Time-Series Forecasting of COVID-19 Cases Using Stacked Long Short-Term Memory Networks

Renato R. Maaliw III
College of Engineering
Southern Luzon State University
Lucban, Quezon, Philippines
rmaaliw@slsu.edu.ph

Zoren P. Mabunga
College of Engineering
Southern Luzon State University
Lucban, Quezon, Philippines
zmabunga@slsu.edu.ph

Frederick T. Villa
College of Industrial Technology
Southern Luzon State University
Lucban, Quezon, Philippines
ftvilla@slsu.edu.ph

2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) | 978-1-6654-4032-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/3ICT53449.2021.9581688

***Abstract*—The extent of the COVID-19 pandemic has devastated world economies and claimed millions of lives. Timely and accurate information such as time-series forecasting is crucial for government, healthcare systems, decision-makers, and policy-implementers in managing the disease's progression. With the potential value of early knowledge to save countless lives, the research investigated and compared the capabilities and robustness of sophisticated deep learning models to traditional time-series forecasting methods. The results show that the Stacked Long Short-Term Memory Networks (SLSTM) outperforms the Exponential Smoothing (ES) and Autoregressive Integrated Moving Average (ARIMA) models for a 15-day forecast horizon. SLSTM attained a collective mean accuracy of 92.17% (confirmed cases) and 82.31% (death cases) using historical data of 419 days from March 6, 2020 to April 28, 2021 of four countries – the Philippines, United States, India, and Brazil.**

Keywords—covid-19, forecasting, stacked long short-term memory networks, machine learning, pandemic, time-series

I. Introduction

The pandemic known as the '2019 Novel Coronavirus' (COVID-19 or SARS-COV-2) has spread swiftly, infecting millions and halting global economic activity. As of this writing, the overall infection is over 130 million, beyond 3 million deaths and the virus resurgences are seen in different countries [1]. Financial analysts conclude that the outbreak has had a detrimental effect on the international economy, resulting in a 4% decline in the gross domestic product (GDP) by 2020 [2]. Governments and policy-makers face an uphill battle in devising steps to combat the outbreak while tolerating the extreme economic and health implications.

Authorities in epidemiology recommend undertaking advanced statistical data analysis to make informed decisions [3]. They stress the importance of investing valuable capital in developing accurate forecasting models rather than contact tracing. It is essential to determine specific steps that safely suppress the virus while having the fewest possible adverse effects on people's health and economic well-being. The present condition cannot be significantly altered before a viable vaccine is discovered [4], which is unlikely to occur for more than a year. Forecasting immediately enables decision-makers and planners to make more informed decisions during current and future pandemics. Researchers used modeling to explain observable trends and prognosticate future patterns to prepare and plan responses from public health providers. Numerous forecasting strategies have been proposed as a result of data science advancements.

Epidemiological approaches seek to model disease states using biological mechanisms such as transmission rates and demographic variables. They are more complicated and inaccurate [5]. For instance, individual behavior is nearly impossible to measure dynamically during real-world outbreaks. The SIR (Susceptible/Infected/Recovered), SEIR model with an exposed parameter, and its variant, the SEIRD with an additional death parameter, is the most widely used infectious disease forecasting method [6]. The model's approach takes infection and recovery rates into account, but it oversimplifies complex pathological processes. Although these models capture fundamental aspects of epidemiology, their parameters involved many assumptions that are not true in actual cases. Based on previous studies [6 - 12], the models were adopted to predict cases spread of malaria, dengue, Ebola virus, tuberculosis (TB), human immunodeficiency virus (HIV), severe acute respiratory syndrome (SARS), and COVID-19.

On the other hand, statistical methods such as time-series (TS) models attempt to determine epidemiological behavior using historical surveillance data with several factors to forecast outbreaks. Disease clusters are categorized but do not consider their mode of transmission or changes in the rate of spread over time. Thus, the model attempts to foretell epidemiological activity using concrete data with fewer postulates. Moreover, they are reasonably straightforward to explain to the general public due to their empirical simplicity and lack of complex mathematics - they rely mainly on the concept of linearity [13]. According to the literature, multiple time-series models determine different affliction occurrences. Previous researches [14 – 17] have used regressions, simple moving averages (SMA), exponential smoothing (ES), and autoregressive integrated moving average (ARIMA) to predict COVID-19 incidence. Although many scientific processes can be adequately represented using linear models, most are intrinsically nonlinear, such as pandemics.

Artificial Intelligence (AI) is a powerful technology for a groundbreaking area of research with numerous applications in academia [18][19], business, and health care systems [20]. Its adaptability distinguishes AI to new domains, ease of integration, and compatibility with existing systems [21]. The research of [22] showed that machine learning offered recent innovations for adaptive disease growth foresight. For instance, in forecasting cases of COVID-19, support vector machines, genetic algorithms, prophet heuristics, and neural networks were implemented. To address the limitations of epidemiological models, which rely heavily on assumptions to its hyperparameters and the linearity of mathematical methods, we built a model centered on 'deep learning' with modification to its implementation to predict COVID-19 cases. Advanced prediction models that can handle nonlinearity [23] are becoming increasingly important in assisting public health care providers and policy-makers in determining effective plans to cope with the influx of potentially infected patients.

The main contribution of the research is the development of an accurate forecasting framework using neural networks to aid the present health crisis faced by humanity. Furthermore, our research results are valuable for streamlining the allocation of resources and optimization of management practices during an outbreak.

