Single and Multilayer LSTM Models for Positive COVID-19 Cases Prediction

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Abstract: COVID-19 is a global pandemic that has been reported first in Wuhan, China in December 2019. According to the World Health Organization (WHO), around 1 out of every 5 people who get COVID-19 get seriously ill and develop difficulty breathing. The virus is spreading from one person to others causing fear and a big struggle in the world. Building accurate learning models for forecasting positive new cases would help to better manage the crisis situation thereby helping to fight COVID-19 and save lives. For this purpose, we use LSTM (Long Short Time Memory) model in Morocco's case and evaluate its performance according to six architectures. The results demonstrate that the architecture with three cells outperforms the other models and shows the best fitting.

1 INTRODUCTION

In the past decades, technologies have played an important role in solving several problems of epidemics and pandemics. For the same purpose, Artificial Intelligence, and data science have emerged with new methods and techniques that help humanity to prevent the spread of pandemics, and mitigate the related risk.

Nowadays, the whole countries in the world suffer from the COVID-19 epidemic and there is no medicine or vaccine that prevents or cures this disease until now. For this reason, researchers are invited to discover and find new solutions to help governments dealing and managing this dilemma. Many papers and work were suggested for different purposes using especially Machine Learning (ML) and Deep Learning (DL) algorithms and techniques. However, new methods and approaches still remain needed to prevent the spread of the global pandemic. In this context, our research aims at finding a solution for this challenging problem using one of the most powerful and known algorithms of DL called Long Short-Term Memory (LSTM).

LSTM is a Recurrent Neural Network (RNN) proposed and developed in 1997 (Hochreiter et al., 1997). It is widely used in solving complex and hard-learned problems in many different fields, especially for time series data. For instance, it is used in the seismic field (one of the most complex fields) to warn from the incoming earthquake in a specific region (BERHICH et al., 2020; Siami-Namini et al., 2019; Wang et al., 2017). Our objective in this work is to evaluate the predictions' accuracy of the infected cases in Morocco by applying six different LSTM model's architectures and comparing their efficiency using the most popular performance metrics: MSE (Mean Squared Error), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and R squared.

The rest of this paper is organized in the following way: Section II presents the related work. Section III gives an overview of our comparative approach by highlighting the important steps of building our models such as the data collection, preprocessing, and parameterization of the learning process. Section IV discusses and evaluates the performance of our applied models. Section V summarizes the conclusions and perspectives of this work.

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2 RELATED WORKS

Recently, several researchers are trying to develop and find suitable solutions and strategies to stop the outbreak of the coronavirus disease. Data scientists suggested some work for predicting and forecasting new positive Covid-19 cases using ML and DL techniques. DL and ML indeed provide effective tools that learn trends from collected data, among them the recurrent neural network LSTM which was used in a lot of work as well as in this case study.

Authors in (Chimmula et al., 2020) predict the possible ending point of coronavirus in Canada. They apply the LSTM algorithm on the available data until March 13, 2020 and they give predictions for 2 successive days from the 2nd to 14th day. The findings of this work expect that the possible stopping time of Coronavirus in Canada could be around June 2020, and a small number of infections may be reported until December 2020. Besides, the aim in (Arora et al., 2020) was to predict the daily and the weekly number of positive cases in 32 states and union territories of India. Four deep learning techniques: LSTM, deep LSTM, convolutional LSTM, and bidirectional LSTM were used. The bidirectional LSTM gives the best performance evaluated using the MAE metric. Moreover, another research in (Tomar et al., 2020) predicts the number of COVID-19 cases, recovered cases, and deceased cases during 30 days ahead in India using the LSTM model and curve fitting. Authors in (Yang et al., 2020) apply a modified Susceptible-Exposed-Infectious-Removed (SEIR) model to derive the epidemic curve and artificial intelligence to predict COVID-19 epidemic trends while giving it peaks and sizes in China. Author in (Bouhamed, 2020) develops DL nested sequence prediction models with also LSTM to predict the cumulative case number and recoveries in 79 countries. The models use the dataset until March 13, 2020, and they are evaluated using the R squared metric. The results were encouraging for the newly infected cases. Predictions of cumulative number of deaths, daily number of new cases worldwide, and cumulative number of cases in Europe and middle east regions were given in (Direkoglu et al., 2020). This research provides the predictions of the next ten days. It is based on the reported time series data of Covid-19 and the LSTM model with the dropout layer. The obtained results were evaluated by the RMSE and were considered promising since they were able to predict the possible scenarios regionally and globally. In the same manner, authors in (Yan et al., 2020) predict the confirmed cases using the LSTM algorithm. They compared the deviation between LSTM results and the results of the digital prediction models (like Logistic and Hill equations) with the real data. They found that the proposed model has a smaller prediction deviation and better fitting effect.

