Attributable Fraction and Forecasting for Covid-19 Confirmed Cases in Nigeria Using Facebook-Prophet Machine Learning Model

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ABSTRACT

Aims: The motivation is to know the attributable fraction among Nigerians, who were tested positive for covid-19 and forecast the covid-19 cases.

Place and Duration of Study: We extracted data from (https://covid19.ncdc.gov.ng/) on 8^{th} September,2021 and covid.19analytics package on 7^{th} September, 2021, from Data Repository by Johns Hopkins University Center for Systems Science and Engineering , Status of Cases in Toronto – City of Toronto , COVID-19: Open Data Toronto ,COVID-19: Health Canada , Severe acute respiratory syndrome coronavirus 2 isolate Wuhan-Hu-1, COViD-19 Vaccination and Testing records from “Our World In Data” and Pandemics historical records from Visual Capitalist. Data in Nigeria contained the number of samples tested, confirmed cases, active cases, discharged cases and deaths.

Methodology: Attributable fraction was used to compute the proportion of patients who tested positive to Covid-19. By using the time for regressor, Prophet model will fit many non-linear and linear functions of time components. Prophet uses the Fourier series to get flexible model to forecast and fit the seasonality effects. A fast solution for L-BFGS which stands for Limited memory Broyden-Fletcher-Goldfarb-Shannon algorithm, is used with Stan backend for the prediction problem.

Results: As at Saturday 11^{th} September 2021,7:18am Nigeria local time, a total of 2884034 samples have been tested for covid-19, with 198239 confirmed cases,9871 active cases,185780 discharged cases and 2588 deaths. The attributable fraction for covid-19 in Nigeria was 0.0687. The r square is very high (0.999), and the p value is very low (2.2e-16).

Conclusion: The attributable fraction gives the percentage of the patients who tested positive to covid-19, among the 2884034 samples tested. It implies that the remaining percentage of patients who tested negative to covid-19 only exhibit covid-19 symptoms or were exposed to the virus. The confirmed cases were found to be highest on Saturdays with the lowest on Tuesdays.

Keywords: Forecasting, Covid-19, Attributable Fraction, Facebook-Prophet, Machine Learning

1. INTRODUCTION

The pneumonia cases of strange sources occurred in Wuhan, China in December 2019, it was confirmed and called corona virus 2019(Covid-19). This deadly disease spread around the world within few months. It has killed at least 5.6 million people in the world with 351 million people infected with the virus. Covid -19 has become a big challenge since the outbreak with many countries still battling with the deadly virus. This transmittable and infectious disease is caused by a recent coronavirus [1]. Researchers have studied the trend, pattern and predicted the covid-19 cases using different methods [2]. A forecast model that uses improved version of adaptive neuro-fuzzy inference system (ANFIS) was developed by [3]. [4] used Fb-Prophet machine learning model to predict daily infections of covid-19 in four countries. [5] applied deep learning methods, these methods can understand trends, dependencies, and structures. Method like multi-layer perception can be used for multivariate inputs and multi-step prediction. The prophet forecasting model, trend model, nonlinear and saturating growth were explained [6]. [7] developed a model called susceptible-exposed -infectious -recovered type epidemiological, to monitor the state of the virus. Parameters that can be interpreted were proposed with a modular regression model, autoregressive integrated moving average was employed because the model is simple [8]. [9] and [10] applied ARIMA, but [10] in addition applied Prophet package which is based on an additive regression time series forecasting algorithm developed by Facebook was used for the forecasting in addition to ARIMA [11] stated that coronavirus disease is caused by acute respiratory syndrome (SARS-CoV-2), [12] also applied autoregressive integrated moving average. In the study of covid-19, [13] examined the relationship between the confirmed, death and recovered was assumed to be linear. [14] used ARIMA, Prophet-an additive regression model and a Holt-Winters Exponential Smoothing model combined with the Generalized Autoregressive Conditional Heteroscedasticity (GARCH). The attributable fraction was computed using the relevant parameters and predisposing factors were modeled using logistic regression by [15].