II. Methodology

A. Dataset, Transformation, and Models

The COVID-19 open data was obtained from the Center for Systems Science and Engineering (CSSE) of Johns Hopkins University. It is accessible in time-series format and includes reported confirmed cases, recoveries, and deaths per country. We have selected the stable versions of datasets for the Philippines, United States, India, and Brazil, from March 6, 2020 to April 28, 2021. These nations are highly affected by the outbreak based on statistics. Moreover, choosing a single data cannot capture the generalization capability of the model. Different characteristics of time-series data removes the bias. The graphical representation of the data is shown in Figure 1 and Figure 2. A normalization (*min-max scaling*) transformation preprocessing method was employed for deep learning models. It is critical because features evaluated at varying scales do not contribute equally to the model fitting, resulting in one-sidedness. Various studies can attest to the technique's validity in improving forecast accuracy [24 - 26]. The dataset was divided into 80% training and 20% testing set for model fitting. Our model forecasts two related variables, the daily reported infected cases and deaths, for a 15-day horizon. Several models such as ES, ARIMA, single-layered long short-term memory (LSTM) network, and stacked long short-term memory (SLSTM) networks were built for comparative analysis of forecast accuracy.

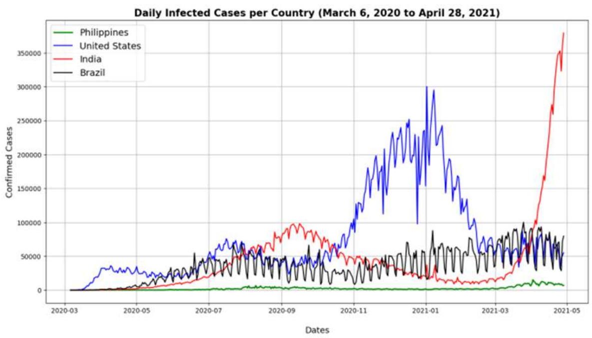

Fig. 1. Daily COVID-19 infected cases per country

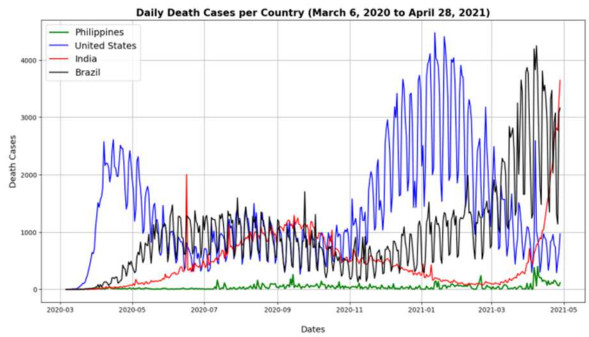

Fig. 2. Daily COVID-19 death cases per country

B. Stationarity Test

Time-series (TS) data has three components such as trend, seasonality, and error. A trend may manifest if a particular pattern frequently occurs due to external causes. Determining the structure of TS is critical in order to apply appropriate forecasting methods. We performed an Augmented Dickey-Fuller (ADF) test to check the nature of the TS. A p-value greater than 0.05 indicates a presence of a unit root, concluding that the data is non-stationary (with trends or seasonality), while a p-value less than or equal to 0.05 means it is stationary. Table 1 shows the test results.

TABLE 1
TIME-SERIES STATIONARITY TEST RESULTS

Time-series data	P-value	Category
Daily infected cases		
Philippines	0.241	Non-stationary
United States	0.441	Non-stationary
India	0.683	Non-stationary
Brazil	0.527	Non-stationary
Daily death cases		
Philippines	0.001	Stationary
United States	0.130	Non-stationary
India	0.961	Non-stationary
Brazil	0.544	Non-stationary

C. Trend and Seasonality Decomposition

Decomposition creates a valuable abstract model for time-series in general and assists in interpreting problems encountered during forecasting. It establishes a structured approach to modeling complexity by estimating the trend and seasonal effects on the data. Interactions between a specific trend and seasonal variability fall into two categories: additive (linear) or multiplicative (exponential). Figure 3 display the decomposition plots. This phase is critical for setting appropriate parameters to different time-series models.

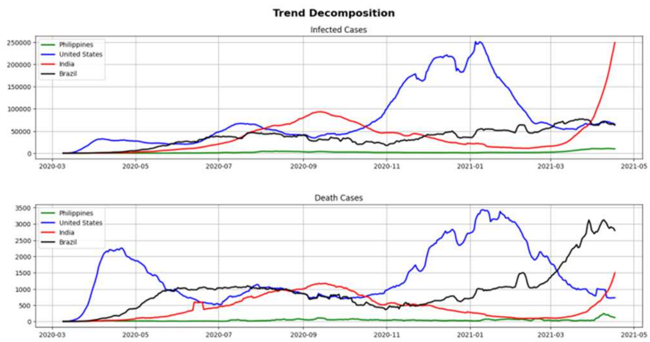

Fig. 3. Trend decomposition per country (infected & death cases)

D. Exponential Smoothing

Exponential smoothing is a moving average method for forecasting time-series data in a univariate form. The model's fundamental assumption is that the time-series pattern is constant or regular and that past trends will continue. It emphasizes the importance of explicitly assigning a declining weight to previous observations. In other words, the more recent the observation, the greater the weight assigned to it. A single exponential smoothing (SES) model implies that the data is reasonably stable around a mean. To mitigate the weakness of the previous model, a double exponential smoothing (DES) or Holt's method introduces an *alpha* (a) smoothing factor that defines weights and a *beta* (b) parameter to measure the effect of trend in a time-series. A triple exponential smoothing (TES) or Holt-Winters method extends DES by using a seasonality parameter of *gamma* (g). Both DES and TES can be modeled as either additive or multiplicative depending on the data's trend or seasonality. Table 2 shows the exponential smoothing models applied for the time-series based on the stationarity test results and decomposition graphs.

