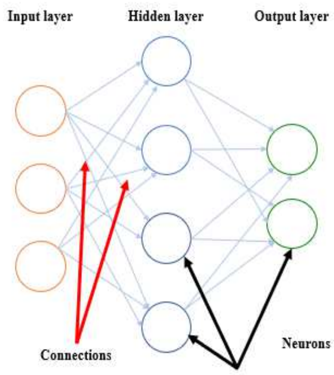

Fig. 3. Traditional Artificial Neural Network

B. Recurrent Neural Network

To define, a Recurrent Neural Network (RNN) [36], [37] is a type of Artificial Neural Network designed to process and analyze streams of sequential data (time-series data) due to its intern memory and several hidden layers [32]. Due to its directed cycle [37], the output of each hidden layer is related to all computations made on previous hidden layers (Fig. 4). RNN are widely used for machine translation [39], text classification [38], speech recognition [40] etc. However, traditional recurrent neural networks present some limitations when handling long input sequences. Firstly, with the use of tanh or relu activation functions, data processing will be unachievable. Secondly, training is considered as a very difficult task. Finally, a standard RNN suffer from the well-known gradient vanishing and exploding problems resulting in the incapability of the network to capture long term dependencies from sequential data [37], [41]. For these, many scientific works [42], [45] were handled in order to develop alternatives that can tackle these drawbacks. Thereby, Gated Recurrent Unit (GRU) [46] and Long-Short Term Memory (LSTM) [42] were considered as the most useful alternatives in time-series data analysis [43], [48], [49], [50].

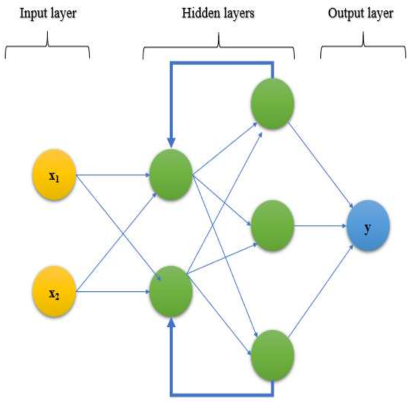

Fig. 4. Standard Recurrent Neural Network architecture

C. Long-Short Term Memory

In order to address the vanishing gradient problem, Hochreiter and Schmidhuber [42] proposed a new architecture named Long Short-Term Memory as an alternative to the standard Recurrent Neural Network. Due to its memory cell encoding memory of previous observed information, LSTM network is able to maintain long term interrelations for a considerable period [43]. As shown in Figure 5 (Fig. 5), each memory cell is mainly composed by three different gates named input, forgot and output gate, that are responsible for data management and control [44]. With reference to [48]-[50], LSTM is considered as an efficient tool, especially, for long duration experimentations.

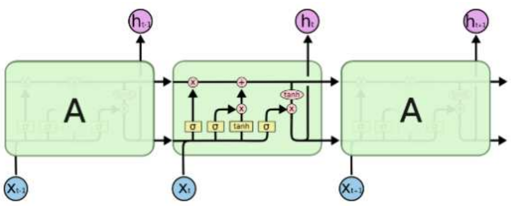

Fig. 5. Long Short-Term Memory cells [47]

5) Performance evaluation

For evaluating the performance of our predictive model, many indicators can be computed. We can mention the Mean Absolute Error (MAE), the Mean Squared Error (MSE), the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE). These are among the foremost efficient measurements useful for assessing the difference between predicted and observed values. In our case, we choose to compute the MAPE indicator that is given by:

$$MAPE(\%) = \frac{100}{N} \times \sum_{i=1}^{N} \left| \frac{yi - \hat{y}i}{yi} \right| \quad (2)$$

Where $\mathbf{y_i}$ and $\mathbf{\tilde{y}_i}$ indicates, respectively, the observed and predictive values and $\mathbf{N}$ is the total number of measurements.

IV. EXPERIMENTS

A. Dataset desciption

COVID-19 historical dataset for COVID-2019 disease for the period from January 22, 2020 to June 22, 2020 were extracted from the official repository relative to the World Health Organization (WHO) [52]. This dataset, presented in CSV format, consists of daily confirmed cases, recovered and fatality cases, followed by two text attributes, namely province/state, country/region (Table I). For transforming these categorical data in numerical data for training, we select to use label encoder.

