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Outbreak prediction of COVID-19 using Recurrent neural network with Gated Recurrent Units

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\textbf{ABSTRACT}

Respiratory infections corona virus 2-caused inflammatory disorders are CORONAVIRUS DISEASE 2019 (COVID-19) (SARS-CoV-2). A serious corona virus acute disease arose in 2019. Wuhan, China, was the first location to find the virus in December 2019, which has now been spreading all over the world. Recurrent neural networks, together with the use of LSTMs, fail to provide solutions to numerous issues (RNNs). So this paper has proposed RNN with Gated Recurrent Units for the COVID-19 prediction. This paper utilizes system, which was developed to assist nations (the Czech Republic, the United States, India, and Russia) combat the early stages of a newly emerging infection. For instance, the system tracks confirmed and reported cases, and monitors cures and deaths on a daily basis. This was done to allow the relevant parties to have an early grasp of the disastrous damage the lethal virus will bring. The implemented is an ensemble approach of RNN and GRU that work has computed the RMSE value for the different cases such as infected, cure and death across the four different countries.

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\textbf{1. Introduction}

A significant increase in COVID-19 cases is already happening in many places because of the fast onset of winter. Mass vaccination programs are initiated in several nations to prevent the spread of COVID-19, yet unfathomable surges in COVID-19 have significantly increased the challenges to public officials\cite{1}. As many parts of the world are reporting an increase in disease transmission and possible lethality, it has been reported that new and potentially more deadly strains have been found, and doubts have been already made about immunizations' ability to combat emerging lethal strains. Scientists have already predicted how awful the problem will get as fresh cases of COVID-19 continue to grow\cite{2}. When confronted with the new wave of infection, fear of the pandemic, and the public’s loss of interest in responding to different intervention efforts, people have responded with reckless behavior. This puts government officials in unexpected situations. Non-pharmaceutical interventions, like the use of effective face masks, the closure of educational institutions, the restriction of travel, and stringent containment measures, have the most significant interventions for flattening the Epidemic Curve\cite{3}. Furthermore, mass testing and tracking are also essential if the continuous transmission chain is to be broken. Government authorities must ensure that access to affordable, quick tests is facilitated. While huge immunization being implemented in several nations to prevent the spread of COVID-19, an unprecedented number of cases have recently developed, resulting in an unprecedented increase in the magnitude of the spread of COVID-19. The related infrastructure of new and potentially lethal types was observed in several regions throughout the world, and several doubts concerning the efficiency of immunizations against emerging dangerous variants had already been raised prior to this date. Concerned experts have previously issued dire warnings about the perilous nature of the increases in COVID-19 because of the tremendous number of new cases\cite{4}. At the moment of a possible new wave of infection, such as a pandemic, many individuals feel bored, distracted, and apathetic. That lack of interest encourages people to take impulsive action, forcing government ministers in new situations. Non-pharmaceutical interventions with effective face covering, the
lockdown of academic institutions, restricted transportation, and additional security are the most powerful interventional tactics to smooth the Pandemic Slope [3,4,5]. This concludes that if the continuous transmission chain is to be disrupted, then widespread testing and tracking are required. Authorities should ensure that affordable, rapid diagnostics are made available to the public. Proactive contact tracing and local follow-up and support can be employed in several nations to help with the ongoing risks posed by a prospective COVID-19 outbreak.

A number of computational and scientific paradigms have proven their value in different nations when predicting the worldwide epidemic situation. Several studies have looked into the transmission of COVID-19. Studies have proven the most efficient management techniques to prevent this pandemic. Though there is no easily available treatment for COVID-19, numerous non-pharmaceutical initiatives have helped combat the pandemic in the worst-hit nations through improving public health policy. It can be difficult to create one all-encompassing computational model to reflect all of the complex and natural relationships found in the real world. Therefore, it is not unusual to assume that there are numerous assumptions which are based on outcomes, and it is unusual for the true breakout scenario to be predicted. But when building a forecasting model that contains both mathematical models and neural networks, robust forecast outcomes may be possible.