TABLE 2
EXPONENTIAL SMOOTHING MODEL CONFIGURATION

Time-series data	Configuration
Daily infected cases	
Philippines	TES (trend = 'multiplicative', seasonality = 'additive', seasonal periods = 7)
United States	TES (trend = multiplicative, seasonality = multiplicative, seasonal periods = 7)
India	TES (trend ='additive', seasonality = 'multiplicative', seasonal periods = 7)
Brazil	TES (trend = multiplicative, seasonality = 'additive', seasonal periods = 6)
Daily death cases	
Philippines	DES (trend = 'additive')
United States	TES (trend = 'additive', seasonality = 'additive', seasonal periods = 7)
India	TES (trend = 'multiplicative', seasonality = 'additive', seasonal periods = 7)
Brazil	TES (trend = 'additive', seasonal = 'additive', seasonal periods = 6)

E. Autoregressive Integrated Moving Average

For the analysis and forecasting of time-series data, an ARIMA model is frequently used. It considers a set of common time-series data structures and provides detailed yet accurate forecasting results. The model contains multiple components. For example, the *AR* (autoregression) uses the dependent relationship between an observation and the number of lags. The *I* (integrated) relates to the differencing of raw observation to make a time-series stationary. The *MA* (moving average) part quantifies the association of a value to its residual error after averaging is applied. Each element is defined as a parameter in the model as *p*, *d*, and *q*. The parameters are the number of lag observations, the degree of differencing, and the magnitude of the moving average, respectively.

An upgraded version of the model (SARIMA) supports data with seasonal features. We resolved the identification of the model's hyperparameters through a grid search technique (*auto-arima*) for computing the lowest Akaike information criterion (AIC) for multiple models. It is an effective way of determining the optimum hyperparameters versus the complexities of manual graph reading. Table 3 shows the different configurations for the model.

TABLE 3
ARIMA MODEL CONFIGURATION

Time-series data	Configuration
Daily infected cases	
Philippines	SARIMA(2,1,3)(1,0,1)[7]
United States	SARIMA(5,1,3)(0,0,1)[7]
India	SARIMA(1,2,1)(1,0,1)[7]
Brazil	SARIMA(5,1,2)(2,0,2)[6]
Daily death cases	
Philippines	ARIMA(3,1,3)
United States	ARIMA(5,1,2)
India	ARIMA(1,2,2)
Brazil	ARIMA(2,1,3)

F. Stacked Long Short-Term Memory Networks

Before delving into the architecture of a Stacked LSTM, it is important to understand the inner working of its memory units. LSTM networks are a form of Recurrent Neural Network (RNN), specifically built to address problems with long sequence prediction by introducing the concept of 'memory lines'. Moreover, it can overcome the limitations of conventional time-series forecasting approaches by adapting to the nonlinear nature of data, improving accuracy. It has an internal state, which means they are explicitly cognizant of the temporal construction of their inputs. They can iteratively step through different input sequences length to generate output sequences, one observation at a time. Before the last LSTM node generates the sequential output, each of its preceding blocks operates on a discrete-time step and transfers its output to the next block. The memory block is the network's most important component as it prevents vanishing gradients by preserving its network's parameters over lengthy periods. Gates in LSTM enables data processing via activation function (sigmoid) to produce a consistent output by feeding positive values to the succeeding gates. Figure 4 illustrates the structure of an LSTM with three different gates: forget, input, and output.

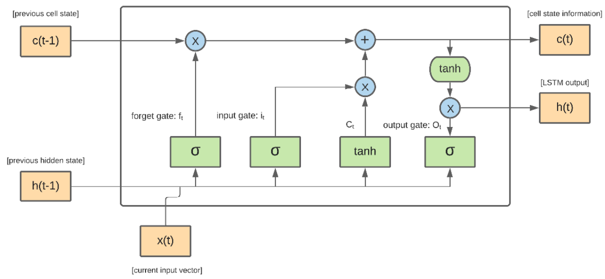

Fig. 4. A LSTM unit structure

The forget gate is in charge of determining what information demands attention and what to disregard. A sigmoid function *(σ)* receives information from the current input *X(t)* and the hidden state *h(t-1)* - it generates values within 0 and 1. Updating of cell's state happens by transferring the current state *X(t)* and a prior hidden state *h(t-1)* to a second sigmoid function. The next phase is the *tanh* function to accept information from both present and hidden states. By feeding the previous and present hidden state entries to a third sigmoid function, the output gate defines the value of the succeeding hidden state. Then, by using another *tanh* function, a new cell state is constructed and transmitted. Finally, the network's prediction *h(t)* output is determined based on stored information *c(t)* in the hidden state. With the intricacies of the process, the deep learning model is a robust algorithm for constructing a sequential time-series model.

A stacked LSTM networks model in Figure 5 comprises multiple hidden LSTM layers, each containing multiple memory cells. The principal reason for stacking is to model complex nonlinear sequences. Input observations are highly abstracted through the addition of layers, recombining learned representations from previous ones. The approach becomes more efficient by adding depth as it requires fewer neurons, resulting in faster training and optimization. It has proven to achieve accurate results for many complicated series prediction tasks [25].

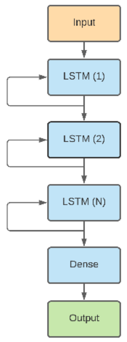

Fig. 5. A stacked LSTM networks architecture

G. Hyperparameter Optimization

Hyperparameter tuning is necessary for machine learning to deliver its best performance as measured on a test or validation set. Because of the complexities of setting hyperparameters for a neural network, we utilized auto-tuning via *scikit-optimize* library for sequential model-based optimization. Based on the extensive test runs, the mean collective optimized configurations are shown in Table 4. It achieved the lowest combined mean RMSE of 11828.37 and 1217.80 for infected and death cases test sets. To compare the effects of addition and reduction of LSTM layers, we also configure a single-layered LSTM network with the same hyperparameters except using 150 neurons. Comparative convergence loss plots are shown in Figure 6 to show the effects of stacking.