TABLE I. EXAMPLES OF ROWS IN COVID-19 DATASET

SNo	Observation Date	Province / State	Country / Region	Last Update	Confirmed	Death	Recovered
28468	05-23-2020	Sardenya	Italy	05-24-2020 02 :32 :43	1356	129	940
6683	03-18-2020	United States Virgin Islands	United States	03-18-2020 00 :13 :13	2.0	0.0	0.0
47658	06-22-2020	Delhi	India	06-23-2020 04 :33 :22	62655	2223	36602

To enhance the model performance, we choose to add the SARS-03 dataset [53], presented in Table II.

TABLE II. EXAMPLES OF ROWS IN SARS-03 DATASET

	Date	Country	Cumulative number of cases	Number of deaths	Number of recovered cases
47	03/21/2003	Italy	01	00	00
1616	06/02/2003	India	03	00	03
56	03/21/2003	United States	13	00	00

In addition to COVID-19 and SARS-03 clinical datasets, a demographic dataset composed of 20 categorical and numerical attributes such as population density, Gross Domestic Product, Infant mortality etc. (Table III – Table VI).

TABLE III. DEMOGRAPHICAL DATASET FOR INDIA, US AND ITALY

Country	Region	Population	Area (sq. mi.)	Population Density (per sq. mi.)
India	ASIA (EX. NEAR EAST)	1095351995	3287590	333.2
United States	NORTHERN AMERICA	298444215,9631420	9631420	31
Italy	WESTERN EUROPE	58133509	301230	193

TABLE IV. DEMOGRAPHICAL DATASET FOR INDIA, US AND ITALY (CONTINUED)

Coastline (coast /area ratio)	Net migration	Infant mortality (per 1000 births)	GDP ($ per capita)	Literacy (%)
0,21	-0.07	56.29	2900	59.5
0,21	3.41	6.5	37800	97
2.52	2.07	5.94	26700	98.6

TABLE V. DEMOGRAPHICAL DATASET FOR INDIA, US AND ITALY (CONTINUED)

Phones (per 1000)	Arable (%)	Crops (%)	Other (%)	Climate
45.4	54.4	2.74	42.86	2.5
898	19.13	0.22	80.65	3
430.9	27.79	9.53	62.68	NaN

TABLE VI. DEMOGRAPHICAL DATASET FOR INDIA, US AND ITALY (CONTINUED)

Birthrate	Deathrate	Agriculture	Industry	Service
22.01	8.18	0.186	0.276	0.538
14.14	8.26	0.01	0.204	0.787
8.72	10.4	0.021	0.291	0.688

V. RESULTS AND DISCUSSION

1) Environment

For the implementation of our simulations, we choose to use python programming language, a very powerful tool widely used in data analytics thanks to its multiple open source libraries such as NumPy, Pandas, Tensorflow, Scikit learn and Keras etc. All experiments were performed on a computer with Intel Core I7-9750H Central Processing Unit (CPU) (6 cores, 12 threads) and NVidia GeForce GTX 1660 Ti 6gb gddr6 Graphic Processing Unit (GPU).

2) Results

This paper aim to use LSTM model for the purposes of estimating the future COVID-19 recovered cases in India, United States and Italy. Clinical data from January 22 to June 22, 2020 are considered as training dataset. The, the seven days ahead (June 22 – June 29, 2020) predictions are used in order to evaluate the accuracy and precision of this Artificial Intelligence based model. For training our Deep Learning model, we choose to use ADAM (Adaptive Moment Estimation) optimizer with learning rate equal to 0.001 and 50 epochs. Regarding the Fig. 6 that represents the model loss function (Mean Square Error), we can confirm the efficiency of this optimization method and its speed of convergence. From Fig. 7 to Fig. 9, it is evident that the foresee cumulative number of recovered cases (blue color) matches with the observed data (orange color) notified by the World Health Organization. Indeed, a total error ranging from 1.46 to 2.65% (Table VII – Table IX) was calculated. Considering all of the above, we can assert the effectiveness of LSTM-based Recurrent Neural Network in providing accurate predictions with the minimum of error. This model can be a good decision support system used by practitioners and health administrators to deal with this uncontrollable pandemic.