The motivation is to know the percentage of patients that had the diseases after being tested, because a lot of people assume that they have covid-19 when they have the symptoms associated with the virus, this is not true this is because the symptoms of covid-19 are common to other diseases. People have been told to always go for test if they exhibit the symptoms of covid-19. We need to know the covid-19 attributable fraction after being tested. There is need to forecast the covid-19 cases, this information will really help to plan for the deadly virus. In this study, attributable fraction for covid-19 in the case of Nigeria was computed and predictions were made. We present how to apply ensemble forecasting model in for covid-19 confirmed cases. The objective is to know the attributable fraction for covid-19 cases and make the relevant predictions for the days of the week where covid-19 cases are at the peak. With our knowledge, we have not found in the literature where attributable fraction was used for covid-19 cases and the days of the week where covid-19 confirmed cases were studied.

2. LITERATURE REVIEW ON MODELLING AND FORCASTING COVID-19

We surveyed different literature to understand, have up to date and in-depth knowledge, on how different researchers have modeled and forecasted covid-19 cases. While traditional methods have been used to forecast the covid-19 cases, some authors also used new methods. A summary of the selected literature is provided in table 1., our focus is on the methods and how covid-19 cases are modelled and predicted. While a lot of methods can be used to forecast covid-19 confirmed cases, there is still a controversy for the best method to use to predict covid-19 cases.

Table 1. Models and methods for forecasting covid-19 reported in literature for forecasting COVID-19 pandemic

Authors	Model or Method	Remarks
3	A forecast model that uses improved version of adaptive neuro-fuzzy inference system (ANFIS) was developed by [3]	Four artificial intelligence models were used for forecasting covid-19 cases
4	A machine learning model called Fb-Prophet to forecast covid-19 infections.	The authors found some underestimation and overestimation of the daily cases.
5,17,21,23	The authors applied deep learning methods, these methods can understand trends, dependencies, and structures.	Deep learning was applied to forecast covid 19.
6	A modular regression that has parameters that can be interpreted was proposed.	The tools for analysts to use their knowledge better for practical prediction of business time series.
7,16,25	The authors developed a model called susceptible-exposed -infectious -recovered type epidemiological, to monitor the state of the virus.	The prediction through SIR model may be used for planning and prepare the health systems. (25) concluded that there is no evidence to conclude that there is a positive impact of lockdown in terms.
8	Parameters that can be interpreted were proposed with a modular regression model,	The uncertainty of the novel virus sparks a global problem. The ARIMA sets of forecasts were closed to

	autoregressive integrated moving average was employed because the model is simple	the recorded confirmed cases.
9,10,12,18	applied ARIMA, but [10] in addition applied Prophet package which is based on an additive regression time series forecasting algorithm developed by Facebook was used for the forecasting in addition to ARIMA ,18 used SARIMA too	ARIMA was used to model covid-19.
13	Linear regression	examined the relationship between the confirmed, death and recovered was assumed to be linear
19	Single spectrum analysis model	The SSA-RF model works best when the data exhibit a stable or consistent pattern over time with a minimum amount of outlier.
20	visibility error of time-variant using inductive logic. The result indicated that the number of data required to perform forecasting work on the basis of forecasting model specifications. In con	One important finding of this framework is that a formula for determining how much data testing is required was given, to perform forecasting.
22	Nonlinear Autoregressive (NAR) Neural Network Time Series (NAR-NNTS) model for forecasting COVID-19	The proposed NAR-NNTS with LM training algorithm and optimized network configuration parameter produce better results. But consumes much time.
24	Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trend	SARIMA based models performed better for India, Russia, Peru, Chile, and the UK and ARIMA model performed better for Brazil. For Mexico and Iran, LSTM model performed better and the GRU model performed better.
26	Mathematical model and machine learning	Study conducted on one country and forecasts for more than 48 days were not considered.

	model	
27	State-space hierarchical models	The model cannot identify the days of the week that we have a higher number of covid-19 confirmed cases.