TABLE 4
SLSTM OPTIMIZED HYPERPARAMETERS

Time-series data	Hyperparameter	Value
Daily infected cases		
	Learning Rate	0.005
Philippines	LSTM-1 Neurons	138
	LSTM-2 Neurons	121
	LSTM-3 Neurons	106
United States	Dropout	0.2
	Dense Layer	1
	Inputs	7
India	Batch Size	1
	Activation Function	RELU
	Loss Function	MSE
Brazil	Optimizer	ADAM
	Training Epochs	400
Daily death cases		
	Learning Rate	0.005
Philippines	LSTM-1 Neurons	118
	LSTM-2 Neurons	102
	LSTM-3 Neurons	88
United States	Dropout	0.2
	Dense Layer	1
	Inputs	7
India	Batch Size	1
	Activation Function	RELU
	Loss Function	MSE
Brazil	Optimizer	ADAM
	Training Epochs	400

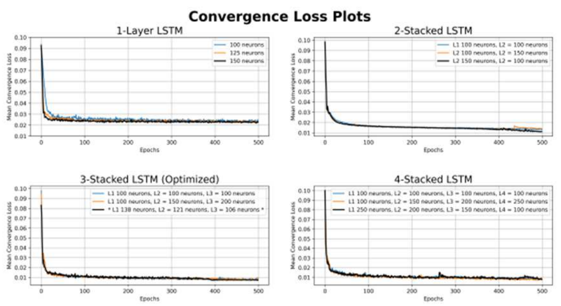

Fig. 6. Convergence loss plots of stacking and unstacking layers

H. Model Evaluation Metrics

We compared the different forecasting model's accuracy using three widely recognized error metrics such as root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean bias error (MBE). Equations 1, 2, and 3 express the details of the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(o_i - p_i)^2}{N}} \tag{1}$$

$$MAPE = \frac{\sum_{i=1}^{N}\left|\frac{o_i - p_i}{p_i}\right| \text{x } 100}{N} \tag{2}$$

$$MBE = \frac{\sum_{i=1}^{N}\left|\frac{o_i - p_i}{p_i}\right|}{N} \tag{3}$$

where o_i is the observed (actual) test value, p_i is the forecast result, and N is the number of testing samples. RMSE is a scale-dependent and excellent general-purpose error metric. It is capable of examining predictions of different models for a specific variable. Another error measure is the MAPE. As opposed to RMSE, it is not scale-dependent and applied for comparing forecasts across time-series data with varying scales. Lastly, the MBE indicates a mean forecast error of a specific model to underestimate or overestimate its prediction.

III. RESULTS

This section examines and compares the accuracy of different time-series forecasting models such as ES, ARIMA, LSTM, and SLSTM. In reality, it is critical to validate the forecast's accuracy against unseen data of actual values to test each model's generalization capabilities. The validation data consists of confirmed and death cases reported in the four countries under consideration from April 29 to May 13, 2021 (15-days) Succeeding subsections discusses the details of the results.

A. Effects of Stacking LSTM Layers

Figure 6 displays the convergence loss function plots of single-layered and multiple-layered LSTM models against the number of epochs. Observed values suggest that SLSTM networks take time to reach equilibrium because of the additional computational parameters compared to a simple LSTM. It also shows that increasing the number of stacked layers beyond three is not a guarantee to improve the performance (see 4-Stacked LSTM). Moreover, a decremental amount of neurons for each layer proved to be beneficial as the first layer must learn the overall structure of data before feeding to the succeeding layers rather than the opposite. (Table 4 & Figure 6).

B. Confirmed Cases Forecast

Table 5 and Table 6 show the forecast outcomes of confirmed cases. The tables show that the SLSTM deep learning method achieves a higher forecasting accuracy for all countries. It is observed that the SLSTM outperformed other models with a reduced RMSE. Empirical data illustrates the SLSTM obtained MAPE values of 6.37%, 6.77%, 9.06%, and 9.02% for COVID-19 data from the Philippines, United States, India, and Brazil, respectively. ES and ARIMA, on the other hand, perform moderately better than a single-layer LSTM except for India and Brazil.

C. Death Cases Forecast

Table 7 and Table 8 detail the predicted outcomes of death instances. The results demonstrated that the SLSTM technique produces an accurate forecast with lower RMSE except for the Philippines. However, the SLSTM achieved better MAPE values of 24.01%, 10.66%, 15.03%, and 21.06% from the Philippines, United States, India, and Brazil. The single-layered LSTM performed relatively better only on two instances than the ES and ARIMA models for the India and Brazil dataset. Lastly, the TES performs poorly for the forecast of death cases compared to other models with MAPE values of 31.43 and 55.50 for India and Brazil.

D. Bias Estimation Results

Table 5 and Table 6 shows that for the confirmed cases, different models generally over focecast the prediction. Still, the MBE of the SLSTM approach is comparatively low to other models, which means that the forecast is relatively closer to the actual values except for SARIMA (United States, 329.4) and LSTM (Brazil, -319.20) with only a slight difference. In terms of death cases, Table 7 and Table 8 reveals that most models over forecast results as compared to the actual values except for models of the Philippines' data where under forecasting were observed with values of -14 (DES), -8.13 (ARIMA), -42.93 (LSTM), and -28.6 (SLSTM).

