Combination of Transfer Learning, Recursive Learning and Ensemble Learning for Multi-Day Ahead COVID-19 Cases Prediction in India using Gated Recurrent Unit Networks

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\textbf{ABSTRACT}

The current COVID-19 pandemic has put a huge challenge on the Indian health infrastructure. With more and more people getting affected during the second wave, the hospitals were over-burdened, running out of supplies and oxygen. In this scenario, prediction of the number of COVID-19 cases beforehand might have helped in the better utilization of limited resources and supplies. This manuscript deals with the prediction of new COVID-19 cases, new deaths and total active cases for multiple days in advance. The proposed method uses gated recurrent unit networks as the main predicting model. A study is conducted by building four models that are pre-trained on the data from four different countries (United States of America, Brazil, Spain and Bangladesh) and are fine-tuned or retrained on India’s data. Since the four countries chosen have experienced different types of infection curves, the pre-training provides a transfer learning to the models incorporating diverse situations into account. Each of the four models then give a multiple days ahead predictions using recursive learning method for the Indian test data. The final prediction comes from an ensemble of the predictions of the combination of different models. This method with two countries, Spain and Brazil, is seen to achieve the best performance amongst all the combinations as well as compared to other traditional regression models.

1. Introduction

The COVID-19 pandemic has placed India’s relatively limited healthcare resource under tremendous pressure. Owing to the nation wide lockdown starting from 24 March 2020, imposed by the Indian government, the number of COVID-19 cases in the first wave were limited. However, with the opening up of the cities, its’ transport systems and allowance of various festivities, India has faced a very severe second wave with the peak at almost 4 lakh new cases a day. Although the peak seems to be over, the actual number of people to be affected in the coming days is very difficult to determine. There had been an exponential rise [14] of new cases in the second wave and as of 13 August 2021, there are close to 4 lakh active COVID-19 cases in India.

According to a worldwide trend, we can simply state that our existing medical capacity cannot meet the high health demands caused by the coronavirus pandemic [16]. The existing circumstances imply that availability of hospital beds, ICU beds, fans, PPEs and qualified medical staff across the country are likely to be depleted. We already have reached our limits on important medical equipment and in the context of the second wave, it is therefore challenging for authorities to supply all sectors of society with required healthcare services.

Researchers have proposed various models for predicting the COVID-19 cases. Various mathematical models have been used to predict and to understand the spread of the disease [3]. Auto-regressive Integrated Moving Average (ARIMA) has been used [21, 11] as the standard model to predict the behaviour of the infection curves in different countries. The model was able to capture the total case statistics because the number of total cases is seen to follow a standard exponential curve. The number of new cases each day is highly uncertain and involves a lot many variables. Therefore, it is much more difficult to handle using ARIMA [16]. Researchers [22] have therefore explored support vector machines to predict the daily COVID-19 cases. Recurrent neural networks (RNNs) have also been tested and have become the state of the art models for predicting the daily number of cases. Researchers [19] have compared various RNN models like Long Short Term Memory (LSTM) [9], Gated Recurrent Unit (GRU) and Bi-LSTMs. They have observed that these models are much more robust when compared to ARIMA or Support Vector Regression (SVR) [24]. Transfer learning and ensemble modelling has also been applied to study the statistics of daily COVID-19 cases [5] and it has shown to perform even better than the standard LSTM-RNNs.

Since the authorities are not aware of how many people might be infected or how many are extremely critical,
2. Preliminaries

2.1. Gated Recurrent Units

The current task relies on gated recurrent units (GRU) as the basic building blocks for multi-day prediction of COVID-19 parameters. GRU, as a member of recurrent neural networks (RNN) has this innate ability to capture trends and seasonality in time-series data. It is therefore a simple go-to method for time series prediction.

GRUs are able to solve the exploding and vanishing gradient problem that is common for vanilla RNNs [6]. With its reset gate and update gate, a GRU is able to decide what information to keep from the previous state and what information to pass on to the next state. This gives GRUs the ability to keep relevant information from long ago in the sequence while removing information that is no longer relevant for the task at hand. For a more detailed description of GRU, the reader can refer [6].