Part of the controversy may be due to the nature of the virus, how it is transmitted, effect of lockdowns, vaccination, and a lot of factors. Since the virus is relatively new, there are insufficient information on it and how it behaves. Some researchers even assume it behaves like other virus. Researchers presume some information about the virus, these assumptions will affect the models and how it is forecasted. In summary, the literature review has shown and highlighted with different remarks, how covid-19 cases have been modelled.

3. MATERIAL AND METHODS

Description and Sources of Data

The data were extracted from the Nigeria Centre for Disease Control (https://covid19.ncdc.gov.ng/) on 8th September,2021 and covid.19analytics package on 7th September, 2021.This package allows us to have access to live data anywhere in the world, from Novel Corona Virus COViD-19 (2019-nCoV) Data Repository by Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) , Status of Cases in Toronto – City of Toronto , COVID-19: Open Data Toronto ,COVID-19: Health Canada , Severe acute respiratory syndrome coronavirus 2 isolate Wuhan-Hu-1, COViD-19 Vaccination and Testing records from "Our World In Data" (OWID) and Pandemics historical records from Visual Capitalist.

Data on 36 states and the capital of Nigeria (Abuja) were extracted, the available data contained the number of samples tested, confirmed cases, active cases, discharged cases and deaths. Fig.1 shows the schematic representation of the procedures for the research, Fig. 2 shows the plot confirmed cases for confirmed covid-19 cases in Nigeria from 28th February 2021 to 7th September,2021.

Attributable Fraction

This is the proportion of incidents found in the population that are attributable to the risk factor.

Prophet Model

Machine learning algorithms for extrapolative analysis are works across training of past data, using deep learning, linear regression, Bayesian algorithms and artificial neural networks. The algorithms will select the most suitable model, using the data features and forecast future results. This study applied similar methods to COVID-19 prediction for the data. The Facebook-Prophet is an open-source framework of Facebook that was created in 2017 to achieve time series forecasting by using additive model.

Facebook built an additive regression time series and is comparable to a generalized additive model (GAM), with time as a regressor, Seasonality is modelled as an additive component in the same way that exponential smoothing is done. The advantage of GAM design is the ability to adapt and easily decompose the different components. Prophet is simply treating the predicting problem as a curve-fitting effort rather than explicitly looking at each observation's time-based dependence. The Facebook-Prophet machine learning model for forecasting analysis the Fb-Prophet model does not require the interpolation of missing data and enhances better forecasting by an accumulation of seasonal modeling.

Prophet fits several linear and non-linear functions of time as components. In its simplest form,it is an algorithm for forecasting [6]. To apply it, a fast solution for L-BFGS which stands for Limited memory Broyden-Fletcher-Goldfarb-Shannon algorithm, can be used with Stan backend for the prediction problem. L-BFGS uses limited amount of computer memory and is common in machine learning for estimating parameters. It is a family of quasi-Newton methods that can approximate Broyden-Fletcher-Goldfarb-Shannon algorithm.L-BFGS can be used instead of BFGS when the sample size is very large.Prophet model can deal with outliers, missing data, strong seasonal effects and shifts in Trend,which ensures it is entirely automatic. Prophet model comprises a decomposable time series model given by

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_i \qquad (1)$$

Where $g(t)$ denotes trend (linear or logistic growth curve for developing non-periodic variations find time series)

$s(t)$ is the seasonal changes (weekly or yearly seasonality)

$h(t)$ is the irregular effects(holidays) and

ε_i is the error term for unusual change in the model.

The $g(t)$ is very useful in modelling the trend, it uses a piecewise saturated model, in conjunction with the time -varying carry capacity defined as

$$g(t) = \frac{C(t)}{1+\exp\left(-(k+\alpha(t)^T \delta\left(t-\left(m+\alpha(t)^T \gamma\right)\right)\right)} \qquad (2)$$

The $C(t)$ stands for the time – varying carrying capacity .

k represents the growth rate.

m is the offset.

