Evaluating the Accuracy of LSTM Forecasting Model and Intervention Programs in Combating Covid-19

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Abstract

This paper extends the research on the accuracy of Long Short Term Memory (LSTM) deep learning model to forecast Covid-19 daily cases in the Philippines with features affecting the transmission of virus. The study utilized a mixed method; qualitative research to analyze and understand experiences to generate ideas and quantitative research to gather measurable data that will be used for statistical analysis. The study examined three factors affecting the forecasting of Covid-19. The modeling procedure was completed using python 3.0. The research results indicate that the forecasting of Covid-19 daily cases using the LSTM forecasting model has an error of no more than 17% error which depicts as an acceptable accuracy. It also specifies that the model shows more meaningful trends in the two (2) week forecast rather than the two (2) month forecast. The study triangulated the trends of forecast with the help of focus group discussion with health experts and health administrative personnel. The results specify that 75 percent wear the necessary PPEs when going out and 60 percent always keep physical distance. Using the LSTM deep learning model, the study provides a framework that helps understand the behavior of the virus and forecast Covid-19 cases months ahead.

Keywords
Long Short Term Memory (LSTM), Covid-19, Python, Healthcare, Forecasting

1. Introduction

The Philippines now suffers from the highest number of coronavirus cases in Southeast Asia (Uddin, 2020). The new variant further stresses hospitals that are already overwhelmed with Covid-19 patients alone and a lot have reached their full capacity. The government and its legislative branch have been under pressure on how to respond to the public health crisis. In this study, it focuses on assessing the capability of the Long Short Term Memory (LSTM) deep learning model in terms of forecasting in order for it to be valuable in assisting in providing insight for the healthcare system with respect to Covid-19 cases. The effect of the enforced intervention programs to combat Covid-19 were also analyzed.

Covid-19 has been liable for infecting billions of individuals and it needs further study of the trend it follows to create an adequate prediction model and according to Nick Reich, an epidemiologist, one of the biggest mistakes is focusing on just one model. Therefore, this study takes on a different perspective of the deep learning model and assesses its capability.

Currently, there is a forecasting model being utilized by the government which is the moving average method. However, it forecasts cumulative cases only. Dr. David of the UP Octa Research Team noted in August that if it's not flattened as claimed to be, Philippines might be going in a "wrong trend". Moreover, to the best of our knowledge, the current forecasting model doesn't include features other than the reproduction rate. Therefore, we would like to propose the LSTM deep learning model that will forecast Covid-19 daily cases with several features that affects the transmission of Covid-19 namely; reproduction rate, infectious period, and the intervention of quarantine protocols to gauge the behavior of the virus carefully and to further study the trend it follows. LSTM units include a 'memory cell' that can maintain information in memory for long periods of time and learn hidden behavior of time series data to predict meaningful values. In this viewpoint, it is conceivable to develop strategic planning in the public health system to control deaths as well as in handling patients (Shahid, Zameer, and Muneeb, 2020).

Deep learning models such as LSTM can accurately forecast future events than any other traditional forecasting method. Andrew Ng, chief scientist who founded Google Brain stated, Deep learning models' performance can continuously increase as we put up larger neural networks and train them with more data. With the recent breakthroughs that have been going on in data science, it is discovered that practically nearly all of the sequence prediction issues, Long Short Term Memory networks, a.k.a LSTMs have been seen as the most successful solution (Srivastava, 2017).

1.1 Objectives

The primary objective of this research is to test the effectiveness of the deep learning model in predicting the future COVID-19 cases more accurately in the coming months.

The researchers' specific objectives are the following:

a) To evaluate the significant factors that affect the forecasting of Covid-19 cases.
b) To identify the optimal hyperparameters in forecasting Covid-19 cases.
c) To determine if the LSTM deep learning model is capable of forecasting Covid-19 cases at 17%.

2. Literature Review

Competence of Deep Learning

According to several studies, traditional forecasting models have a higher percentage error compared to deep learning models which depict lower accuracy. According to Andrew Ng, deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance - that as we construct larger neural networks and train them with more and more data, their performance continues to increase.

Current Forecasting Model in the Philippines

According to Nick Reich, an epidemiologist, one of the mistakes occurred in the middle of the pandemic was focusing on just one forecasting model. In the Philippines, the policymakers currently utilized the forecast by UP Octa Research Team. The team forecasts in a moving average method and only the cumulative cases. This helps the researchers to formulate an idea to actually generate a forecast of daily cases using the LSTM deep learning model to totally gauge the behavior of the virus.

RNN Difficulty and LSTM Capability

As indicated by a study of Recurrent Neural Networks (RNNs); LSTM cells and Network Architectures, RNNs have been broadly received in research worried about sequential data, for example, text, sound, and video. In any case, RNNs consisting of sigma cells or tan (h) cells can't learn the significant information of data when the input gap is enormous. By bringing gate functions into the structure of the cell, the long short memory (LSTM) could deal with the issue of long term conditions well.