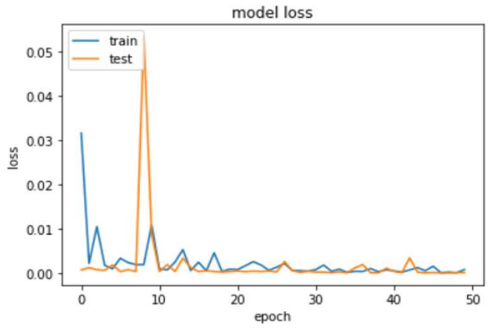

Fig. 6. Convergence of loss function over training and testing data

TABLE VII. UNITED STATES PREDICTIONS VS REAL VALUES

Date	United States		
	LSTM	Real values	Error (%)
23/06	654 965, 75	647 548	1,145513537
24/06	666 810, 6	656 161	1,623016302
25/06	678 597, 8	663 562	2,265922401
26/06	689 777, 06	670 809	2,827639462
27/06	683 192, 4	679 308	0,571817202
28/06	695 849, 6	685 164	1,55956822
29/06	706 933, 94	705 203	0,245452728
Total Error (%)	**1,462704265**		

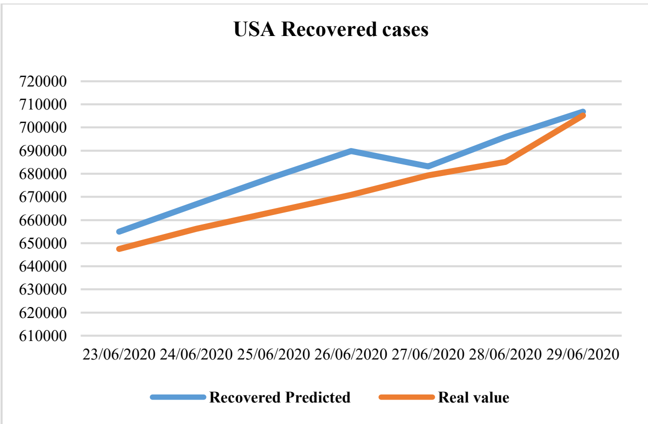

Fig. 7. The comparaison between USA official COVID-19 recovered cases announed by the World Health Organization and LSTM's simulations.

TABLE VIII. INDIA PREDICTIONS VS REAL VALUES

Date	India		
	LSTM	Real values	Error (%)
23/06	253 166, 25	258 685	2,133386165
24/06	268 762, 06	271 697	1,080225398
25/06	289 413, 7	285 637	1,322202656
26/06	287 880, 72	295 881	2,703884332
27/06	305 836, 12	309 713	1,251765344
28/06	315 739	321 723	1,859985142
29/06	338 794, 1	334 822	1,186331842
Total Error (%)	**1,648254411**		

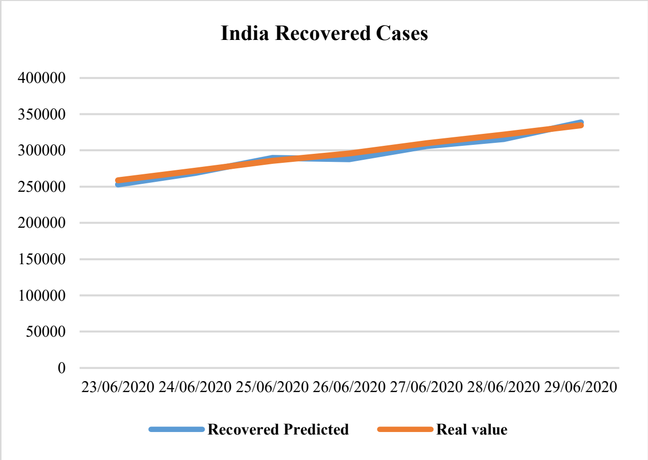

Fig. 8. The comparaison between India official COVID-19 recovered cases announed by the World Health Organization and LSTM's simulations.

TABLE IX. ITALY PREDICTIONS VS REAL VALUES

Date	Italy		
	LSTM	Real values	Error (%)
23/06	188 855, 94	184 585	2,313806647
24/06	189 678, 28	186 111	1,916748607
25/06	195 235, 45	186 725	4,557745347
26/06	189 576, 55	187 615	1,045518749
27/06	192 747, 56	188 584	2,207801298
28/06	193 630, 98	188 891	2,509373131
29/06	196 780, 12	189 196	4,008604833
Total Error (%)	**2,65137123**		