A hybrid model is applied in (Zandavi et al., 2020) to forecast the number of cases and deaths in the top ten most affected countries in Australia. This model combines the algorithm LSTM with dynamic behavioural models. The proposed approach considers the effect of multiple factors, and the parameters are optimized using the genetic algorithm. The results showed that the hybrid model outperforms the LSTM model. From another angle, authors in (Alakus et al., 2020) use laboratory data to predict which patients are likely to receive coronavirus. Their predictive model based on DL approaches identified patients that have COVID-19 with good accuracy.

In addition, three approaches were applied in (Kırbaş et al., 2020) to predict the confirmed cases in Europe: Autoregressive Integrated Moving Average (ARIMA), Nonlinear Autoregressive neural network (NARNN) and Long-Short term Memory (LSTM). The LSTM model was more efficient for forecasting 14 future days. It expects that the rate of positive cases will decrease slightly in many countries. In (Ayyoubzadeh et al., 2020) LSTM and Linear Regression (LR) models are suggested to forecast the number of positive COVID-19 cases in Iran. The results showed that LR predicted the incidence with an RMSE of 7.5 and LSTM with an RMSE of 27.18.

These works and predictions have been performed for different purposes under the scope of COVID-19 outbreak forecasting and would help the governments to face the COVID-19 pandemic and help the authorities and decision-makers to manage and deal with their strategies. The LSTM model used according to different learning approaches was seeming to be promising in most of them. However, it would be interesting to explore more approaches using this model in order to reach better accuracy. Besides, no study with accurate predictions, has considered the case of the outbreak of COVID-19 in Morocco using LSTM. Only three research contributions consider the Morocco's case while using LSTM-based models (Ayris et al., n.d.; Bouhamed, 2020; Ksantini et al., 2020). In (Ayris et al., n.d.), authors use DSPM (Deep Sequential Prediction Model) which is a stacked LSTM to predict cumulative number of confirmed cases in different countries in the world, among them Morocco. Note that the obtained average MAE Error Rate was 388.43 which is not a good result if we consider Morocco's case. We note that the studied period matches with the confinement period in Morocco until May 5, 2020 and that on this date, there were 5219 confirmed cases reported while the predicted value is 7422. Authors in (Ksantini et al., 2020) use LSTM to predict new weekly cases of COVID-19 pandemic based on the confinement and the protection tools factors for different countries, among them Morocco. We outline that this paper was received in March 6, 2020 while the first confirmed case in Morocco was reported in March 2, 2020, only 7 confirmed cases were reported in March 13, 2020, and the confinement strategy was applied in March 20, 2020. We think that exploring LSTM with more data would be interesting to have more reliable and credible results.

In (Bouhamed, 2020), author uses LSTM to predict the cumulative confirmed cases number in 79 countries, among them Morocco, and also considers a dataset that range from the beginning of COVID-19 until only March 25, 2020. As we have mentioned above, we think that this period and related data are not sufficient to perform predictions about the virus spread in Morocco. In addition, it is worth noting that this work only provides projections for the next day, which would not be interesting for decision makers since it does not give them enough time to be able to react to a critical situation. In this context and given all of these reasons, our work was conducted.

3 METHODOLOGY

COVID-19 is a global pandemic and every day millions of infected cases are reported around the world. Our work aims to accurately predict the new positive COVID-19 cases. For this purpose, we explore different architectures of the LSTM algorithm which is suitable to be used for forecasting such time series data, and we experiment and evaluate them in Morocco's case. This section presents at first the basis architecture of this recurrent neural network before explaining the important steps that we follow to build our models and perform our comparative study.