The piecewise $\alpha(t), \gamma$ *and* δ are the structures, the growth rate is not constant.

Trend

The trend will be developed and fit a piece wise linear curve, over the trend or the non-periodic portion of the time series. With this, we can take care of the missing data or anything that can affect the spike. Prophet uses the Fourier series to get flexible model, this is to forecast and fit the seasonality effects. These effects of seasonality are estimated by

$$s(t) = \sum_{n=1}^{N}\left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{T}\right)\right) \qquad (3)$$

P is the period, and $[a_1, b_1, \ldots, a_N, b_N]$ will be estimated.

We have formulated Prophet class, using predictive techniques that can fit data. We have two features which is the time and the covid-19 confirmed cases in Nigeria.

4. RESULTS

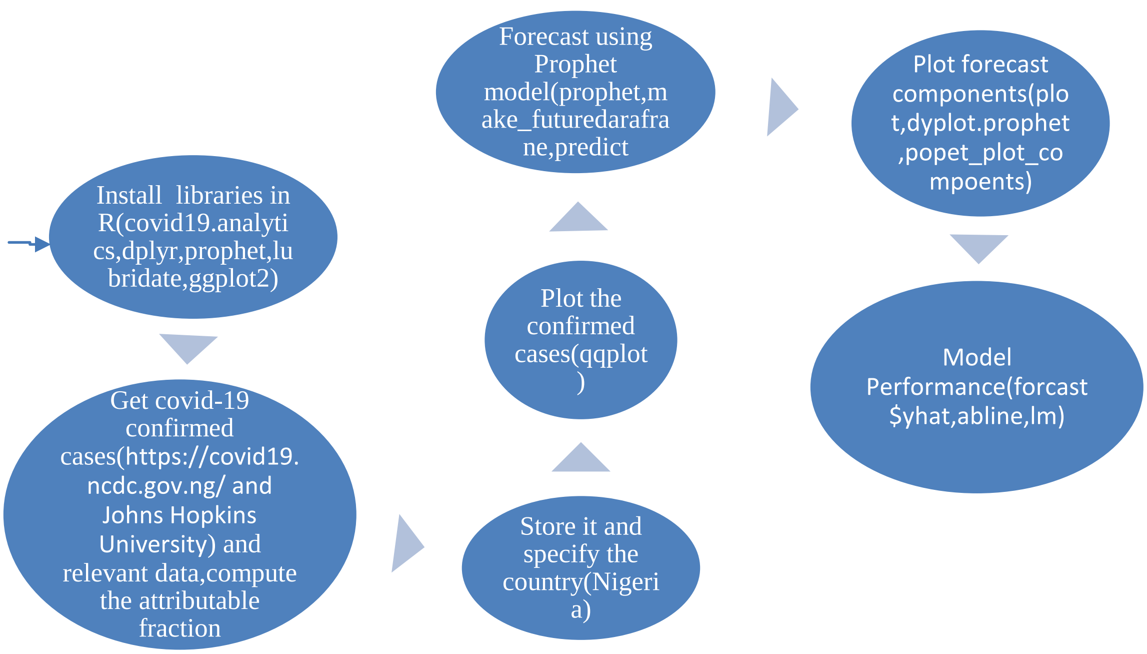

Fig. 1. Schematic representation of the procedures. This explains the procedures used for the analysis, after the relevant installation of R packages, the diagram explains how to carry out the research