TABLE 5

ACTUAL VALUES, 15-DAY FORECAST AND MODEL EVALUATION METRICS (CONFIRMED CASES - PHILIPPINES & USA)

No.	Date	Philippines					United States				
		Actual	Forecast				Actual	Forecast			
			TES	SARIMA	LSTM	SLSTM		TES	SARIMA	LSTM	SLSTM
1	2021-04-29	8,243	8,128	7,658	7,660	7,732	58,199	52,639	53,561	54,450	59,230
2	2021-04-30	8,722	9,172	9,167	7,591	8,353	57,922	51,135	53,276	51,435	51,323
3	2021-05-01	9,193	8,982	8,521	7,529	8,683	45,303	40,871	46,378	47,877	47,768
4	2021-05-02	8,330	7,941	8,486	7,320	8,378	29,367	27,598	36,127	44,094	32,289
5	2021-05-03	7,242	7,603	7,556	7,133	7,390	50,560	42,317	44,372	46,371	45,871
6	2021-05-04	5,667	6,294	7,015	6,818	6,134	40,733	40,701	43,348	46,894	42,838
7	2021-05-05	5,663	5,992	5,763	6,749	6,358	44,735	42,988	44,780	47,380	43,603
8	2021-05-06	6,617	7,359	7,248	6,616	6,732	47,514	43,008	49,930	46,712	45,699
9	2021-05-07	7,713	8,410	8,342	6,539	6,834	47,289	41,780	41,638	45,545	42,538
10	2021-05-08	6,964	8,228	8,213	6,514	7,259	34,493	33,393	43,342	44,308	34,235
11	2021-05-09	7,141	7,198	7,016	6,314	7,430	21,392	22,549	23,534	43,286	25,013
12	2021-05-10	6,836	6,863	6,882	6,252	6,732	36,898	34,575	38,472	43,307	35,329
13	2021-05-11	4,721	5,561	5,521	6,032	5,439	33,651	33,255	33,818	43,067	37,351
14	2021-05-12	4,812	5,268	5,213	5,885	5,623	35,878	35,123	36,951	42,782	34,332
15	2021-05-13	6,365	6,641	6,577	6,183	6,459	38,199	35,140	37,547	42,274	36,289
Evaluation Metrics		RMSE	558.03	640.78	946.32	**485.24**	RMSE	3,995.25	4,161.94	8,623.69	**3,142.79**
		MAPE	7.10	7.86	12.40	**6.37**	MAPE	6.97	8.15	20.94	**6.77**
		MBE	360.73	329.93	-206.26	**87.13**	MBE	-3,004.06	**329.4**	4,509.93	-561.66

TABLE 6

ACTUAL VALUES, 15-DAY FORECAST AND MODEL EVALUATION METRICS (CONFIRMED CASES - INDIA & BRAZIL)

No.	Date	India					Brazil				
		Actual	Forecast				Actual	Forecast			
			TES	SARIMA	LSTM	SLSTM		TES	SARIMA	LSTM	SLSTM
1	2021-04-29	386,555	388,588	386,504	385,571	387,362	69,389	70,417	64,007	73,167	74,488
2	2021-04-30	401,993	399,112	392,388	392,503	394,812	68,333	73,154	65,723	67,720	69,230
3	2021-05-01	392,488	406,341	407,801	398,640	401,144	66,964	60,934	62,770	61,655	64,785
4	2021-05-02	368,060	413,391	406,802	403,963	388,203	28,935	36,145	37,644	38,007	37,143
5	2021-05-03	357,316	397,343	395,323	408,554	389,123	24,619	34,953	41,389	33,966	32,096
6	2021-05-04	382,146	433,457	434,294	412,486	406,474	77,359	77,432	67,012	69,524	71,471
7	2021-05-05	412,431	445,795	444,476	415,869	408,352	73,295	79,204	75,465	73,105	74,903
8	2021-05-06	414,188	457,826	457,976	418,782	418,059	73,380	72,341	69,810	66,537	75,932
9	2021-05-07	401,078	468,351	448,342	421,283	419,483	78,886	75,083	65,539	74,247	73,302
10	2021-05-08	403,405	475,579	463,418	423,433	421,661	63,430	62,868	56,834	66,738	67,293
11	2021-05-09	366,494	482,630	448,533	425,241	423,425	38,911	38,084	39,981	33,097	34,433
12	2021-05-10	329,942	466,581	458,151	426,760	420,307	25,200	36,897	37,652	27,894	28,392
13	2021-05-11	348,421	502,695	473,678	428,044	419,836	72,715	79,380	61,632	69,642	67,482
14	2021-05-12	362,727	515,034	488,549	429,124	418,136	76,692	81,157	74,972	78,883	73,339
15	2021-05-13	343,144	527,065	483,009	430,035	416,484	74,592	74,299	69,026	73,730	77,593
Evaluation Metrics		RMSE	93,889.65	77,037.65	49,618.14	**43,047.30**	RMSE	5,610.48	8,444.24	5,223.42	**4,637.34**
		MAPE	20.53	17.25	10.66	**9.06**	MAPE	10.90	16.11	9.88	**9.12**
		MBE	73,960	61,257	36,660	**30,831**	MBE	2643	-1,549.60	**-319.20**	612.133

TABLE 7

ACTUAL VALUES, 15-DAY FORECAST AND MODEL EVALUATION METRICS (DEATH CASES - PHILIPPINES & USA)