3.1 RNNs Architecture and LSTM

RNNs are a category of Artificial Neural Networks (ANNs) characterized by their state of memory. They are composed of hidden states which are distributed over time, allowing them to store a lot of information about the past. They are mostly used in forecasting applications because of their capacity to handle sequential data of variable length (Graves, 2013). However, their major disadvantage is their lack of reducing and handling the problems of vanishing gradient and explosion gradient. They can only store short term memory because they require activations of only the hidden layer of the pre-previous time step (Hochreiter et al., 1997a).

The main goal of RNNs is to consider the influence of past information in producing the output result. To this end, they use cells represented by gates which influence the generated output according to the historical observations. They are especially effective for learning temporal information (Oksuz et al., 2019). In RNNs, a hidden state ht can be calculated for a given input xt sequence by the equation 1 where Whh is the weight of the previous hidden state ht-1, xt is the current input, Wxh is the weight of the current input state, tanh is the activation function. The output state yt is computed according to the equation 2 where Why is the weight at the output state.

$$h_t = \tanh (W_{hh} h_{t-1} + W_{xh} x_t) \qquad (1)$$

$$y_t = W_{hy} h_t \qquad (2)$$

LSTM is considered as a sophisticated RNN and gated memory unit, designed to avoid and resolve the vanishing gradient problems that limit the efficiency of simple RNNs (Hochreiter et al., 1997a). The LSTM cells are supported by three components called gates: the input gate, the forget gate and the output gate. This makes it possible to address the limitations of traditional time series forecasting techniques by adapting the non-linearities of a given dataset and to produce state-of-the-art results on the temporal data. Each block of LSTM works at different time steps and passes its output to the next block until the final LSTM block generates the sequential output. Besides, LSTM is hence a powerful algorithm for implementing a sequential time series model. Its key component is memory blocks which have been released to tackle vanishing gradients by memorizing network parameters for long durations. The memory blocks in the LSTM architecture are similar to the differential storage systems of a digital system. The gates in LSTM help to process the information using an activation function (sigmoid) which generates a value between 0 and 1 as an output. The main reason why the sigmoid activation function is used is to transmit only positive values to the following gates to get a clear output (Chimmula et al., 2020).

LSTM is flexible and estimates dependencies of different time scales. The commonly used RNN variations such as LSTM use gates and memory cells for sequence's prediction. In the beginning, LSTM starts with a forget gate layer (ft) that uses a sigmoid function combined with the previous hidden layer (ht-1) and the current input (xt) as described in the following equations (3, 4, 5, 6, 7 and 8) where it, čt, ft, ot, ct, ht are the input gate, cell input activation, forget gate, output gate, cell state, and the hidden state respectively. Wi, Wc, Wf and Wo are their weight matrices respectively. bi, bc, bf, and bo are the biases. Xt is the input, ht-1 is the last hidden state, ht is the internal state. σ is the sigmoid function.

$$i_t = \sigma (W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\check{c}_t = \tanh (W_c \; [h_{t-1}, x_t] + b_c) \quad (4)$$

$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

$$o_t = \sigma (W_o \, [h_{t-1}, x_t] + b_o) \quad (6)$$

$$c_t = f_t * c_{t-1} + i_t * \check{c}_t \quad (7)$$

$$h_t = ot * \tanh (c_t) \quad (8)$$

3.2 Our Approach for Predicting COVID-19 Positive Cases by Single and Multilayer LSTM

In this work, we apply six different LSTM architectures to predict the new positive COVID-19 cases in Morocco for the 7 future incoming days. The six-architecture called LSTM1, LSTM2, LSTM3, LSTM4, LSTM5 and LSTM6, are respectively single, two, three, four, five and finally six LSTM layers. The aim of this work is to compare the relevance of the mentioned architectures in the context of COVID-19 spread prediction.

In the following subsections, we present the dataset we use in this work, the preprocessing steps of our models, the feature selection, the applied parametrization, and finally the performance metrics used to evaluate and compare the results.

3.2.1 Dataset

The COVID-19 dataset we use in this work is from "Our World in Data" Website4. It shares and reports data collected from the European Center for Disease Prevention and Control (ECDC). The COVID-19 data are updated daily on this website which provides data collected from around the world.