Current LSTM models have obtained extreme accomplishments on numerous activities. However, there are still few headings to increase RNNs with all the more impressive properties (Shewalkar, Nyavanandi and Ludiwg, 2019). Relating this information in our study, the researchers aim to explore selection and tuning of hyper-parameters for the LSTM Deep Learning Model to produce better results.

Different Applications of LSTM Model: Weather Forecasting

The LSTM Model and ARIMA Model are compared in weather forecasting. The visibility variable of the weather is utilized in this investigation since it is the main variable that has a huge effect on all periods of flight, particularly when the aircraft is moving on or near the ground. The LSTM model of this research established visibility as the indicator variable (Salman, Heryadi, Abdurahman and Suparta, 2018).

Forecast Performance Evaluation

The mean absolute percentage error (MAPE) is probably the most widely used goodness-of-fit measure. Based on a study of Measure of Error, a MAPE less than 5% is considered as an indication that the forecast is acceptable and accurate. A MAPE greater than 10% but less than 25% indicates low, but acceptable accuracy and MAPE greater than 25% very low accuracy, so low that the forecast is not acceptable in terms of its accuracy (Swanson, 2015).

Reasons the LSTM Model is Preferred

According to Prasad Natarajan of Mindboard Data Science Team, there are several time-series forecasting techniques like autoreression (AR) models, moving average (MA) models, Holt-winters, ARIMA etc., to name a few. LSTMs can almost seamlessly model problems with multiple input variables. All we need is a 3D input vector that needs to be fed into the input shape of the LSTM. This adds a great benefit in time series forecasting, where classical linear methods can be difficult to adapt to multivariate or multiple input forecasting problems.

Multivariate forecasting; keep in mind that when we use multivariate data for forecasting, then we also need "future multivariate" data to predict the future outcome). LSTMs offer a lot of flexibility in modeling the problem - meaning we have a good control over several parameters of the time series (Natarajan, 2019).

3. Methods

This study extends the research on the accuracy of the Long Short Term Memory (LSTM) deep learning model to forecast Covid-19 daily cases in the Philippines with features affecting the transmission of the virus or the significant variables affecting the forecasting of Covid-19.

To achieve these objectives, mixed research design is adapted; qualitative research to analyze and understand experiences to generate ideas and quantitative research to gather measurable data.

This study must determine how many Covid-19 cases to expect in the coming months thus historical data is a priority. Covid-19 daily cases, reproduction number, isolation period, and quarantine protocols were gathered from the Department of Health and John Hopkins University. 427 days of Covid-19 cases were utilized.

Based on the objectives of the study, the forecast output is obtained through the modeling procedure which was completed in PyCharm using python 3.0 with open-source libraries including Pandas and NumPy. To visualize and compare the statistics of Covid-19 cases, the raw data were analyzed using a scikit-learn library in python 3.0, MinMaxScaler. Selection and tuning of hyper-parameters for LSTM are chosen carefully via GridSearchCV. The trial starts at data pre-processing, training of results, building of the model, and finally, performance evaluation.

To assess the hyperparameters, Root Mean Square Error (RMSE) is performed. Moreover, to evaluate the performance of the model, Mean Absolute Percentage Error (MAPE) is utilized.

Additionally, the researchers conducted a focus group discussion with health care professionals and hospital administrative personnel in order to triangulate the trends between the actual and the forecasted cases of Covid-19 and gain deeper understanding of the situation the study focuses on. Participants were selected based on their experience and background in healthcare and those who expressed interest in participating in the focus group were sent detailed information about the procedures and topics to be discussed along with an overview of the research proposal. The focus group has seven (7) participants which consists of three (3) nurses, a nurse engineer, two (2) doctors and a senior manager for risk management and patient safety.

4. Data Collection

This research utilizes a mixed methods namely qualitative research method to analyze and understand opinions or experiences to generate new ideas and quantitative research method to gather measurable data that will be used for statistical analysis.

5. Results and Discussion

This chapter contains the results of the predictive modeling and focus group discussion conducted to answer the research questions; (1) What are the significant factors affecting the forecasting of Covid-19 cases? (2) What are the optimal hyperparameters in forecasting Covid-19 cases? (3) Is the LSTM deep learning model capable of forecasting Covid-19 cases at 10% error?

In this section, our forecasting model trial is explained in detail. First, the procedures in gathering the Covid-19 data are discussed as well as the significant steps in order to acquire the specific parameters that need to be utilized. We use Covid-19 cases as our data set provided by the Department of Health and John Hopkins University. The Covid-19 data we used includes one (1) year data. Statistics on Covid-19 data in the Philippines are counted each day. The dataset includes 424 rows. The trial is to be completed in Google Colaboratory initially, however, because of the slow response of the interface, the researchers resorted to Pycharm still using python 3.0 with open source libraries including Pandas and Numpy. Though, before the forecasting model trial was executed, a Focus Group Discussion was conducted first.