No.	Date	Philippines					United States				
		Actual	Forecast				Actual	Forecast			
			DES	ARIMA	LSTM	SLSTM		DES	ARIMA	LSTM	SLSTM
1	2021-04-29	114	98	102	89	96	865	931	913	945	842
2	2021-04-30	89	111	106	93	93	738	798	848	829	809
3	2021-05-01	120	110	118	94	107	715	662	635	706	705
4	2021-05-02	77	101	100	86	108	332	227	462	376	329
5	2021-05-03	94	89	116	75	95	486	401	455	465	453
6	2021-05-04	97	104	113	77	85	876	654	687	639	798
7	2021-05-05	178	113	112	78	86	778	1062	892	872	805
8	2021-05-06	191	100	114	75	91	793	942	933	919	912
9	2021-05-07	108	113	115	77	89	754	809	821	849	824
10	2021-05-08	170	111	114	75	104	617	673	638	709	683
11	2021-05-09	203	103	114	71	105	242	238	484	441	398
12	2021-05-10	90	105	113	67	78	400	412	497	469	471
13	2021-05-11	58	106	114	65	65	676	665	678	621	639
14	2021-05-12	94	115	113	63	78	849	1073	866	815	823
15	2021-05-13	107	101	104	61	81	802	953	914	891	806
Evaluation Metrics		RMSE	**45.09**	42.52	61.47	48.65	RMSE	131.80	113.34	107.07	**67.54**
		MAPE	26.06	27.12	32.04	**24.01**	MAPE	14.71	18.92	16.37	**10.66**
		MBE	-14	**-8.13**	-42.93	-28.6	MBE	38.46	53.33	41.53	**24.93**

TABLE 8
ACTUAL VALUES, 15-DAY FORECAST AND MODEL EVALUATION METRICS (DEATH CASES - INDIA & BRAZIL)

No.	Date	India					Brazil				
		Actual	Forecast				Actual	Forecast			
			TES	ARIMA	LSTM	SLSTM		TES	ARIMA	LSTM	SLSTM
1	2021-04-29	3,498	3,648	3,658	3,771	3,683	3,001	2,670	3,374	2,275	2,832
2	2021-04-30	3,523	3,858	3,809	4,118	4,412	2,595	2,682	2,930	3,047	2,934
3	2021-05-01	3,689	4,048	3,905	4,637	4,329	2,656	2,695	2,205	3,027	2,734
4	2021-05-02	3,417	4,213	4,023	4,192	4,239	1,202	2,707	1,742	1,450	1,438
5	2021-05-03	3,449	4,390	4,132	4,780	4,583	983	2,719	1,880	1,252	1,144
6	2021-05-04	3,780	4,677	4,244	3,693	4,803	2,966	2,731	2,507	2,939	2,783
7	2021-05-05	3,980	4,871	4,355	3,593	4,139	2,811	2,743	3,150	3,121	3,013
8	2021-05-06	3,915	5,078	4,467	3,078	3,139	2,550	2,755	3,331	2,607	2,593
9	2021-05-07	4,187	5,290	4,578	4,222	4,312	2,165	2,767	2,924	3,110	3,231
10	2021-05-08	4,077	5,479	4,690	4,323	4,239	2,202	2,779	2,241	3,004	2,593
11	2021-05-09	3,769	5,643	4,801	4,967	4,835	1,024	2,792	1,792	1,557	1,483
12	2021-05-10	3,876	5,821	4,913	4,319	4,123	889	2,804	1,907	1,307	1,359
13	2021-05-11	4,205	6,107	5,024	4,352	4,934	2,311	2,816	2,491	2,881	1,839
14	2021-05-12	4,120	6,302	5,136	4,873	4,039	2,494	2,828	3,104	3,123	2,159
15	2021-05-13	4,000	6,509	5,247	4,733	3,643	2,383	2,840	2,758	3,053	3,449
Evaluation Metrics		RMSE	1,411.49	710.65	701.25	**672.03**	RMSE	950.89	590.78	533.38	**483.01**
		MAPE	31.43	16.38	15.68	**15.03**	MAPE	55.50	34.06	24.99	**21.06**
		MBE	1,229.93	633.13	411.06	397.80	MBE	606.40	406.93	368.06	223.46

IV. DISCUSSIONS

The deep learning-based algorithms' reliability exhibited exceptional performance in time-series or sequence predictions due to the repeated optimization process to determine the optimal outputs. Empirical results show that high-level algorithms such as SLSTM outperform traditional regression-based models, including a single-layered LSTM. The evaluation metrics have a collective mean forecast accuracy of 92.17% (confirmed cases) and 82.31% (death cases). Compared with traditional time-series models such as ES and ARIMA, the SLSTM reduces the forecast error rates by an average of 15.88% (confirmed cases) and 38.35% (death cases). Time-series prediction is a complex problem to tackle because of fluctuating trends, seasonality, and random noise factors. The deep learning model's ability to handle nonlinearity, complexities, remember extended information, and intuitively learn the internal representation of time-series data regardless of its distinct characteristics has established its claim to improve forecast performance. Our results are comparable to the works of [27 - 30] and a viable alternative to statistical methods as proven by the forecast accuracies.