3.2.2 Preprocessing and Feature Selection

The preprocessing and feature selection are fundamental stages in ML and DL approaches. The preprocessing gives many ways and operations to convert and transform the source data into a clean dataset ready to be feed in the ML and DL models. It affects the quality of the model and its results. The feature selection provides the relevant features that adequately affect the learning process, and may reduce the number of variables to evolve the model efficiency and to avoid costly computations. Eventually, in this work we are following these steps to prepare and select feature from the source data: extracting the targeted data inputs, selecting appropriate feature, filling null values, normalizing data and adapting the timesteps to be considered for prediction.

The source data report the worldwide COVID-19 pandemic data. Therefore, we selected just data related to Morocco's case we desire to study. The time of our analyzed dataset starts from the beginning of this pandemic in Morocco on March 02, 2020 to June 15, 2020. This period matches with the confinement period in Morocco. It was selected in order to allow analysing the performance of the proposed models in the same context since the deconfinement data are not sufficient and could influence their accuracy.

The source data give multiple features but not all of them are registered for the instances of Morocco, and not all of them are important for use in the prediction. In our case, we have selected five important features: the new cases, the total cases, the new deaths, the total deaths and population. These features are the most and highly correlated variables to the targeted output (new COVID-19 positive cases). Note that the correlations of total cases, new cases, total deaths, new deaths and population are respectively 96,63%, 100%, 96,17%, 86,75% and 67,67%.

To impute null values, we used two methods: the first one consists of filling with the median value whereas the second consists of applying the Key Nearest Neighbor (KNN) algorithm. We have experimented our data with both methods and we have proceeded with the median since it gave better results than the KNN algorithm.

The features in a given dataset are generally presented in different scales. In our case, for example, the population is presented by millions, total cases are presented by thousands since they describe the

[4] https://ourworldindata.org/coronavirus-source-data

cumulative number of cases, and the new cases are presented by hundreds. To make all these values on the same scale and to add the uniformity to our dataset, we apply the Min-Max scaler that transforms all values between the range 0 and 1. This will delete the noise from our data and facilitate the learning process of our models.

Besides, COVID-19 data are time series, and hence, the values of the actual data are required as inputs to perform predictions for the following days. Time series data cannot use future values as input features, then the inputs of a time series model are the past feature values. In this work, we adapt our model to learn from the past timesteps in order to predict the positive COVID-19 cases for the future 7 timesteps. This choice was adopted due to the data size and also in order to consider a minimum sufficient time to be given for decision makers.

3.2.3 Parametrization

The architectures of our six LSTM models are differentiated by the number of LSTM cells. Table I illustrates the architecture and parametrization of each model. All the models are using Adam optimizer which is one of the most used stochastic optimizers thanks to its ability to learn faster as it has been demonstrated in (Kingma et al., 2015) using empirical experiments. The other mentioned parameters have been fixed after we have tuned and tested multiple parameters until larger batch sizes were giving better results. The adopted size is 64. In addition, the activation function that was giving good fitting is the Tanh function. We also note that time lag and timestep were respectively fixed to 2 and 7 days.

3.2.4 Performance Metrics

DL and ML models' results are measured according to various metrics. There is exist several methods to evaluate regression models. In our work, we are using four performance metrics MAE, MSE, RMSE and R squared (R2), as mentioned above.

MAE presents the average of the absolute difference between the real and the predicted values. MSE represents the average of the square of the difference between the original and the predicted values. It is sensitive to outliers and data containing a lot of noise. RMSE is the root of the value of MSE and it presents the standard deviation of errors. It is useful when high errors are present. Finally, R squared indicates the efficiency of the model fitting.

Table 1: architectures and parametrization of our models.

Mode l	Parametrization			
	Layers	Activation function	optimize r	Batch size
LSTM-1	LSTM cell of 75 units Dense layer of 7 outputs	Tanh	Ada m	64
LSTM-2	LSTM cell of 75 units LSTM cell of 70 units Dense layer of 7 outputs	Tanh	Ada m	64
LSTM-3	LSTM cell of 75 units LSTM cell of 70 units LSTM cell of 60 units Dense layer of outputs	Tanh	Ada m	64
LSTM-4	LSTM cell of 75 units LSTM cell of 70 units LSTM cell of 65 units LSTM cell of 60 units Dense layer of outputs	Tanh	Ada m	64
LSTM-5	LSTM cell of 75 units LSTM cell of 70 units LSTM cell of 65 units LSTM cell of 63 units LSTM cell of 60 units Dense layer of outputs	Tanh	Ada m	64
LSTM-6	LSTM cell of 75 units LSTM cell of 70 units LSTM cell of 65 units LSTM cell of 63 units LSTM cell of 60 units LSTM cell of 55 units Dense layer of outputs	Tanh	Ada m	64

4 RESULTS AND DISSCUSSION

In this section, we present and discuss the results of our LSTM models which are based on six different architectures. The fitting curves of each model are shown in Fig. 1. Unlike LSTM-1 and LSTM-2, the loss curves of the other models indeed converge to the minimum error corresponding to the training loss. We can see that they do not present any limitation of overfitting or underfitting.