GRUs is one of the simplest recurrent neural network models and has been used for time series prediction tasks in multiple domains like GRUs being used for traffic flow prediction [7], energy load forecasting [12], stock market forecasting [1], air pollution forecasting [23] etc. It has also been used for COVID-19 prediction with the help of deep learning based models on LSTMs, GRUs and Bi-LSTMs [20].

This work of multi-day COVID-19 prediction has been done using GRUs as the basic building blocks in order to harness its effective sequence modelling function and also to prevent over-fit in our relatively small dataset.

2.2. Transfer Learning

Transfer learning is the scenario where a pre-trained model for one particular problem is applied to a second, different but related problem. Transfer learning tries to take advantage of what has already been learned in a problem and applies it to improve the generalization in another related problem.

The domain in which the model is trained is called the source domain and the domain in which the model is applied is called the target domain. The source and the target domain can be different enough but needs to have some of a connection. The learning of the model in the source domain needs to be relevant in the target domain. Transfer learning is mainly applied in such target domains where sufficient labeled data is not available in the target domain.

Transfer learning has been applied in the COVID-19 scenario for different tasks. It has been used for classification of COVID-19 from Non-COVID-19 patients by using chest CT images [17], for face-mask detection in public areas [10], COVID-19 cases and death forecasts using long short term memory networks [8] etc.

Transfer learning has been chosen for this task of COVID-19 case prediction to take into account the early COVID-19 affected countries. Countries with different circumstances, different climate, different measures for infection control etc are chosen as the source domain and COVID-19 cases prediction for India is done as the target domain. Transfer learning has given good results for next day prediction for COVID-19 cases using LSTMs in the previous work [4].

2.3. Recursive Learning

The GRU model built in this work is able to predict the next day parameter after looking at the parameters over a period of past days (called the look-back period). In order to achieve a multi-day prediction of COVID-19 cases, a recursive learning methodology is adopted. The process of recursive learning adopted is shown in the Figure 1.

![Figure 1: Explanation of recursive learning used in the multi-day COVID-19 prediction](image)

Input to Prediction Model: Day1 Day2 Day3 Day4 Day5 Day6 Day7

Prediction: Day5 Day6 Day7

This work of multi-day COVID-19 prediction has been done using GRUs as the basic building blocks in order to harness its effective sequence modelling function and also to prevent over-fit in our relatively small dataset.
In a recursive way, the prediction output of the model is added to the input in the next step to get the subsequent prediction. As an example, data for day 1 to day 4 is used as input to the model to predict the data for the day 5. In the next step, the data for day 5 is added to the input and day 2 to day 5 of data is taken as input to the model to predict the data for the day 6. This process is repeated recursively till the required days of prediction is obtained. In this work, this recursive learning methodology works for 7 iterations to predict the COVID-19 cases for the next 7 days.

### 2.4. Error Metric

Two error metrics have been used for this study. First is the relative mean squared error (RMSE) and the second one is relative mean absolute error (RMAE). Rather than actual value of the error, calculating the error as a fraction of the actual value has been used in this study. As the error value is compared relative to the actual value of the parameter, hence the term relative has been used for the standard error metrics of mean squared error and mean absolute error.

The error metrics are described in the following equations 1 and 2 below:

\[
RMSE = \sum_{i=1}^{d} \left( \frac{\text{original}(i) - \text{predicted}(i)}{\text{original}(i)} \right)^2
\]

\[
RMAE = \sum_{i=1}^{d} \left| \frac{\text{original}(i) - \text{predicted}(i)}{\text{original}(i)} \right|
\]

where, \( \text{predicted}(i) \) is the predicted value on the \( i^{th} \) day and \( \text{original}(i) \) is the actual value on the \( i^{th} \) day. \( d \) is the total number of days involved.

For each of the 3 COVID-19 parameters predicted (daily new cases, daily new deaths and total active cases), these two errors have been showed separately in order to find the right model which gives the best performance for all the 3 parameters.

### 3. Proposed Method

The proposed model is an ensemble combination of four different models pre-trained on data from four different countries (USA, Brazil, Spain and Bangladesh) in order to predict the COVID-19 daily new cases, daily new deaths and active cases for India for the next 7 days. In order to incorporate the population density into account, the data of each country is divided by the corresponding population densities of the different countries.