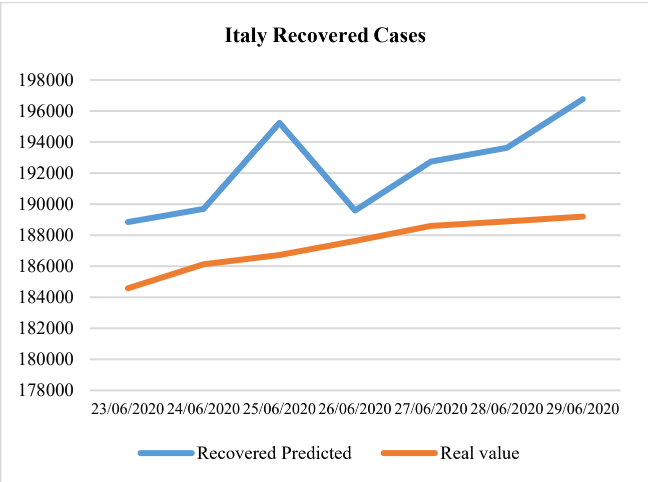

Fig. 9. The comparaison between Italy official COVID-19 recovered cases announed by the World Health Organization and LSTM's simulations.

VI. CONCLUSION

In this study, a Long Short-Term Memory-based forecasting model has been proposed with the objective of predicting the future cumulative number of COVID-19 recovered cases, for seven days ahead, in India, USA and Italy. Our Deep Learning model can successfully fit the dynamic of evolution of observed COVID-19 recovered cases and provide accurate predictions with a total error ranging from 1,46 to 2.65%. As announced in [21] and [22], LSTM model is considered as a promising tool for practitioners, helping them to monitor the prevalence of this coronavirus worldwide. For further works, the same deep learning model can be tested for other epidemic like influenza, Ebola…

ACKNOWLEDGMENT *(Heading 5)*

REFERENCES

[1] World Health Organization. (September 28, 2020). Coronavirus disease 2019 (COVID-19) Weekly Epidemiological Update, Available: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200928-weekly-epi-update.pdf?sfvrsn=9e354665_4

[2] Y. Liu, A.A. Gayle, A.Wilder-Smith and J. Rocklöv, "The reproductive number of COVID-19 is higher compared to SARS coronavirus". Journal of travel medicine, vol. 27, issue 2, pp. 01-04, 2020.

[3] World Health Organization. "COVID 19 Public Health Emergency of International Concern (PHEIC). Global research and innovation forum: towards a research roadmap", 2020.

[4] N. Chen, M. Zhou, X. Dong, J. Qu, F. Gong, Y. Han, ... and T. Yu. "Epidemiological and Clinical Characteristics of 99 cases of 2019 Novel Coronavirus pneumonia in Wuhan, China: a descriptive study". The Lancet, 2020, 395(10223), 507-513.

[5] Novel Coronavirus Pneumonia Emergency Response Epidemiology Team. "The epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (COVID-19) in China [in Chinese]". Zhonghua Liu Xing Bing Xue Za Zhi 2020 ;41(2) :145–151.

[6] Z. Wu and J.M. McGoogan. "Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China : summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention". Jama, 2020, 323(13), 1239-1242.

[7] L. Pan, M. Mu, P. Yang, Y. Sun, R. Wang, J. Yan, ... and Y. Jin. "Clinical characteristics of COVID-19 patients with digestive symptoms in Hubei, China: a descriptive, cross-sectional, multicenter study". The American journal of gastroenterology, 2020, 115.

[8] A. Grifoni, D. Weiskopf, S. I. Ramirez, J. Mateus, J. M. Dan, C.R. Moderbacher, ... and D. Marrama. "Targets of T cell responses to SARS-CoV-2 coronavirus in humans with COVID-19 disease and unexposed individuals". Viruses 2020, 12, 254, 01-15

[9] W. Wang, W., Tang, J., and F. Wei. "Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China". Journal of medical virology 2020, 92(4), 441-447

[10] M. C. Wong, S. J. J. Cregeen, N. J. and J. F. Ajami Petrosino. "Evidence of recombination in coronaviruses implicating pangolin origins of nCoV-2019". Biorxiv 2020.

[11] P. Gautret, J.C. Lagier, P. Parola, L. Meddeb, M. Mailhe, B. Doudier, ... and S. Honoré, S. "Hydroxychloroquine and azithromycin as a treatment of COVID-19: results of an open-label non-randomized clinical trial". International journal of antimicrobial agents 2020, 105949.