Regarding the prediction quality, the results illustrated in Table II, show that the LSTM model with three layers outperforms the other models. LSTM-3 provided the lowest MAE, MSE and RMSE values which are respectively equal to 19.95, 685.65 and 25.66. It also globally provided good predicted total positive cases per week. As shown in Table III, the total predicted cases provided by LSTM-3 are fairly close to the real ones at least for two among three weeks (week 1 and week 3). In other terms, it generally provided low deviations from the total real cases in the way that it was able to predict values which were equal respectively to the predicted cases minus 5% and plus 8% in the third and first weeks. It is also worth noting, that these values as well as the quality metrics (RMSE, MSE and MAE) confirm a good prediction capacity and fairly high accuracy, especially, in comparison with all related work presented in this paper.

Table 2: test results for 21 days.

Model	Performance metrics			
	MAE	MSE	RMSE	R2
LSTM-1	23.78	830.51	28.82	0.03
LSTM-2	22.7	809.58	28.45	0.05
LSTM-3	**19.95**	**658.65**	**25.66**	**0.23**
LSTM-4	22.63	791.78	28.14	0.07
LSTM-5	21.73	759.59	27.56	0.11
LSTM-6	25.1	981.71	31.33	-0.15

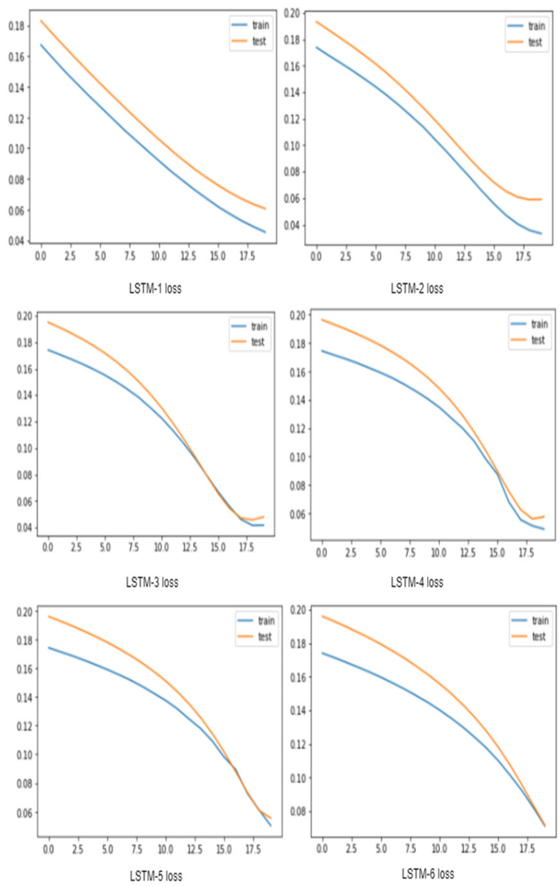

Figure1: Fitting curves of prediction LSTM models.

Accordingly, we calculate the total number of real and predicted cases: of the whole test set 21 days), the first week, the second week, and the third week (Table 3).

Besides, Fig. 2 presents the daily real and predicted new cases' curves corresponding to 21 days. We can see that LSTM-3 projections still remain very close to the real values, except for some high peaks that LSTM-3 doesn't catch and also for the period ranging from June 1, 2020 to June 3, 2020.

The peaks and the bending could be explained by the industrial and residential clusters which are reported from time to time in the last month of confinement in Morocco. However, we think that the reported deviation in general could be due to the fact that our model doesn't take into account other important feature such as test kits, clusters, asymptomatic case that would influence the COVID-19 spread. Hence, we think that the obtained results are promising. However, we suggest trying other features in future work in order to help the models to learn faster and easier the epidemic trend.