Still, this is an emerging area of research for which there is still much to be done and tried. Deep learning algorithms are especially effective in analyzing and forecasting diverse epidemic outbreak scenarios. With suitable intervention strategies, these techniques can often yield effective forecasts for public officials that can help them conduct suitable interventions to stop the spread of highly infectious illnesses. In the research by Wang et al., the LSTM model was used to predict the number of new COVID-19 cases for 120 days. This paper however, discovers that the LSTM model is unable to pick up the correct pattern. The bottom line is that Iran, Russia, and Peru see continuous declines. This makes perfect sense, however the fact remains that the second COVID-19 wave struck these countries by now. Researchers Arora et al. constructed a model that combines convolutional LSTM with notions of the “Convolutional LSTM” in an effort to forecast the introduction of Indian neural networks [5]. This model performed well for three days of predictions, but failed after that.

While it may not deliver substantial insight with commendable accuracy, it does show that the LSTM architecture doesn’t deliver noteworthy insight and noteworthy accuracy in time-series forecasts over the long run. Long-term forecasting is a vital aspect of both policymaking and strategic planning. The LSTM model can accommodate a big database whenever it is important to identify strain series analysis [6]. But, the model is susceptible to predict with less data points, and it does not find a trend.

As previously stated, CNN architectures are highly suited for finding essential features from datasets as well as learning local data patterns. Researchers carried out a rigorous comparison of the long-term memory, Convolutional Neural Networks (CNN) [7], Gated Recurring Unit (GRU) [8], and Multivariate Convolutional Neural Network (MCNN), alongside an analysis of the projections on the number of new COVID-19 cases daily for Brazil, Russia, and the United Kingdom for the four deep learning methods: short-term memory, CNN, Gated Recurring Unit (GRU), and MCNN. The robustness of the model was tested using mean absolute percent error (MAPE) and standard root mean square error (nRMSE) [9]. This shows that CNN is a superior deep learning model than the competition. Because of this, CNN has found that the best way to recognize accurate forecasts in many kinds of situations is through their use. CNN and MCNN are two different but nonetheless popular methods for utilizing deep learning: Nations such as France, Germany, and the UK were at a high risk of the approaching second wave of COVID-19 due to their rising COVID-19. Since it has proven to consistently deliver high-quality results in the health care systems, it can be sure to plan for catastrophic scenarios with our proven methods. It arranges the entire chapter like this. The section “Materials and methods” is made up of information about the materials and methods used in the experiment. Using COVID-19 data from Brazil, Russia, and Great Britain, findings of forecasts were discussed in real-time under ‘Results and Discussion.’ Finally the conclusion is followed by reference.

2. Background study

The analysis of current and future Italy condition is conducted by A. and G. Remuzzi [10] is part of a larger COVID-19 effort. The author has utilized a forum pollination method, and the Salp Swarm Algorithm, to determine how many COVID-19 patients there will be in the following 10 days. Perc et al. [11] created a way to track COVID-19’s daily values with a limited number of iterations. The technique investigates predicted returns and fatalities, as well as steady and decreasing growth from exponential growth, and finds the maximum allowable daily growth rates for stable and declining growth. According to the projections, growth rates must be less than 5% each day in order to have plateaus soon. Zhang et al. [12] segmented Poisson model evaluates the available database for the COVID-19 outbreaks in the six different countries, Canada, Italy, the United Kingdom, France, Germany, and the United States of America.

FANELLI and PIAZZA examined the system changes of the COVID-19 outbreak, which began on January 22nd, 2020, and ended on March 15th, 2020, from China, Italy, and France [13]. This article, titled offers an efficient COVID-19 model that starts on February 1, 2020, and ends on March 11, 2020. The authors break the time prediction window into four rounds of ten days each. The initial examples, which included projections ranging from February 11, 2020 to March 01, 2020, are remarkably consistent with the projections generated through extrapolation. Based on Cleo Anastassopoulou et al data [14], the study and forecast of the coronavirus outbreak are conducted. Data gathered by the public was used in Hubei, China, to study critical epidemiological factors from January 11, 2020 to February 10, 2020. Furthermore, the COVID-19 epidemic demonstrates another model of forecast, which has not previously been shown.

Researchers found two sets of data: One dataset is comprised of large-scale information provided by the World Health Organization, while the other consists of government databases. An assessment of a pandemic could be done using several limitations, including the influence of naturally occurring components, the time it takes to breed, the geographic isolation, age and sex. These procedures and rules that were employed earlier are distributed evenly throughout their projects. An ability to pinpoint their challenges is shared alongside approaches to determining their issues (specialized and conventional). A major research project is investigating these difficulties and identifying solutions for the worldwide COVID-19 pandemic, which may be implemented by the people affected by the epidemic [15]. Moreover researchers are proposing various protocols in the field of healthcare [16–21] and vehicle communication [22–28] to protect the information exchanged among various devices to devices.