The researchers contracted with seven (7) Healthcare Professionals to conduct a focus group discussion. The role of the focus group is to help triangulate the trends between the actual and predicted cases of Covid-19. This would help validate the outcome of the prediction model and to seek further explanations of the key issue from the experts. The primary means of communication initially was by telephone and email which alleviated some costs and time constraints. This would also help formulate strategies the policymakers and healthcare system shall adapt or improve in handling Covid-19 cases. Those who expressed interest in participating in the Focus Group Discussion were sent more information about the procedures and topics to be discussed along with a copy of our dissertation proposal. Each of the members of the focus group were asked to sign an informed consent form and each was asked to participate with as little input as they felt comfortable in providing. The discussion then evolved as the members of the focus group engaged with one another and responded with their thoughts and experiences.

The results establish the fact that the strength of Focus Group Discussion relies on allowing the healthcare professionals to agree or disagree with each other and it provides an insight into how a group thinks about such significant factors that need to be considered in the prediction of Covid-19 cases from their experiences and practices. A focus group is generally more useful when outcomes of research are very unpredictable and allows the participants to express clear ideas and share opinions that don't typically come out in a quantified survey. The analysis of the significant factors needed to be considered based on collected views and rich understanding of the participants' experiences, opinions, and beliefs.

Community Quarantine Classification of the Philippines

In relation to the result of the Focus Group Discussion, it may be considered that the Philippine government has become more transparent with the release of guidelines and protocols to curb the spread of Covid-19.

Table 1. Quarantine Classification

ECQ Critical Zone (CRZ)	**Modified ECQ Containment Zone (CZ)**	**GCQ Buffer Zone (BZ)**	**Modified GCQ Outside Buffer Zone (OBZ)**
• No movement regardless of age and health status • Minimal economic activity except for utility services • No transportation activity • Suspension of physical classes	• Limited movement within ECQ zone for obtaining essential services and work • Operation of selected manufacturing and processing plants up to 50% workforce • Limited transporting services for essential goods and services • Suspension of physical classes	• Limited movement to services and work within GCQ zone • Operation of government offices and industries up to 75% workforce • Limited transporting services to support government and private operations • Flexible learning arrangements; operate at limited capacities to cater to student	• Permissive socio-economic activities with minimum public health standards

Table 1 indicates the general guidelines from IATF-EID for LGUs under Enhanced Community Quarantine (ECQ), Modified Enhanced Community Quarantine (MECQ), General Community Quarantine (GCQ), and Modified General Community Quarantine (MGCQ). Delving deeper into the tables, the protocol on ensuring minimum public health standards yields the most critical protocol for implementing the Modified General Community Quarantine (MGCQ) which according to Omnibus Guidelines on the Implementation of Community Quarantine in the Philippines, it refers to the transition phase between GCQ and the New Normal, when the following temporary measures are relaxed and become less necessary.

As one of the participants from the Focus Group Discussion stated, "One of the causes of the spikes of confirmed cases are people slacking on health and safety protocols and the government's inability to formulate a concrete plan to help decrease the number of cases". Additionally, the government allows all other localities to establish the Modified General Community Quarantine (MGCQ) which in that case companies can work on-site though at-risk workers must telecommute.

Nonetheless, according to the Social Weather Stations (SWS) survey regarding the continuity to comply with basic safety protocols against Covid-19, out of the 1,200 surveyed 75% of the respondents always wore face masks when going out while 67% of the respondents answered they washed their hands several times a day. Moreover, the DOH collaborated with the World Health Organization to launch CovidKaya - a mobile application that assists healthcare workers with contact tracing and case monitoring and regarding the PPE ReachHealth supported as well the distribution of PPE donated by the US Defense Threat Reduction Agency to 50 hospitals, rural health units, and quarantine facilities in exposed areas across the country.

Reproduction Rate/R0

Another significant factor is the reproduction rate (R0) which is the basic reproduction number that is the expected number of secondary infections produced by an infected individual during their entire infectious period. It indicates how contagious and infectious disease is or how many people can an infected person infect. In reference to the Focus Group Discussion, one participant stated that "Hospitals in Manila are seeing a spike in Covid-19 infections as more transmissible variants of the coronavirus spread. As Mr. David of UP Octa said, unlike past surges, the current surge has spread very quickly in a short period." Some studies indicate that the new variant has a spreading dominance of 0.4 to 0.7 points higher in reproduction rate compared with the initial strain.

Infectious Period

Rapid escalation in daily induction rates, seriousness of the cases, and death toll demonstrated that the disease is highly transmissible and infectious. Infectious period is the period between exposure to an infection and the appearance of the first symptoms and it reaches up to 14 days. According to WHO Philippines (refer to Table 2), even if a person gets tested for Covid-19 it is not an assurance that a certain person doesn't have the virus. A person might have been exposed and tested during the virus' incubation period.

Table 2: World Health Organization Cited Scenario Regarding the Infectious Period Vaccination

Day	Scenario
0	A person was exposed to Covid-19
5	A person was tested for Covid-19 and the results were negative
8-9	He was exposed to a lot of people for 48 hours before symptoms appeared and those people he associated with were exposed as well
14	Showed symptoms and tested positive for Covid-19

According to Our World In Data, Covid-19 vaccination in the Philippines started in March 2021 and the country aims to vaccinate 58 million people by the end of the year. As of July 4, 2021, about 8.8 million people already received the first of two doses of the Covid-19 vaccine in the Philippines. With the initial limited supply, frontline health workers and uniformed personnel are prioritized since they have higher risk of exposure while on duty and to allow them to continue fulfilling their duties in both the public and private sectors.