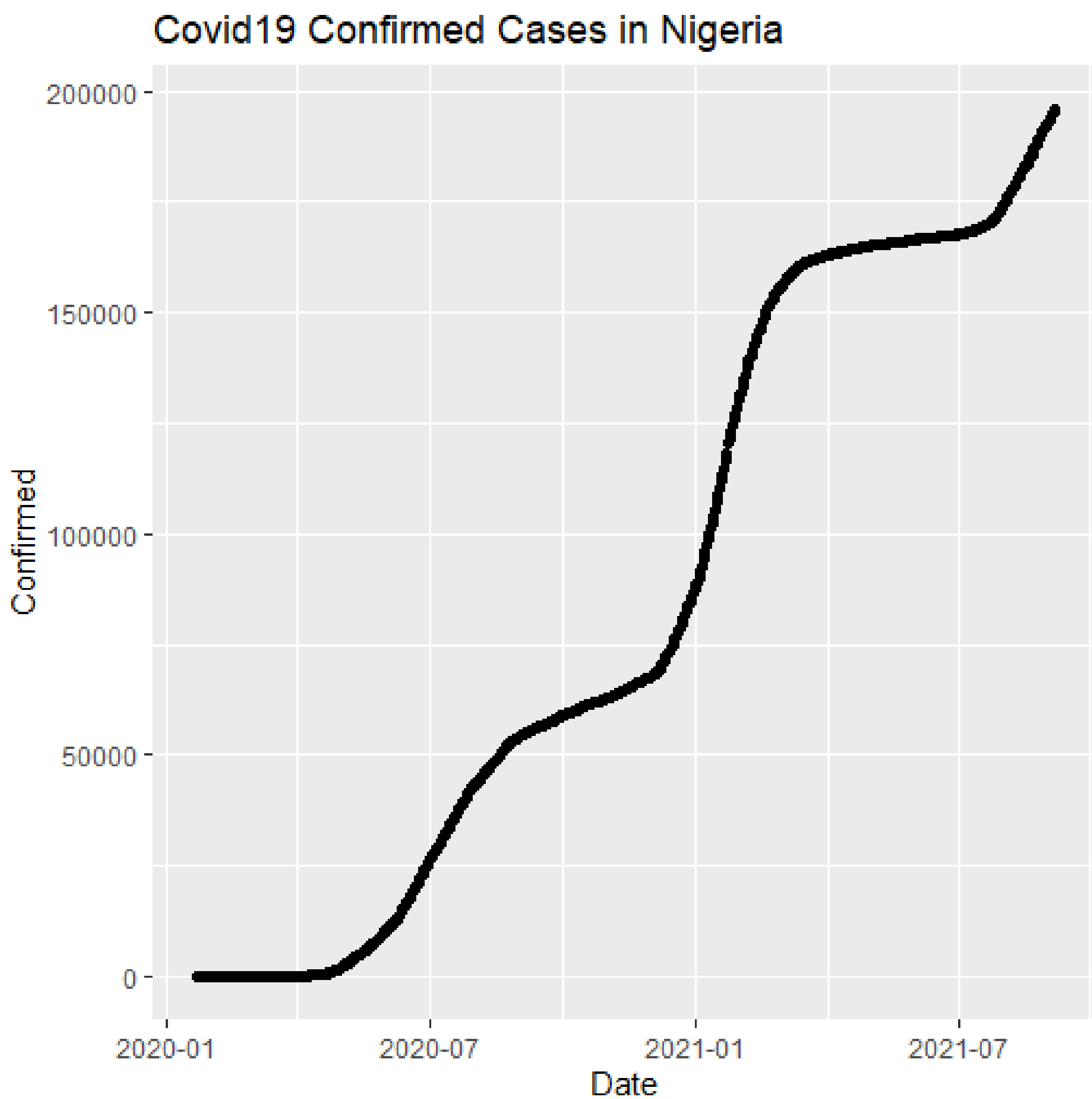

Fig. 2. Confirmed Cases for Covid-19 in Nigeria. The graph shows the covid-19 confirmed cases from 28th February, 2020 to 7th September,2021.

Fig. 3. Actual confirmed cases versus Predicted cases. The graph shows the actual confirmed cases against the predicted confirmed cases for the next 28 days, the predicted confirmed cases are the ones in blue.