Interpretation of the graphs in Figure 8 and Figure 9 suggested that the four countries' situations vary. The Philippines has observed a second temporary surge of confirmed cases after strict lockdowns and travel restrictions are lifted in mid-April of 2021. The graph predicted a daily average of 6,200 confirmed cases, and 87 death cases are predicted for the month of May. As of this writing, only 0.22% of the population is fully vaccinated [31]. With this rate, the likelihood of another surge is highly imminent. The situation in the United States is entirely different despite recording the most cumulative number of infected cases at around 30 million. With 40% of the population vaccinated [32], the country's confirmed cases will continue to decline at an average of 12,000 confirmed cases and 350 death cases for June. Still, the downward projection must not mislead the public as the threats of virus mutations are a real possibility. A massive surge in India is attributed to a new highly transmissible unnamed variant (B.1.6.17) of the virus, recording a record single-day high of infected cases of more than 400,000 [33]. Authorities are caught off-guard on the resurgence of a second wave that devasted the nation. Based on the graphs, it is expected to decline from 240,000 daily confirmed cases at the end of May, to 120,000 at the start of June. In Brazil, a new variant (P.1) of the virus is driving the surge. Despite having a universal healthcare system, it accounts for a fourth of the world's weekly fatalities from the disease [34]. At the onset of the pandemic, its government underestimated the virus' threat and maintained its reluctance to impose a national lockdown. Currently, 8% of its population is immunized. The country is expected to have an average of 60,000 confirmed and 1,800 death cases for May.

As with any other forecasting model, a sudden surge or immediate decline in the number of cases will force our model to over forecast (see Figure 7 & Figure 8 for India) or under forecast (see Figure 8 for Philippines) due to related mitigating actions taken such as lockdowns and vaccinations.

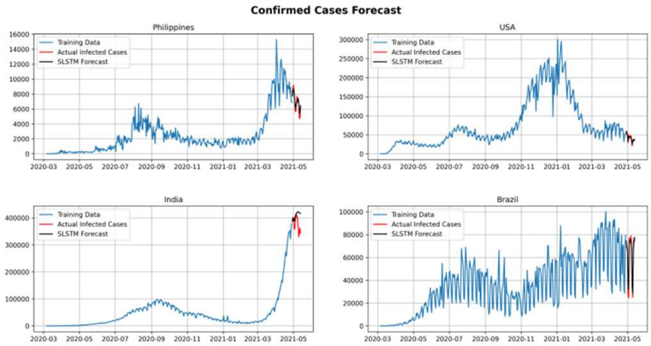

Fig. 7. Stacked LSTM confirmed cases forecast

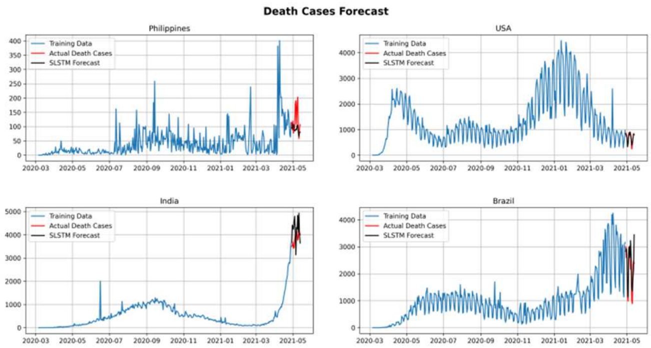

Fig. 8. Stacked LSTM death cases forecast

V. CONCLUSIONS AND RECOMMENDATIONS

On a global scale, the COVID-19 pandemic has expanded tremendously, impacting the economy and putting highly affected countries' healthcare systems on the brink of collapse. Therefore, accurate forecasting of confirmed and death cases gives vital information to governments and decision-makers. This inferential knowledge is helpful as it gives a broader and clearer perspective on the needed measures to slow down or eradicate the virus. Moreover, it can motivate the general public on the measures imposed to deter further transmissions and as a basis to ease or tighten lockdowns – thus saving priceless lives. The research discovered the promising potential of deep learning-based algorithms for prognosticating time-series data, specifically, the Stacked Long Short-Term Memory Networks. We examined four countries' historical data spanning 419 days since March 6, 2020. Empirical results show that the model outperforms conventional time-series forecasting methods such as Exponential Smoothing and ARIMA. The authors plan to construct an ensemble of deep learning machine learning models to improve forecast accuracy by considering other temporal components such as transmissions, recovery, and vaccination rates for future scope of work.

REFERENCES

[1] World Health Organization, "Weekly epidemiological update on COVID-19", WHO Bulletin, Available at: https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19---27-april-2021, 2021.

[2] H. Feyisa, "The world economy at COVID-19 quarantine: contemporary review", International Journal of Economics, Finance and Management Sciences, 8(2), pp. 63-74, 2020.

[3] P. Cirillo and N. Taleb, "Tail risk of contagious diseases", Nature Physics, 1-8, 2020.

[4] T. Le, Z. Andreadakis, A. Kumar., R. Román, S. Tollefsen, M. Saville and S. Mayhew, "The COVID-19 vaccine development landscape", Nat Rev Drug Discov, 19(5), pp. 305-306, 2020.

[5] S. Moein, N. Nickaeen, A. Roointan et al., "Inefficiency of SIR models in forecasting COVID-19 epidemic: a case study of Isfahan", Scientific Reports, 11(1), pp. 1-9, 2021.

[6] E. Piccolomini and F. Zama, "Monitoring Italian COVID-19 spread by a forced SEIRD model", Plose One, 15(8), 2020.

[7] A. Basing and S. Tay, "Malaria transmission dynamics of the anopheles mosquito in Kumasi, Ghana", International Journal of Infectious Diseases, 21(2), 2014.

[8] A. Jajarmi, S. Arshad and D. Baleanu, "A new fractional modeling and control strategy for the outbreak of dengue fever", Physica A: Statistical Mechanics and Its Applications, 535(1), 2019.

[9] C. Viboud, K. Sun, R. Gaffey, M. Ajelli, L. Fumanelli, S. Merler and A. Vespignani, "The RAPIDD ebola forecasting challenge: Synthesis and lessons learnt", Epidemics, 22, pp. 13-21, 2018.

[10] T. Cohen and M. Murray, "Modeling epidemics of multidrug-resistant tuberculosis of heterogeneous fitness", Nature medicine, 10(10), pp. 1117-1121, 2004.