These four countries are particularly chosen due to their diverse nature of the COVID-19 infection curve. The United States of America has witnessed the most number of cases. The first wave in USA was prolonged and the second wave has resulted in an increased number of deaths per day. However, USA is has not witnessed a plateau in the total number of cases (i.e. daily new cases have decreased considerably) after the first wave. Brazil has the third highest number of cases and currently the death rate is 2,273 per million population. However, the total case curve in Brazil shows an increasing trend which suggest that the second wave is going to be for a prolonged duration. Spain, on the other hand has already witnessed its third wave and the number of cases are currently declining. Although Bangladesh is an overly populated country, shares borders with India (where the infection rate is high) and has similar climatic conditions as India, it has not witnessed as much fatalities or infections as India.

India is witnessing a decline in the number of daily cases which suggests that the second wave is gradually ending. This obviously brings us to the crucial question about the condition in India about the third wave. Now, since all of the four countries have shown different trends, it is not sure as to which path Indian trend would follow. This is why all possible combinations of these four countries were taken into account. More countries could have been taken for pre-training, but that would have added more complexity to the model without adding anything significant to the performance. Training of each of these models have been done using sliding window technique with a look back period of 14 days. This look back period has been varied from 7 to 19 in order to find the best look back period for the 7 day ahead prediction task. The proposed model consists of three main steps which are discussed in the subsequent sections.

#### 3.1. Step 1: Transfer Learning

As stated earlier, the proposed model consists of of all possible combinations of four GRU networks, each of which is pre-trained on data from four different countries. To pre-train each model, the data of each of the countries is taken for more than 1 year from 15 February 2020 to 16 April 2021. The models built on the individual countries need to be fine-tuned on Indian data in order to take into account the recent trend of COVID-19 infections in the target country, India. Therefore, the pre-trained models have been fine-tuned on Indian data for the period 01 January 2021 to 31 March 2021.

This method of pre-training and then fine-tuning introduces a transfer learning [25] ability in the individual models. Li et. al. [13] has shown that transfer learning can assist improve forecasting models based on deep learning. Countries throughout the globe are at various phases of the COVID-19 trend, including lockdown steps by many to prevent its transmission. Taking such information from different countries, the COVID-19 prediction in India can be predicted in a better way.

#### 3.2. Step 2: Recursive Learning

To get 7 day ahead predictions, we have incorporated recursive learning in each of these models. If the COVID-19 parameters for the next 7 days is being predicted at \( n^{th} \) day, in the first step, the COVID-19 parameter for just the next day \( (n + 1)^{th} \) day) is predicted by the model. This prediction for the \( n + 1^{th} \) day is then appended to the input to make the new input frame for prediction, which predicts the COVID-19 parameter for the \( n + 2^{th} \) day. This is process is repeated...
7 times to get the output prediction for the 7 days \((n + 1^{th} \text{ day to } n + 7^{th} \text{ day})\). An example of the process involved is shown in the Figure 1.

3.3. Step 3: Ensemble

After the predictions are obtained for subsequent 7 days, the predictions from the combination of models are aggregated using a weighted averaging. The weights are calculated based on the relative mean squared error (RMSE) obtained on validation data. 15 days of data for India (01 April 2021 to 15 April 2021) is kept aside for this validation task.

The relative mean squared error and the relative mean absolute errors (RMAE) for \(d\) number of days are calculated using the equations 1 and 2. The weights \((w_i)\) for a model \(i\) are given by the equation 3. And the final prediction on any date \(D\) is given by the equation 4.

\[
w_i = \frac{\text{RMSE(Model } i)}{\sum_{j=1}^{n}\text{RMSE(Model } j)}, \tag{3}
\]

where, \(\text{RMSE(Model } i)\) is the relative mse obtained for \(i^{th}\) model on validation data, \(n\) is the number of models involved in the ensemble.

\[
prediction(D) = \sum_{i=1}^{n} w_i \times \text{prediction}_i(D), \tag{4}
\]

where, \(\text{prediction}_i(D)\) is the prediction by \(i^{th}\) model for date \(D\).

4. Experimental Results

4.1. Dataset

The data for this study has been taken from the website worldometers.info. The Worldometers website has been giving COVID-19 related data including new cases, new deaths, active cases, total tests etc for 222 different countries all along the period of the pandemic. Data related to daily new cases, daily new deaths, and active cases were taken for five different countries: the United States of America, Brazil, Spain, Bangladesh and India for the period from 15 February 2020 to 04 June 2021.