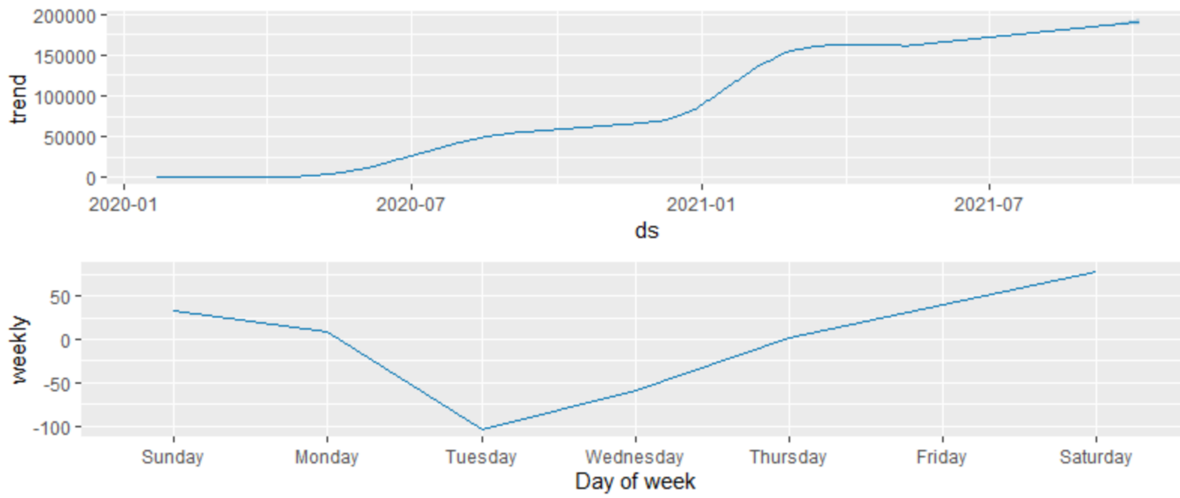

Fig. 4. Plots of the Forecasts Components. This graph shows the weekly trend, we can know which day(s) the week has the highest or lowest Covid-19 confirmed cases.

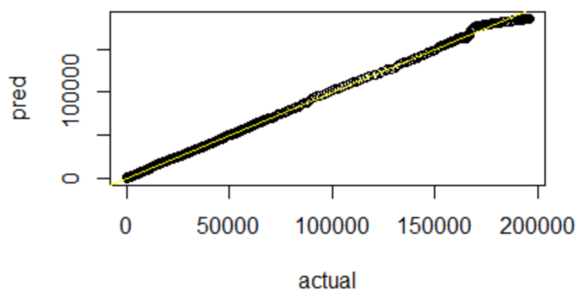

Fig. 5. Plot of Predicted versus Actual for the model performance. This graph shows how well the model has performed.

5. DISCUSSION

The aim of this paper is to compute to the covid-19 attributable fraction and make predictions of the cases. It is very important to know the proportion of people who tested positive to covid-19 among all the samples tested and forecast the covid-19 cases, to enable proper planning for the future.

The new confirmed case on the 10th of September 2021 was 466 and 3 deaths were recorded in Nigeria. The 466 new occurred in 13 states- Lagos (134), Rivers (82), Edo (69), Gombe (39), FCT (32), Kaduna (21), Plateau (20), Benue (19), Kwara (17), Delta (16), Akwa Ibom (10), Bayelsa (5) and Kano (2). As at Saturday 11th September 2021,7:18am Nigeria local time, a total of 2884034 samples have been tested for covid-19, with 198239 confirmed cases,9871 active cases,185780 discharged cases and 2588 deaths. The analysis showed that the attributable fraction for covid-19 in Nigeria was 68.7%. This means that the remaining percentage of patients who did not test positive to covid-19 probably had travelled to countries with the virus, or have close contacts with someone who tested positive to the virus or were exposed to covid-19 patients or exhibit covid-19 symptoms or cannot be explained by the model. The result has shown that there is a relationship between the number of patients who tested positive and the total samples. The results showed that the 95% confidence interval is between 68.40% and 68.99%, we were 95% confident that the patients who had covid-19 lies in this range.