[12] D. P. Walsh, T. F. Ma, H. S. Ip, and J. Zhu. "Artificial intelligence and avian influenza: Using Machine Learning to enhance active surveillance for avian influenza viruses". Transboundary and emerging diseases 2019, 66(6), 2537-2545.

[13] M. P. Lythgoe and P. Middleton. "Ongoing clinical trials for the management of the COVID-19 pandemic". Trends in Pharmacological Sciences 2020, vol. 41, issue 6, pp. 363-382.

[14] Z. S. Wong, J. Zhou and Q. Zhang. "Artificial Intelligence for infectious disease big data analytics". Infection, disease & health 2019, vol. 24, issue 1, pp. 44-48.

[15] Z. Liang, A. Powell, I. Ersoy, M. Poostchi, K. Silamut, K. Palaniappan, ... and J. X. Huang, J. X. "CNN-based image analysis for malaria diagnosis". In 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 493-496). IEEE.

[16] R. Vaishya, M. Javaid, I. H. Khan and A. Haleem. "Artificial Intelligence (AI) applications for COVID-19 pandemic". Diabetes & Metabolic Syndrome : Clinical Research & Reviews 2020, vol. 14, issue 4, pp. 337-339

[17] X. Mei, H. C. Lee, K. Y. Diao, M. Huang, B. Lin, C. Liu, ... and A. Bernheim. "Artificial intelligence–enabled rapid diagnosis of patients with COVID-19". Nature Medicine 2020, vol. 26, pp 1224-1228.

[18] Y. Y. Ke, T. T. Peng, T. K. Yeh, W. Z. Huang, S. E. Chang, S. H. Wu, ... and W. H. Lin. "Artificial intelligence approach fighting COVID-19 with repurposing drugs". Biomedical Journal 2020.

[19] B. R. Beck, B. Shin, Y. Choi, S. Park and K. Kang. "Predicting commercially available antiviral drugs that may act on the novel coronavirus (SARS-CoV-2) through a drug-target interaction deep learning model". Computational and structural biotechnology journal 2020, vol. 18, pp 784-790.

[20] S. Lalmuanawma, J. Hussain and L. Chhakchhuak. "Applications of Machine Learning and Artificial Intelligence for Covid-19 (SARS-CoV-2) pandemic: A review". Chaos, Solitons & Fractals, 2020, vol. 139, 110059.

[21] İ. Kırbaş , A. Sözen, A. D. Tuncer and F. Ş. Kazancıoğlu. Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches. Chaos, Solitons & Fractals, 2020, vol. 138, 110015.

[22] A. Tomar and N. Gupta. "Prediction for the spread of COVID-19 in India and effectiveness of preventive measures". Science of The Total Environment 2020, vol. 728, 138762.

[23] P. Arora, H. Kumar and B. K. Panigrahi. "Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India". Chaos, Solitons & Fractals 2020, vol. 139, 110017.

[24] M. H. D. M. Ribeiro, R. G. da Silva, V. C. Mariani and L. dos Santos Coelho. "Short-term forecasting COVID-19 cumulative confirmed cases: Perspectives for Brazil". Chaos, Solitons & Fractals 2020, vol. , 109853.

[25] J. Budd, B. S. Miller, E. M. Manning, V. Lampos, M. Zhuang, M. Edelstein, ... and M. J. Short. "Digital technologies in the public-health response to COVID-19". Nature medicine 2020, vol. 26, pp 1183-1192.

[26] S. Deb and M. Majumdar. "A time series method to analyze incidence pattern and estimate reproduction number of COVID-19". arXiv preprint arXiv:2003.10655, 2020.

[27] M. Panda. "Application of ARIMA and Holt-Winters forecasting model to predict the spreading of COVID-19 for India and its states". medRxiv, 2020.

[28] V. K. R. Chimmula and L. Zhang. "Time series forecasting of COVID-19 transmission in Canada using LSTM networks". Chaos, Solitons & Fractals 2020, vol.135 109864.

[29] J. H. Garrett. "Where and Why Artificial Neural Networks Are Applicable in Civil Engineering". Journal of Computing in Civil Engineering 1994, vol. 8, 129-130.

[30] F. Rosenblatt. "The perceptron: a probabilistic model for information storage and organization in the brain". Psychological review 1958, vol. 65, issue 6, 386.