The data from the period 15 February 2020 to 15 April 2021 has been used for training the models for the individual four countries. Indian data from the period 01 January 2021 to 31 March 2021 has been used for fine-tuning the transfer learning models before testing them on Indian data for the period 16 April 2021 to 04 June 2021. The remaining period of 01 April 2021 to 15 April 2021 for the Indian data has been used as a validation data-set for the ensemble weighted averaging as mentioned in the previous section.

4.2. Results

In order to predict the cases on any date, we needed to know the optimum value of the look-back period for the model at hand. Finding the optimum value of the look-back period is crucial for the proposed method. This is because, depending on the look-back period, the performance of the models varies rapidly. We have, therefore experimented on the variation of RMSE with the look-back period. After experimenting, the look-back period of 14 days has been found out to giving the best results. A grid search methodology was also followed for finding the right hyper-parameters (learning rate, epochs of training etc) for the GRU model.

Figure 2: Average RMSE along with the standard deviation, for new cases prediction, for all the models (20 runs)

Figure 3: Average RMSE along with the standard deviation, for new deaths prediction, for all the models (20 runs)
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The RMSE and RMAE results for all possible combinations of the four countries (with four different COVID-19 scenario) chosen, along with support vector regression (SVR) and auto-regressive integrated moving average (ARIMA) models are shown in the Table 1. The results are shown separately for the 3 COVID-19 parameters predicted in this study. For doing an in-depth analysis, the effect of fine-tuning on Indian data is also seen by showing the results for the above mentioned methods without fine-tuning in Table 2. To see the stability of the analysis, all the results have been shown as an average of 20 independent runs, with the standard deviation in the results shown as well in Figures 2 to 4. It is seen that the combination model of Spain and Brazil gives the best results for multi-day forecasting of all the three predicted variables.

In order to study the effect of the look-back period on the results, the variation of RMSE for the three predicted variables is shown in Figures 5 to 7. It is seen that the RMSE is the least for 7 days prediction task when the look-back period was set to 14 days. Since we are relying on a recursive learning based multi-day prediction where the predicted values are used as inputs for the later predictions, we cannot afford to take the look-back to be smaller than the number of days in the multi-day prediction task. This will result in the last few predictions (of the recursive learning methodology) being made only on predictions and not on any actual data.

5. Discussion

As a first deduction from the results, it is clearly visible that the results for all the models improve with the fine-tuning with Indian data. As expected in transfer learning, the model pre-trained in the source domain needs to be fine-tuned if possible for the target domain. This is quite evident in the comparison of results in the two Tables 1 and 2.

For the single country models, Spain model gives the best results. The model built using the data from Spain is...
able to predict the trend in Indian data in a very accurate way. For the combination of two country models, the presence of Spain, with better trend tracking behaviour for Indian data, influences the performance in a positive way. Spain-Brazil combination gives the best result with the RMSE of 0.0193 and gives the best result amongst all the combinations. For the combination of more than two country models, the performance does not improve further than the Spain-Brazil model. Hence the two country combination of Spain-Brazil model gives the best performance.

Both India and Spain were vigilant in the start of the pandemic and had imposed strict infection control measures like lock downs, social distancing etc. One such study [2] compared the spread of COVID-19 infection in Spain and India by analysing the policy implications using epidemiological and social media data. Spain was also one of the early COVID-19 infected countries, which is already in the third wave of infections. Whereas, India is perhaps at the end of the second wave. Also the pattern of infection spread in sharp increases and then a rapid fall is common for both