Furthermore, experts say it's unlikely that the Philippines rollout of the vaccine is behind the declines in Covid-19 cases given that so far only 8.2% of Filipinos have gotten at least one (1) vaccine dose and 2.7% have been fully vaccinated. But at some point, when enough people have been vaccinated, the country can continue this downward trajectory.

Before the LSTM forecasting model was produced, this study first identified the optimal hyper-parameters. While building the LSTM forecasting model, there are hyperparameters that have to be set up properly and adjusted to get an accurate forecast when the model was evaluated. Hyper tuning or "searching" the hyperparameter space for the optimum values for the LSTM model needs to be done carefully. Each model would be fit to the training data and evaluated on the validation data. However, this is an exhaustive sampling of the hyperparameter space and quite inefficient. Therefore, the researchers resorted to Manual Search – trained the model and evaluated the hyperparameters were chosen based on trial and error. The researchers trained the model and evaluated the hyperparameters' accuracy. This loop is repeated until a consistent and satisfactory accuracy is scored. RMSE was used as a default metric for evaluation of the performance hyperparameters. It tells how concentrated the data around the line of best fit. The RMSE formula is seen in (1)

$$(1) = \quad RMSE = \sqrt{(f - o)^2}$$

Where: f = forecasts (expected values or unknown results)

o = observed values (known results)

The hyperparameters chosen and used in the trial are listed in the table below along with their corresponding values and information.

Table 3: Grid Search for Optimal Hyperparameters

Grid Search for Optimal Hyperparameters													
Number of Batches													
		5		10		20		30		40		50	
		mean	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*
Number of Neurons	10	0.00858	0.00277	0.009482	0.00362	0.0106	0.00393	0.01075	0.00344	0.01246	0.0042	0.01113	0.00394
	20	0.00655	0.00291	0.008103	0.00282	0.00954	0.00295	0.00931	0.00334	0.0111	0.00412	0.00967	0.00435
	30	0.00558	0.00301	0.007076	0.00283	0.00855	0.00281	0.0087	0.0031	0.01029	0.00311	0.00924	0.00366
	40	0.00478	0.00336	0.006359	0.00314	0.00828	0.00302	0.00824	0.00297	0.00969	0.00326	0.00884	0.00319
	50	0.00458	0.00317	0.005734	0.0033	0.00781	0.00284	0.00773	0.00271	0.0096	0.0031	0.0085	0.00347

The researchers specifically looked for the batch size and the number of neurons. Each batch size should be partnered with a certain number of neurons.

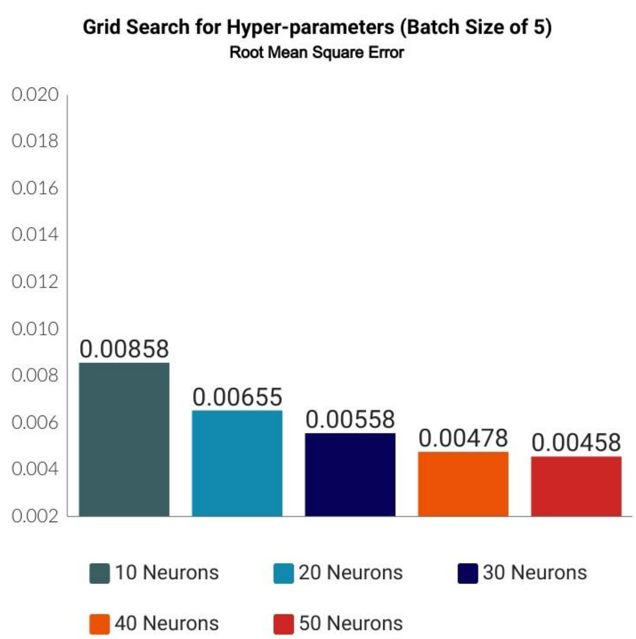

Figure 1: Grid Search for Hyperparameters – Batch Size of 5

Figure 1 shows the optimal hyperparameters for batch size of five (5). It illustrates that fifty (50) neurons yielded the lowest RMSE of 0.00458 which depicts that fifty (50) neurons is better among all other neurons in batch size of five (5).