From figure 2, the confirmed cases column is cumulative numbers, which can give us the sum at any date, we were able to disable yearly and daily seasonality because we do not have enough data to capture the seasonality. Figure 3 shows the predicted the covid-19 confirmed cases for the next 28 days from 7th September 2021 and the conditions are valid if the current conditions did not change. The confidence bound was also included because it can be lower or higher. From figure 4, the average, the confirmed cases were found to be lowest on Tuesdays, there were fluctuations in the confirm cases, it may be due to under or over reporting of covid-19 cases or the procedures for being tested for covid-19 cases. We have many confirmed cases on Sunday, Friday, and Saturday. This does not imply that Nigerians have a higher risk of getting covid-19 on these days. Figure 5 shows a linear pattern, and no many under or over estimation, the r square is very high (0.999), and the p value is very low (2.2e-16), which means we have a high confidence that it is statistically significant.

6. **CONCLUSION**

We have proposed and demonstrated how attributable fraction and confirmed covid-19 cases can be predicted, using the prophet Facebook model, with the data available from the Nigeria Centre for Disease Control (NCDC) and Novel Corona Virus COViD-19 (2019-nCoV) Data Repository by Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) , Status of Cases in Toronto – City of Toronto , COVID-19: Open Data Toronto ,COVID-19: Health Canada , Severe acute respiratory syndrome coronavirus 2 isolate Wuhan-Hu-1, COViD-19 Vaccination and Testing records from “Our World In Data” (OWID) and Pandemics historical records from Visual Capitalist.

The attributable fraction has shown that not all asymptotic patients of covid-19 symptoms are having the virus.

A prophet model is good for nonlinear trends that can fit daily, weekly, yearly seasonality and holiday effects. The effects of vaccines, booster dose, lockdown, use of nose masks, bans on travels, bans on large gatherings and sports will enhance research significance.

The model suggested in this research substantially helps to know the percentage of the attributable fraction of covid-19, study the trends of the virus and make predictions in Nigeria to aid the relevant agencies to plan for health policy interventions.

Because of the nature of covid-19 virus, availability of data and the nature of transmission, modelling the confirmed cases and the prediction are problematic.

We are constrained by the type of data available online. Because of the aim of the research and availability of data, we can only use single variable, which is the number of covid-19 confirmed cases. This will leave behind gap for future research. Irrespective of the high prediction accuracy, the implemented Fb-Prophet model has some limitations. Because of the lack of clearer data on daily and yearly seasonal data, thorough projections are not viable, although these models are useful in predicting the upcoming cases. The results from this work are good for understanding the covid-19 predictions and to curb the problems. We hope to use generalizable, nonparametric neutral and advanced methods when we are not constrained by the types of data. There is a need to investigate further the reason for why some days have high number of confirmed covid-19 cases.

The attributable fraction for covid-19 in Nigeria was 68.7%, the remaining percentage cannot be explained by the model. We have the lowest on Tuesdays, though we have fluctuations in the confirm cases, which may be due to under or over reporting of covid-19 cases or the procedures for being tested for covid-19 cases. We have many confirmed cases on Sunday, Friday, and Saturday. This does not imply that Nigerians have a higher risk of getting covid-19 on these days. We hope that the results will aid the country and individuals to contain the virus.

COMPETING INTERESTS

No competing interests exist.

AUTHORS' CONTRIBUTIONS

Ibidoja Olayemi Joshua designed the study, performed the statistical analysis, wrote the protocol, and wrote part of the draft of the manuscript. Fowobaje Kayode Rapheal wrote the introduction, completed the draft and interpretations of the results. All authors read and approved the final manuscript.

CONSENT

Not Applicable

ETHICAL APPROVAL

Not Applicable

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