| Method (Results with fine-tuning on Indian data) | New Cases | New Deaths | Active Cases |
|------------------------------------------------|-----------|------------|-------------|
| Spain                                          | 0.0239    | 0.1196     | 0.0128      |
| Brazil                                         | 0.0338    | 0.1394     | 0.0131      |
| USA                                            | 0.0468    | 0.1646     | 0.0222      |
| Bangladesh                                     | 0.0456    | 0.1620     | 0.0174      |
| Spain - Brazil                                 | 0.0193    | 0.1069     | 0.0103      |
| Spain - USA                                    | 0.0224    | 0.1147     | 0.0114      |
| Spain - Bangladesh                             | 0.0222    | 0.1146     | 0.0109      |
| Brazil - USA                                   | 0.0273    | 0.1253     | 0.0106      |
| Brazil - Bangladesh                            | 0.0258    | 0.1214     | 0.0105      |
| USA - Bangladesh                               | 0.0342    | 0.1398     | 0.0114      |
| Spain - Brazil - USA                           | 0.0212    | 0.1115     | 0.0102      |
| Spain - Brazil - Bangladesh                    | 0.0204    | 0.1095     | 0.0102      |
| Spain - USA - Bangladesh                       | 0.024     | 0.1183     | 0.0106      |
| Brazil - USA - Bangladesh                      | 0.0285    | 0.1283     | 0.0104      |
| Spain - Brazil - USA - Bangladesh               | 0.0222    | 0.1137     | 0.0102      |
| India Model                                    | 0.0568    | 0.1760     | 0.0249      |

Table 1
Comparison of results from all possible combinations of four countries considered in this study. The models have been fine-tuned on Indian data. Results are also shown for SVR and ARIMA models.

| Method (Results without fine-tuning on Indian data) | New Cases | New Deaths | Active Cases |
|------------------------------------------------|-----------|------------|-------------|
| Spain                                          | 0.0274    | 0.1218     | 0.0118      |
| Brazil                                         | 0.0367    | 0.1429     | 0.0201      |
| USA                                            | 0.0472    | 0.1638     | 0.0145      |
| Bangladesh                                     | 0.0457    | 0.1625     | 0.0146      |
| Spain - Brazil                                 | 0.0209    | 0.1101     | 0.0129      |
| Spain - USA                                    | 0.0253    | 0.1193     | 0.0107      |
| Spain - Bangladesh                             | 0.0227    | 0.1141     | 0.0108      |
| Brazil - USA                                   | 0.0292    | 0.1302     | 0.0182      |
| Brazil - Bangladesh                            | 0.028     | 0.1272     | 0.0135      |
| USA - Bangladesh                               | 0.0362    | 0.1447     | 0.0124      |
| Spain - Brazil - USA                           | 0.0228    | 0.1148     | 0.013       |
| Spain - Brazil - Bangladesh                    | 0.0224    | 0.1141     | 0.0116      |
| Spain - USA - Bangladesh                       | 0.0241    | 0.1179     | 0.0107      |
| Brazil - USA - Bangladesh                      | 0.0298    | 0.1311     | 0.0139      |
| Spain - Brazil - USA - Bangladesh               | 0.024     | 0.1179     | 0.0118      |
| India Model                                    | 0.0568    | 0.1760     | 0.0249      |

Table 2
Comparison of results from all possible combinations of four countries considered in this study. The models have not been fine-tuned on Indian data. Results are also shown for SVR and ARIMA models.
India and Spain. These kind of similar characteristics must be responsible for the low RMSE obtained for the models build with Spain data.

For the two country models, the combination models of Spain and Brazil gives a lower RMSE than Spain alone. There is a slight improvement in the result when Brazil data learnt model is combined with the Spain data learnt model. This can be attributed to the fact that Brazil has a long coastline, similar to that of India and also has a climate similar to that of the severely affected parts of India like Kerala and Mumbai.

After the combination of Spain-Brazil models have been built, further addition of models built with the other two country (Bangladesh, USA) data does not reduce the error any further.

6. Conclusion and future work

The proposed method with the combination of Spain-Brazil models, outperforms the other combinations as well as the other traditional regression models. This is because the proposed method leverages the capabilities of both transfer learning and ensemble learning, while taking into account the excellent sequence modelling capabilities of GRUs. The multi-day ahead prediction using recursive learning provides an added benefit of knowing the COVID-19 statistics multiple days ahead. The proposed method has currently been tested only on the whole country data of India. Similar study and prediction can be done for other countries by choosing relevant countries with the transfer learning relevance.

Regional study of the COVID-19 cases is also necessary and the proposed method can be extended to individual states in India by incorporating transfer learning of trends in other states or even smaller countries with comparable features with that of the individual Indian states. These areas look to be studied as an extension for this work.

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