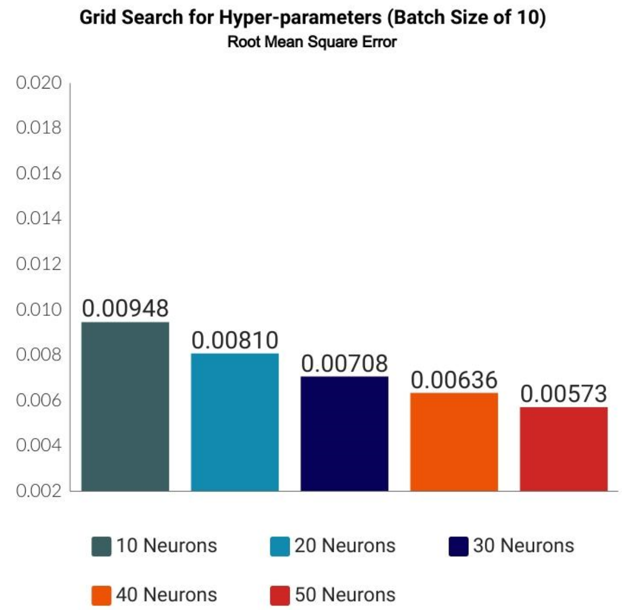

Figure 2: Grid Search for Hyperparameters – Batch Size of 10

Figure 2 shows the optimal hyperparameters for batch size of ten (10). It is illustrated that fifty (50) neurons yielded RMSE of 0.00573 which depicts that fifty (50) neurons is better among all other neurons in a batch size of ten (10).

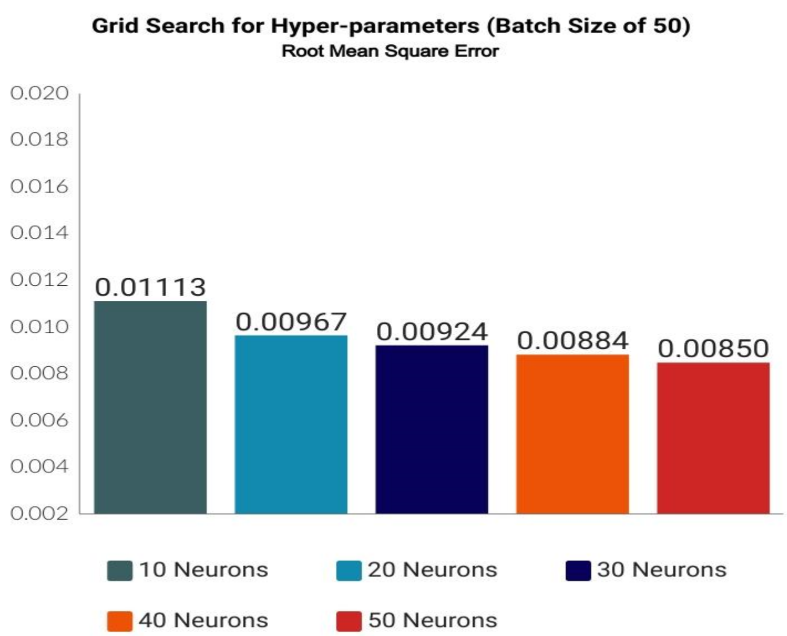

Figure 3: Grid Search for Hyperparameters - 50 Neurons

In figure 3, the batch sizes with 50 neurons were shown and the result whose that the batch 5 yielded the lowest RMSE value which depicts that 50 neurons with batch size of 5 is better among all other values. Moreover, the LSTM model was accompanied by a dropout layer. This layer helped prevent overfitting by ignoring randomly selected neurons during training, and hence reduced the sensitivity to the specific weights of individual neurons. Furthermore, in a hidden layer, the researchers want to find the most optimal number of neurons for each layer. After several iterations, the number of neurons that yielded lowest mean error was 50 with the number of 5 batch sizes that yielded lowest mean error.

The number of epochs is also determined. After several iterations, the number of epochs that yielded the most consistent loss was 500. Additionally, Adam also was used as an optimizer since its high performance and fast convergence in handling sparse gradients on noisy problems compared to other alternative optimizers and was recommended to use as a default. Statistics on Covid-19 data in the Philippines are counted each day. The data set includes 424 rows. The trial was completed in Google Colaboratory initially, however, because of the slow response of the interface, the researchers resisted Pycharm still using Python 3.0 with open source libraries.