Table 3: LSTM-3 deviation per week.

		Week 1	Week 2	Week 3
Real new cases		374	352	560
LSTM-3	Predicted new cases	409,43	480,15	528,98
	Deviation	35,43	128,15	-31,02
	Deviation percentage	9,47	36,41	-5,54

5 CONCLUSIONS

In this paper, we give a comparative study of six LSTM models' architectures in order to predict new positive COVID-19 cases using data of Morocco from March 2, 2020 to June 15, 2020. The study shows that the LSTM with three cells gives better results and avoids both the overfitting and the underfitting. The results are very close to the real values for two among three weeks, and fairly close to the other week. Therefore, we think that the powerful DL model LSTM which is suitable for time series problems, could also be a suitable and promising model to learn complex insights from COVID-19 data. Our findings and conclusions are demonstrated and enhanced by various illustrations we provide in this paper. Nevertheless, we plan to more explore this potential model under other perspectives by including other important features and investigating also the

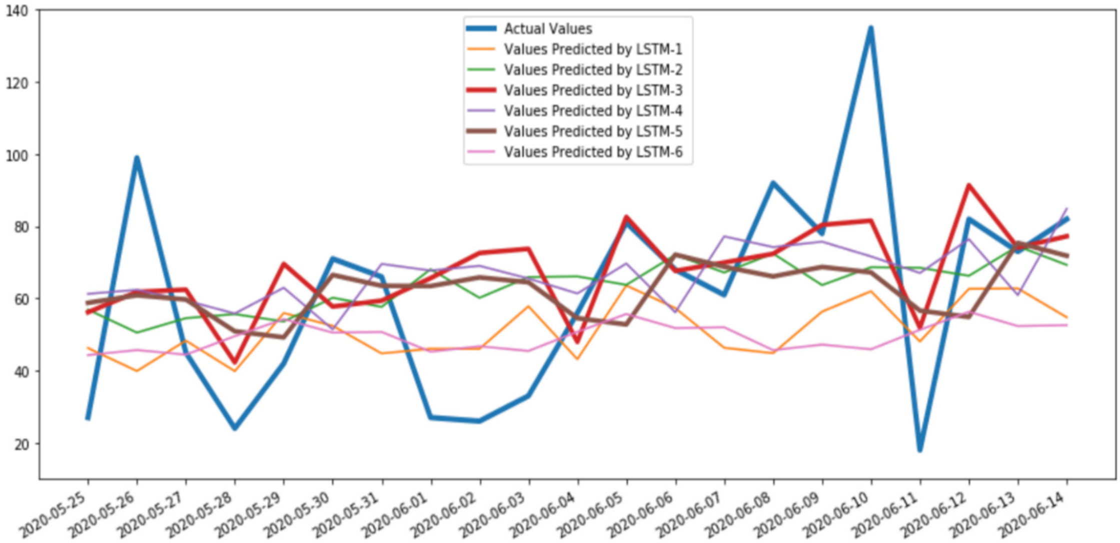

Figure 2: Real and predictive cases curves for 21 days.

deconfinement period in order to improve the prediction accuracy and adapt the model to various crisis situations.

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REFERENCES

Alakus, T. B., & Turkoglu, I. (2020). Comparison of deep learning approaches to predict COVID-19 infection. Chaos, Solitons and Fractals, 140, 110120. doi: 10.1016/j.chaos.2020.110120

Arora, P., Kumar, H., & Panigrahi, B. K. (2020). Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. Chaos, Solitons and Fractals, 139, 110017. doi: 10.1016/j.chaos.2020.110017

Ayris, D., Horbury, K., Williams, B., Blackney, M., Shi, C., See, H., Afaq, S., & Shah, A. (n.d.). Deep Learning Models for Early Detection and Prediction of the spread of Novel Coronavirus (COVID-19).