2.1. Datasets and methods

In this work, 4 different type of dataset has been taken. These dataset belongs to 4 different countries which are India, USA, Czech Republic and Russia. The dataset is in csv format and consist of 4
features which includes date, cured, deaths and confirmed. The dataset represent the datewise COVID-19 patients which are categorized into three cases such as number of curable patients, number of died patients on the particular date and last one shown the number of confirmed cases. Indian dataset consist of 103 records, Czech Republic contains 136 records, Russia dataset consist of 73 records and US dataset contains 112 records. The months considered in this study is from January to June 2020.

2.2. Proposed methodology

In the proposed work we have implemented recurrent neural network with LSTM for the prediction of COVID –19 across the 4 different countries India, USA, Czech Republic and Russia. Before applying the deep learning model in the form of recurrent neural network, data preprocessing is done using the Min max scaler. In this study, dropout layer is used during the sequential regression analysis with LSTM (Long short term memory).

2.3. Sequential regression

Consider that we have to anticipate the result of process consisting of \( n \) stages and previously we have observed \( m \) cases. Consider that the covariates released by stages \( j \) as \( \{ A_1, A_2, \ldots, A_j \} \), where \( j = 1, \ldots, m \) and the final outcome is given by \( B \). Here \( A_0 \) is the collection of covariant at stage \( k \) and thus this form a matrix. Now consider the covariates dataset represented by \( A = [A_1, A_2, \ldots, A_0] \). In addition the \( i^{th} \) observation of \( A \) by \( a_{ki} \) and \( i^{th} \) observation of \( A' \) the result is given by \( a_{i}' \). Therefore the data are \( \{a_{0i}, a_i\}, \quad k = 1, \ldots, n, \quad i = 1, \ldots, m \). Now in the other section sequential regression and the naïve sequential regression is described. Third sub section consist of combination of sequential measurement error regression technique with regression with measurement error methods.

2.4. RNN (Recurrent neural Network)

Fig. 1 depicts the suggested RNN model to identify the risk score. When \( j \) is set to 1, 2, 3, 4, 5, and so on, the model will feed it with a patient’s entry of value \( x_i \) and the previous hidden state of value \( h_{j-1} \) and output the current hidden state value of value \( h_j \) for \( j = 1,2,\ldots,q \) here \( q \) represent total visit of patient . In this work, we applied a GRU to the RNN model. LSTM is the extensively used RNN cell across all RNN types, and for larger datasets, LSTM generally outperforms GRU, while on short datasets, GRU shows equivalent or higher performance. In the supplementary material, preliminary results of the GRU are made available. Fig. 2.

2.5. GRU: Gated Recurrent Unit

The input \( x \) that is multi-hot encoded is mapped into a low-dimensional embedding with an embedding layer (described below) [29]. The patient’s demographic information vector and then fully linked layers with hyperbolic tangent activation, with the hidden state at the final timestamp, are combined in the end to generate a fully connected layer. A final fully connected layer is added on top of the patient’s output, which uses a single neuron with sigmoid activity (i.e. logistic regression layer) to compute the patient’s risk score. Below are the given equations of the different component.

Reset Gate: \( r_t = \sigma(W_{ir}x_t + W_{hr}h_{t-1}) \)

Update Gate: \( z_t = \sigma(W_{iz}x_t + W_{hz}h_{t-1}) \)

Process input: \( \tilde{h}_t = \text{tanh}(W_{ih}\tilde{x}_t + W_{hh}h_{t-1}) \)

Hidden state: \( h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \)

Output state: \( y_t = h_t \)
In the above equation $W$ represents the weight and it is updated by the equation $z\cdot h_t$ is the hidden state, $\tanh$ is the activation function. The output state is represented by $y_t$, which takes the input processed by activation function.

### 3. Experiment and results

This work is performed by using python programming language and keras for the implementation of Recurrent Neural Network. The parameters used for the evaluation of the performance of the proposed model are RMSE. The proposed deep learning model is used for the prediction of COVID-19 cases in the future.

Table 1, 2 and 3 has shown the comparison of the models based on the three different types of cases such as infected, cured and death cases.