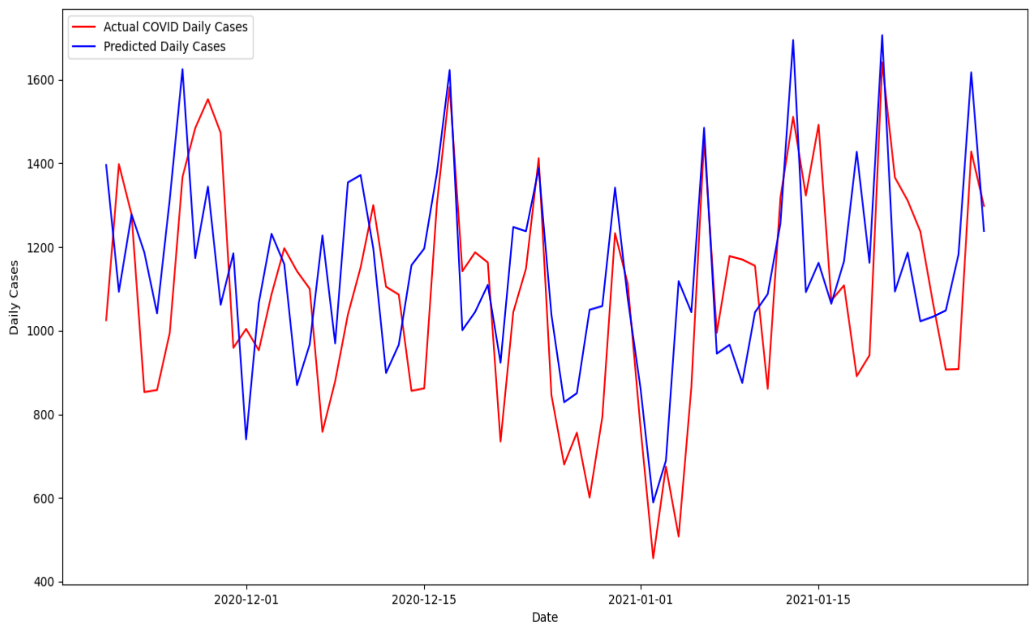

Figure 4: Actual and Forecasted Covid-19 Daily Cases (January 31, 2020-January 30, 2021)

The initial dataset was transformed into a new dataset with dimensions that are acceptable to the LSTM model. This was designed in this way to mimic the incubation period of the virus. The training phase used 80% of the total data, which constitutes the first 339 days as the training data for the model. After several iterations, the number of epochs that yielded the most consistent loss was 500.

As seen in Figure 4, the result of the LSTM model daily cases prediction is close to the actual output. The significant factors and the optimal hyper parameters we incorporate in the model greatly help in the development of the model. The explanation for the rapid fluctuations of value which cause aggressive adjustment of the model's decision to predict highs and lows. In reality, the journey of a simple data element, from infection to tabulation, has many nuances along the way such as reported backlogs in the Covid-19 daily cases in the country due to CovidKaya technical issues and testing lags which takes up to one week.

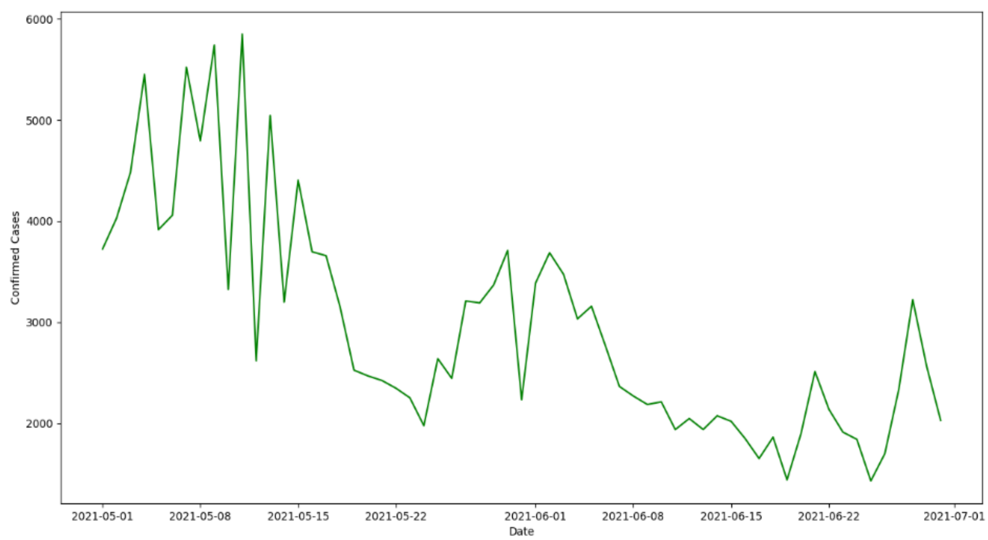

Figure 5: Three (3) month forecast of Covid-19 daily cases (May 1, 2021-July 1, 2021)

Figure 5 shows that our forecast for 3 months has fluctuating trends. The model has days which forecasts are off however it can detect hidden behaviors therefore being capable of forecasting peaks and lows. This result is influenced by the reliability of the data, vested interests, and what variables are being predicted.