Ayyoubzadeh, S. M., Ayyoubzadeh, S. M., Zahedi, H., Ahmadi, M., & R Niakan Kalhori, S. (2020). Predicting COVID-19 incidence using Google Trends and data mining techniques: A pilot study in Iran. JMIR Public Health and Surveillance, 6(2), e18828. doi: 10.2196/18828

BERHICH, A., BELOUADHA, F., & KABBAJ, M. I. (2020). LSTM-based Models for Earthquake Prediction. 6. doi: https://doi.org/10.1145/3386723.3387865

Bouhamed, H. (2020). Covid-19 Cases and Recovery Previsions with Deep Learning Nested Sequence Prediction Models with Long Short-Term Memory (LSTM) Architecture. International Journal of Scientific Research in Research Paper. Computer Science and Engineering, 8(2), 10–15. Retrieved from https://github.com/henibouhamed/COVID-19-LSTM

Chimmula, V. K. R., & Zhang, L. (2020). Time series forecasting of COVID-19 transmission in Canada using LSTM networks. Chaos, Solitons and Fractals, 135, 109864. doi: 10.1016/j.chaos.2020.109864

Direkoglu, C., & Sah, M. (2020). Worldwide and Regional Forecasting of Coronavirus (Covid-19) Spread using a Deep Learning Model. MedRxiv, 2020.05.23.20111039. doi: 10.1101/2020.05.23.20111039

Graves, A. (2013). Generating Sequences With Recurrent Neural Networks. Retrieved from http://arxiv.org/abs/1308.0850

Hochreiter, S., & Schmidhuber, J. (1997a). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. doi: 10.1162/neco.1997.9.8.1735

Hochreiter, S., & Schmidhuber, J. (1997b). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. doi: 10.1162/neco.1997.9.8.1735

Kingma, D. P., & Ba, J. L. (2015). Adam: A method for stochastic optimization. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings.

Kırbaş, İ., Sözen, A., Tuncer, A. D., & Kazancıoğlu, F. Ş. (2020). Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches. Chaos,

Solitons and Fractals, 138, 110015. doi: 10.1016/j.chaos.2020.110015
Ksantini, M., Kadri, N., Ellouze, A., & Turki, S. (2020). Artificial Intelligence Prediction Algorithms for Future Evolution of COVID-19 Cases. Ingénierie Des Systèmes d Information, 25(3), 319–325. doi: 10.18280/isi.250305
Oksuz, I., Cruz, G., Clough, J., Bustin, A., Fuin, N., Botnar, R. M., Prieto, C., King, A. P., & Schnabel, J. A. (2019). Magnetic resonance fingerprinting using recurrent neural networks. Proceedings - International Symposium on Biomedical Imaging, 2019-April, 1537–1540. doi: 10.1109/ISBI.2019.8759502
Siami-Namini, S., Tavakoli, N., & Siami Namin, A. (2019). A Comparison of ARIMA and LSTM in Forecasting Time Series. Proceedings - 17th IEEE International Conference on Machine Learning and Applications, ICMLA 2018, 1394–1401. doi: 10.1109/ICMLA.2018.00227
Tomar, A., & Gupta, N. (2020). Prediction for the spread of COVID-19 in India and effectiveness of preventive measures. Science of the Total Environment, 728, 138762. doi: 10.1016/j.scitotenv.2020.138762
Wang, Q., Guo, Y., Yu, L., & Li, P. (2017). Earthquake Prediction based on Spatio-Temporal Data Mining: An LSTM Network Approach. IEEE Transactions on Emerging Topics in Computing, 6750(c), 1–1. doi: 10.1109/tetc.2017.2699169
Yan, B., Tang, X., Liu, B., Wang, J., Zhou, Y., Zheng, G., Zou, Q., Lu, Y., & Tu, W. (2020). An Improved Method for the Fitting and Prediction of the Number of COVID-19 Confirmed Cases Based on LSTM. Materials & Continua CMC, 2020. Retrieved from http://arxiv.org/abs/2005.03446
Yang, Z., Zeng, Z., Wang, K., Wong, S. S., Liang, W., Zanin, M., Liu, P., Cao, X., Gao, Z., Mai, Z., Liang, J., Liu, X., Li, S., Li, Y., Ye, F., Guan, W., Yang, Y., Li, F., Luo, S., … He, J. (2020). Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. Journal of Thoracic Disease, 12(3), 165–174. doi: 10.21037/jtd.2020.02.64
Zandavi, S. M., Rashidi, T. H., & Vafaee, F. (2020). Forecasting the Spread of Covid-19 Under Control Scenarios Using LSTM and Dynamic Behavioral Models. Retrieved from http://arxiv.org/abs/2005.12270