[11] P. Ghys, E. Kufa and M. George, "Measuring trends in prevalence and incidence of HIV infection in countries with generalised epidemics", Sexually transmitted infections, 82(1), pp. 52-56, 2006.

[12] C. Dye and N. Gay, "Modeling the SARS epidemic", Science, 300(5627), pp. 1884-1885, 2003.

[13] M. Maleki, M. Mahmoudi, D. Wraith and K. Pho, "Time series modelling to forecast the confirmed and recovered cases of COVID-19", Travel medicine and infectious disease, 37, 101742, 2020.

[14] M. Ekum and A. Ogunsanya, "Application of hierarchical polynomial regression models to predict transmission of COVID-19 at global level", International Journal of Clinical Biostatistics and Biometrics, 6(1), 6:027, 2020.

[15] J. Wu, M. Mamas, M. Rashid, C. Weston, S. Hains et al., "Patient response, treatments, and mortality for acute myocardial infarction during the COVID-19 pandemic", European Heart Journal-Quality of Care and Clinical Outcomes, 7(3), pp. 238-246, 2021.

[16] S. Harini, "Identification COVID-19 cases in Indonesia with the double exponential smoothing method", Jurnal Matematika MANTIK, 6(1), pp. 66-75, 2020.

[17] D. Benvenuto, M. Giovanetti, L. Vassallo, S. Angeletti and M. Ciccozzi, "Application of the ARIMA model on the COVID-2019 epidemic dataset", Data in Brief, 29, 105340, 2020.

[18] R. Maaliw III and M. Ballera, "Classification of learning styles in virtual learning environment using J48 decision tree", Proceedings of the 14th International Conference on Cognition and Exploratory Learning in Digital Age, Algarve, Portugal, pp. 146-156, 2017.

[19] R. Maaliw III, "Early prediction of electronics engineering licensure examination performance using random forest", IEEE 2021 World Artificial Intelligence and Internet of Things Congress (AIIOT), pp. 41-47, Seattle, Washington, USA, 2021.

[20] A. Holzinger, G. Langs, H. Denk, K. Zatloukal and H. Müller, "Causability and explainability of artificial intelligence in medicine", Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9(4), e1312, 2019.

[21] R. Maaliw III, "Adaptive virtual learning environment based on learning styles for personalizing e-learning system: Design and implementation", International Journal of Recent Technology and Engineering, 8(6), pp. 3398-3406, 2020.

[22] N. Peiffer-Smadja, T. Rawson, R. Ahmad, A. Buchard, et al., "Machine learning for clinical decision support in infectious diseases: a narrative review of current applications", Clinical Microbiology and Infection, 26(5), pp. 584-595, 2020.

[23] N. Bakalos, A. Voulodimos, A. Doulamis and N. Doulamis, "A Deep-narma Filter for Unusual Behavior Detection from Visual, Thermal and Wireless Signals, "2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 4005-4009, 2019.

[24] M. Sahrani, M. Zan, I. Yassin, A. Zabidi and M. Ali, "Artificial Neural network non-linear auto regressive moving average (narma) model for internet traffic prediction", Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 9(1-3), pp. 145-149, 2017.

[25] Y. Geng and S. Li, "A LSTM Based Campus Network Traffic Prediction System", 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS), pp. 327-330, 2019.

[26] M. Kaselimi, A. Voulodimos, N. Doulamis, A. Doulamis and D. Delikaraoglou, "A Causal Long Short-Term Memory Sequence to Sequence Model for TEC Prediction Using GNSS Observations", Remote Sensing, 12(9), 1354, 2020.

[27] L. Wang, A. Adiga, S. Venkatramanan, J. Chen, B. Lewis and M. Marathe, "Examining deep learning models with multiple data sources for COVID-19 forecasting", IEEE International Conference on Big Data (Big Data), pp. 3846-3855, 2020.

[28] S. Bodapati, H. Bandarupally and M. Trupthi, "COVID-19 time series forecasting of daily cases, deaths caused and recovered cases using long short term memory networks", IEEE 5th International Conference on Computing Communication and Automation (ICCCA), pp. 525-530, 2020.

[29] F. Succetti, A. Rosato, R. Araneo and M. Panella, "Multidimensional Feeding of LSTM Networks for Multivariate Prediction of Energy Time Series", 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), pp. 1-5, 2020.

[30] V. Marmarelis, "Predictive Modeling of Covid-19 Data in the US: Adaptive Phase-Space Approach", IEEE Open Journal of Engineering in Medicine and Biology, vol. 1, pp. 207-213, 2020.

[31] Philippine Daily Inquirer, "0.22% of PH population fully vaccinated", Available at: https://newsinfo.inquirer.net/1425804/0-22-of-ph-population-fully-vaccinated, 2021.

[32] R. Mendez, "Twelve US states have 70% of adults at least partially vaccinated", Available at: https://www.cnbc.com/2021/06/02/covid-19-cases-deaths-and-vaccinations-daily-us-data-on-june-2.html, 2021.

[33] Business Standard, "Data Story: India reports 400,000+ COVID cases for 3rd straight day, over 4,000 deaths", Available at: https://www.business-standard.com/article/current-affairs/data-story-india-reports-400-000-covid-cases-for-3rd-straight-day.html, 2021.

[34] D. Biller and M. Savarese, "Brazil accounts for one-quarter of the world's daily COVID-19 deaths, experts warn the worst may lie ahead, Available at: https://www.chicagotribune.com/coronavirus/ct-aud-nw-brazil-covid-deaths-20210327-jhrenbxsnzayriwkhz2j7drchu-story.html, 2021.