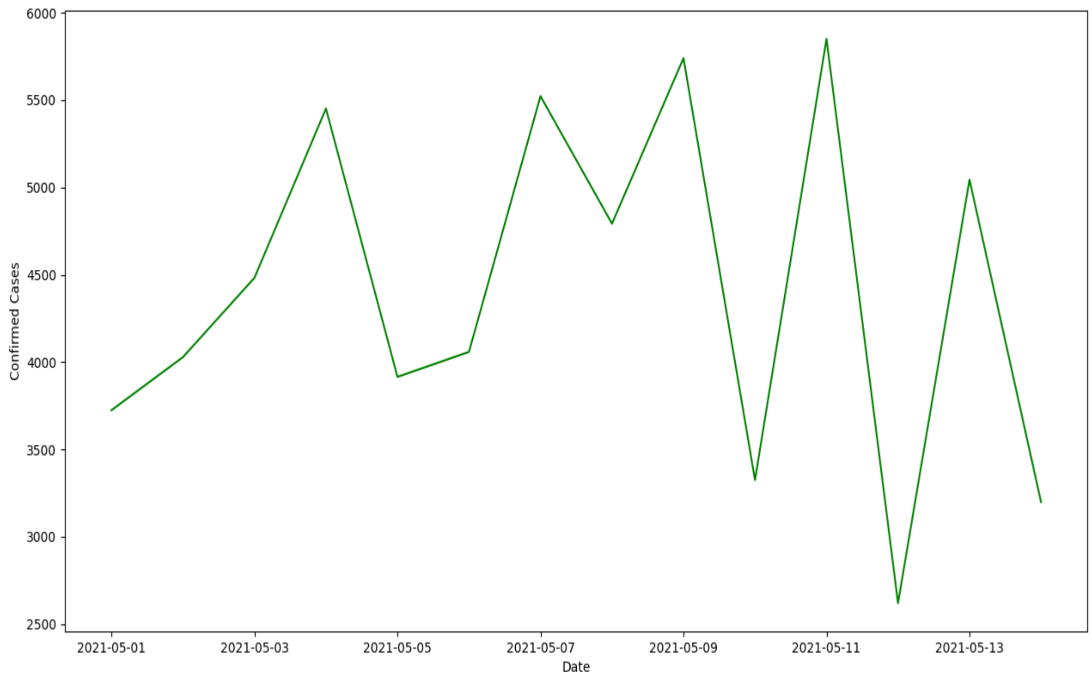

Figure 6: Two (2) week Forecast of Covid-19 daily cases (May 1, 2021-May 13, 2021)

Figure 6 shows that our forecast for two weeks shows the model is capable of predicting high and lows which is very important particularly the peak value. The peak value as you can see in the graph is the highest value in a time-series. On the other hand, according to focus group participants, the low points tell us that the restrictions that have been put in place in the beginning of this pandemic are really effective and will only be effective with the right political support and decision.

Performance Evaluation

$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

n = number of fitted points
At = actual value
Ft = forecast value
Σ = summation notation

Table 4: Absolute Percentage Error of Each Data Points in the LSTM Forecasting Model

Table 4.3.1
Absolute Percentage Error of each data points in the LSTM forecasting model

MAPE: **17.6**

Forecast Value	Actual Value	Percentage Error
1373	1025	**34**
1086	1398	**22**
1269	1277	**1**
1060	853	**24**
1048	858	**22**
1217	995	**22**
1339	1367	**2**
1328	1484	**11**
1387	1553	**11**
1389	1473	**6**
1237	959	**29**
1064	1004	**6**
969	953	**2**
1013	1087	**7**
1050	1197	**12**
1055	1142	**8**
1186	1100	**8**
1209	758	**59**
1082	879	**23**
1079	1038	**4**
1116	1151	**3**
1119	1300	**14**
1105	1105	**0**

Forecast Value	Actual Value	Percentage Error
1150	1086	**6**
1125	856	**31**
1162	862	**35**
1280	1303	**2**
1552	1582	**2**
1071	1142	**6**
985	1187	**17**
1231	1163	**6**
1081	735	**47**
965	1044	**8**
1132	1148	**1**
1297	1412	**8**
1062	846	**26**
985	680	**45**
1052	756	**39**
938	601	**56**
990	793	**25**
1133	1233	**8**
998	1112	**10**
1004	769	**31**
932	456	**94**
932	675	**38**
867	508	**71**

Forecast Value	Actual Value	Percentage Error
1058	865	**22**
1354	1456	**7**
1061	995	**7**
1099	1178	**7**
1159	1170	**1**
1148	1155	**1**
1091	861	**27**
1212	1318	**8**
1466	1511	**3**
1216	1323	**8**
1264	1492	**15**
1297	1072	**21**
1143	1108	**3**
1129	891	**25**
1271	941	**35**
1529	1641	**7**
1122	1366	**18**
1200	1311	**8**
1292	1237	**4**
1222	1065	**15**
1060	907	**17**
1120	908	**23**
1285	1428	**10**
1171	1298	**10**

Table 4 shows the gap between the actual cases and forecasted cases per day of the testing set is depicted as the absolute percentage error. The gap between the actual cases and forecasted cases is due to the rapid fluctuations of value which cause aggressive adjustment of the model's decision to predict high and lows.