[31] A. Shenfield, D. Day and A. Ayesh. "Intelligent intrusion detection systems using artificial neural networks". ICT Express 2018, vol. 4, issue 2, pp 95-99.

[32] H. Patel, A. Thakkar, M. Pandya and K. Makwana. "Neural network with deep learning architectures". Journal of Information and Optimization Sciences 2018, vol. 39, issue 1, pp 31-38.

[33] N. S. El_Jerjawi and S. S.Abu-Naser, S. S. "Diabetes prediction using artificial neural network". International Journal of Advanced Science and Technology 2018. vol. 121, pp. 55-64.

[34] R. M. Sadek, S. A. Mohammed, A. R. K. Abunbehan, A. K. H. A Ghattas, M. R. Badawi, M. N. Mortaja, ... and S. S. Abu-Naser. (2019). "Parkinson's Disease Prediction Using Artificial Neural Network". International Journal of Academic Health and Medicam Research (IJAHMR) 2019, vol. 3, issue 1, pp 01-08.

[35] S. Walczak. "Artificial neural networks". In Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction. IGI Global 2019, pp 40 – 53.

[36] L. Medsker and L. C. Jain (Eds.). "Recurrent neural networks: design and applications". CRC press 1999.

[37] D. Ravì, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo and G. Z. Yang. "Deep learning for health informatics". IEEE journal of biomedical and health informatics 2016, vol. 21, issue 1,pp 04-21.

[38] I. Banerjee, Y. Ling, M. C. Chen, S. A. Hasan, C. P. Langlotz, N. Moradzadeh,….. and O. Farri. "Comparative effectiveness of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures for radiology text report classification". Artificial intelligence in medicine 2019, vol. 97, pp 79-88.

[39] X. Wang, C. Chen and Z. Xing. "Domain-specific machine translation with recurrent neural network for software localization". Empirical Software Engineering 2019, vol. 24, issue 6, pp 3514-3545.

[40] A.Graves, A. R. Mohamed and G. Hinton. "Speech recognition with deep recurrent neural networks". In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 6645-6649.

[41] S. Li, W. Li, C. Cook, C. Zhu and Y. Gao. "Independently Recurrent Neural Network (IndRNN): Building a longer and deeper RNN". In Proceedings of the IEEE conference on computer vision and pattern recognition 2018, pp. 5457-5466.

[42] S. Hochreiter and J. Schmidhuber. "Long short-term memory". Neural computation 1997, vol. 9, issue 8, pp 1735-1780.

[43] J. Lei, C. Liu and D. Jiang. "Fault diagnosis of wind turbine based on Long Short-term memory networks". Renewable energy 2019, vol. 133, pp 422-432.

[44] R. DiPietro and G. D. Hager. "Deep learning: RNNs and LSTM". In Handbook of Medical Image Computing and Computer Assisted Intervention, 2020, pp. 503-519. Academic Press.

[45] F. A. Gers, J. Schmidhuber and F. Cummins. "Learning to forget: Continual prediction with LSTM", Technical Report IDSIA, January, 1999.

[46] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk and Y. Bengio. "Learning phrase representations using RNN encoder-decoder for statistical machine translation". arXiv preprint arXiv:1406.1078, 2014.

[47] O. Christopher. "Understanding LSTM networks". Understanding LSTM Networks-Colah's Blog. Github, 2015.

[48] B. Athiwaratkun and J. W. Stokes. "Malware classification with LSTM and GRU language models and a character-level CNN". In 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March 2017, (pp. 2482-2486). IEEE.

[49] D. Britz, A. Goldie, M.-T. Luong, and Q. Le, "Massive exploration of neural machine translation architectures," 2017, arXiv:1703.03906.

[50] T. Van Steenkiste, J. Ruyssinck, L. De Baets, J. Decruyenaere, F. De Turck, F. Ongenae and T. Dhaene. "Accurate prediction of blood culture outcome in the intensive care unit using long short-term memory neural networks". Artificial intelligence in medicine 2019, vol. 97, pp 38-43.

[51] N. Yudistira. COVID-19 growth prediction using multivariate long short term memory. arXiv preprint arXiv:2005.04809, 2020

[52] World Health Organization. Novel Corona virus 2019 dataset (updated: 29-06-2020). Available: https://cutt.ly/1gguYqe

[53] SARS 2003 Outbreak dataset. Kaggle 2003. Available: https://cutt.ly/sghRLUp