### 4. Conclusion

To predict the COVID-19 pandemic growth among countries, we developed an RNN using the GRU prediction model. The COVID-19 data is time-series, of which the total number of confirmed COVID-19 cases increases monotonously over time until a specific converging peak curve has been reached. Given extensive training data, GRU records the pattern of dynamic RMSE growth compared to RNN graphs. The results suggest that LSTM is a promising tool for predicting COVID-19 pandemics by learning from big data. In this work, data collected is in CSV format. In the future, the COVID-19 analysis will be done using images and with the help of other deep learning models such as Convolutional Neural Network, Capsule networks, etc.

### 5. Credit author statement

**Sathish Natarajan**: Conceptualization, Data curation, Formal analysis, Funding acquisition.

**Mohit Kumar**: Visualization, Writing - original draft, Writing - review & editing.

**Sai Kiran Kumar Gadde**: Investigation, Methodology, Project administration.

**Vijay Venugopal**: Resources, Software, Supervision, Validation.

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**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### References

1. V. Chomola, V. Hassija, V. Gupta, M. Guizani, “A Comprehensive Review of the COVID-19 Pandemic and the Role of IoT, Drones, AI, Blockchain, and 5G in Managing its Impact,” IEEE Access 8 (2020) 90225–90265.

2. T. Ozturk, M. Talo, E.A. Yildirim, U.B. Baloglu, O. Yildirim, U. Rajendra Acharya, Automated detection of COVID-19 cases using deep neural networks with X-ray images, Comput. Biol. Med. 121 (2020) 103792, https://doi.org/10.1016/j.compbiomed.2020.103792.

3. R. Nair, S. Vishwakarma, M. Soni, T. Patel, S. Joshi, Detection of COVID-19 cases through X-ray images using hybrid deep neural network, World J. Eng. (2021), https://doi.org/10.1016/j.wje.2020.0529.

4. S. Gomathi, R. Kohli, M. Soni, G. Dhiman, R. Nair, Pattern analysis: predicting COVID-19 pandemic in India using AutoML, World J. Eng. (2020), https://doi.org/10.1016/j.wje.2020.0529.

5. P. Arora, H. Kumar, B.K. Panigrahi, Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India, Chaos Solit. Fract. 139 (2020) 116017, https://doi.org/10.1016/j.chaos.2020.116017.

6. R. K. Pathan, M. Biswas, M. U. Khandaker, “Time series prediction of COVID-19 by mutation rate analysis using recurrent neural network-based LSTM model,” Chaos, Solitons and Fractals, 2020.

7. J. Schirrmeister et al., Deep learning with convolutional neural networks for visualizing, Writ-
Conference on Computing Methodologies and Communication (ICCMC), Erode, 2018, pp. 539-543, doi: 10.1109/ICCMC.2018.8487887.

[25] Soni M., Rajput B.S., Patel T., Parmar N. (2021) Lightweight Vehicle-to-Infrastructure Message Verification Method for VANET. In: Kotecha K., Piuri V., Shah H., Patel R. (eds) Data Science and Intelligent Applications. Lect. Note. Data Eng. Commun. Technol., vol 52. Springer, Singapore. Doi: 10.1007/978-981-15-4474-3_50.

[26] U. Chaudhary, A. Patel, A. Patel, M. Soni, Survey Paper on Automatic Vehicle Accident Detection and Rescue System. In: Kotecha K., Piuri V., Shah H., Patel R. (eds) Data Science and Intelligent Applications. Lecture Notes on Data Engineering and Communications Technologies, vol 52. Springer, Singapore. 2021, Doi: 10.1007/978-981-15-4474-3_35.

[27] M. Soni, B.S. Rajput, Security and Performance Evaluations of QUIC Protocol. In: Kotecha K., Piuri V., Shah H., Patel R. (eds) Data Science and Intelligent Applications. Lect. Not. Data Eng. Commun. Technol., vol 52. Springer, Singapore, 2021, Doi: 10.1007/978-981-15-4474-3_51.

[28] M. Soni, A. Jain, T. Patel, “Human Movement Identification Using Wi-Fi Signals,” 2018 3rd International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 2018, pp. 422-427, doi: 10.1109/ICICT43934.2018.9034451.

[29] J. Lee, C. Ta, J. H. Kim, C. Liu, C. Weng, “Severity Prediction for COVID-19 Patients via Recurrent Neural Networks (preprint),” medRxiv, p. 2020.08.28.20184200, 2020.