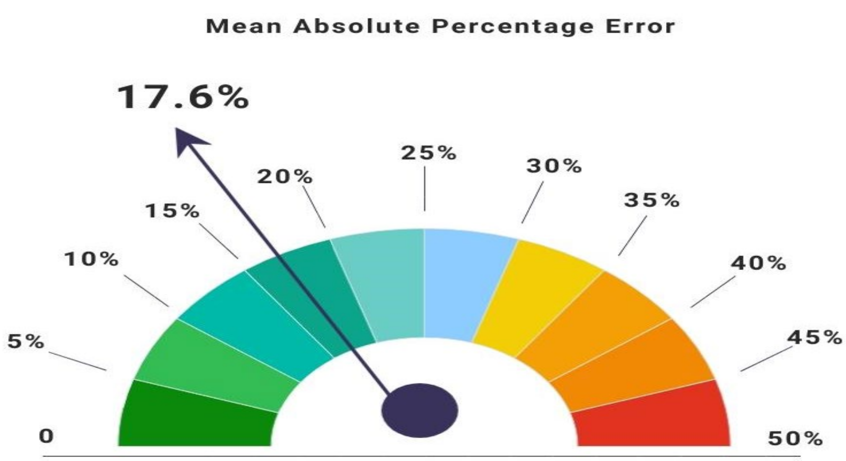

Figure 7: Mean Absolute Percentage Error of LSTM forecasting model

As seen in Figure 7, the model has generated a mean percentage error of 17.6092. Initially, this study intended to compare the LSTM forecasting model to the accuracy of the current forecasting model of Covid-19 cases utilized in the Philippines. However, along with the study we discovered that the current forecasting model only includes the cumulative cases of Covid-19 in the Philippines where the behavior of the virus cannot be totally gauged.

6. Conclusion

This study analyzed the gathered information from the focus group discussion to accumulate the significant factors that would help further in forecasting Covid-19 daily cases. Moreover, the forecasted Covid-19 daily cases were analyzed to collate the trends of the virus and the reasons behind it which was triangulated by the discussion result of focus group discussion.

According to the results, we can conclude that the four significant factors analyzed such as Community Quarantine Classification of the Philippines Government, Reproduction Rate/R0, and Infectious Period greatly affect the forecasting of the Covid-19 in the Philippines. However, we did not include vaccination rate in the feature set since according to experts, it's unlikely that the Philippines rollout of the vaccine is behind the declines in Covid-19 cases given that so far only 8.2% of Filipinos have gotten at least one vaccine dose. Moreover, there could also be a more rigorous optimization of the hyperparameter and must be performed using a suitable amount of iterations and well defined parameter limits. According to OCTA Research, if the number is less than 1, the epidemic curve is flattening but a number higher than 1 means the virus is spreading. It was stated that the reproduction rate in Metro Manila since it makes the highest daily cases in the Philippines from January to April is 1.17, 1.22, 1.91, and 1.16 respectively.

The number of epochs that yielded the most consistent loss was 500 which helped avoid underfitting in the model. On the other hand, the 20% dropout layer was a rule of thumb which helped prevent overfitting and retain model accuracy. The effect of hyper-parameter tuning of deep learning models depends on the algorithm and data set. However, it must be performed using a suitable amount of iterations and well defined parameter limits. Looking at our results, there could be a more rigorous optimization of the hyper-parameter. To sum it up, the optimal hyper-parameter that yields better results is having a 500 epoch, batch size of five (5), fifty (50) neurons, and 20% dropout layer.

The forecasting of Covid-19 daily cases using the LSTM forecasting model has an error of no more than 17%. Using MAPE, the evaluated performance of the model resulted in an error of 17.6092. MAPE was utilized because it is a good accuracy measure since it is scale independent (Kumar, 2020). The model has days which forecasts are off however it can detect hidden behaviors therefore being capable of forecasting peaks and lows. The model shows more meaningful trends in the two (2) week forecast rather than the two (2) month forecast.

Furthermore, the researchers can conclude that the significant factors and the optimal hyper parameters incorporated in the model greatly help in the development of the model. The model has days which forecasts are off, however the model is capable of predicting highs and lows which is very important particularly the peak value. Forecasting these values are vital in planning for healthcare resources and assuring available care for the country facing the uncertainty of a rapidly infectious disease.

However, it is worth acknowledging that our model, as many others, relies on detection of infections through testing and reporting. In reality, the journey of a simple data element, from infection to tabulation, has many nuances along the way such as reported backlogs in the Covid-19 daily cases in the country due to CovidKaya technical issues and testing lags which takes up to 1 week. Nonetheless, despite the limitations of the study, we can conclude that the opportunity for practical application of our forecasting model to provide insight for resource planning and policy-making remains invaluable.

It should also be noted that since the quarantine policy started in March 2020 and the rest of the data gathered started in January 2020, there are 47 rows under quarantine policy data with NaN or null values therefore we converted it to zero (0). Nonetheless, despite the limitations of the study, we can conclude that the opportunity for practical application of our forecasting model to provide insight for resource planning and policy-making remains invaluable.

We believe that the methods used in this study can be used to enlighten and encourage the general public and other committees to assist in planning better strategies, grasp productive decisions, and take well-coordinated and collaborative exertion to manage and control the pandemic particularly the nature and degree of government responses to mandating public health practices. Moreover, our study will ensure and help the healthcare system to prepare in terms of bed availability and handle the Covid-19 patients in a greater course of action and to help the hospitals as well to prepare hospital beds and isolation rooms in advance.

In the future work, it is significant to further enhance the corresponding models and also impart powerful variability quantification both in data and model hyperparameters. Though our LSTM forecasting model has a great importance and an acceptable accuracy, it is also important to consider in terms of a deep learning model is to better use a deeper set since such algorithms will have better results if a deeper set of data will be used and more research is required in this direction for better results as well.

Furthermore, it is beneficial as well to improve and add up more relevant questions in doing the Focus Group Discussion and find the best possible way of dealing with NaN or Null values which is one of the most frequent problems while dealing with data.

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