**Methods**

Here, we used five time series and two trending analysis (i.e Simple Exponential Smoothing (SES), Auto-Regressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX), Bayesian Structural Time Series (BSTS), Automatic forecasting time-series model (Prophet. We also used the Mann-Kendall (M-K) trend analysis to identify existence of any trend and the direction of the trend (increasing or decreasing). Finally, we developed beta-regression model of explanatory variables to identify whether the variables have any relationship between the country’s rCFR of COVID-19. All these different analysis approaches helped us to make a specific conclusion on the global trend of COVID-19 CFR and weather factors affecting the CFR of COVID-19 in Bangladesh. All analyses were doing by using the statistical software R version 3.5.2.2.

**COVID-19 Data**

The fundamental COVID-19 related data, including daily new cases, daily new deaths, total deaths, total deaths per million, and total cases from the WHO daily COVID-19 situation reports in Bangladesh was collected from January 01 to December 31, 2020 for this analysis. The ARIMA, SES, ARIMAX, BSTS, M-K and Prophet models were appearing for the full dataset.(1)

**Reported case-fatality rate (rCFR)**

We calculated total rCFR COVID-19 case as the number of deaths per 100 COVID-19 confirmed cases. There is a fraction between total case and death case, we considered the term as reported CFR or simply as rCFR.(2)

**Time series model to predict the trend**

Here, we used five time-series model to define the relation between COVID-19 and the weather variables in Bangladesh. We selected all these time series models as the outcome variable (cumulative rCFR) are subordinate to the past records and all these eight models can take this under consideration. SES was utilized as a benchmark to compare the execution of the ARIMA and Prophet models. We used M-K and SLOPE analysis to different between every day or every week total drift (expanding or diminishing) of COVID-19 rCFR.

**Simple Exponential Smoothing (SES):**

Simple exponential smoothing is one of the most widely used methods for forecasting procedures.(3)(4)(my1). SES is a short-term used for forecasting model that define data fluctuates around a relatively stable mean.(5) The simple exponential smoothing equation is

*Ft*+1 = *α yt* + (1 *−α*) *Ft*

here yt is the actual, known series value at the time t; Ft is the forecast value of the variable Y at the time t; Ft+1 is the forecast value at the time t + 1; α is the smoothing variable(4). The SES model for this study had been carried out using R package ‘fpp2’.(6)

**Auto-Regressive Integrated Moving Average (ARIMA):**

We used an ARIMA model to forecast the trend of global weekly cumulative rCFR. The ARIMA model is a statistical, data-oriented analysis that interpret a perfect model by using the structure of the data itself.(7) This model shows that the time series values are linearly related and defines the extract prediction by deleting high-frequency noise from the data.(8)

The benefit of ARIMA models is the ability to dynamically oriented analysis which using recent data and make future prediction.(9). For this studies R package ‘forecast’ had been using f eliminating or the ARIMA model (10).

**The Statistical method of the ARIMA model**

p of order, denoted by AR , is

****

q order, denoted by MA , is

****

p and q order, denoted by ARMA , is

****

Here,   is a time series, p and q are order and  is the random error term(11).

**Autoregressive Integrated Moving Average with Explanatory Variables (****ARIMAX)**

Adding explanatory variable (X) with the ARIMA model is called ARIMAX (p, d, q)(12). The equation of the ARIMAX is (12)(13)



and the variable calendar effect equation is (13)



**Automatic Forecasting time-series model (Prophet):**

We also used a construe automatic forecasting time-series model called ‘Prophet’ using R package “prophet” to predict the 10-days fatality rate and distinguished with rCFR.(14) The Prophet model doesn’t want the temporal dependence of the irregular observations are allowed in the data set and the model fits very quickly(15).The benefit is, it collect missing data also and manages outliers well generally.(16). There are three main factors of the model, i.e., trend, seasonality, holidays. It can be represented as,

*Y (t) = g(t) + s(t) + h(t) + ∈t*

where the model parameters g(t), s(t), h(t), ∈t is piecewise linear curve for modelling non-periodic changes in time series, periodic changes, the effects of holidays with irregular schedules considered in the model by some parameters, respectively. The error term for any unexpected changes of the analysis that the model does not allow for(16) .

**Mann-Kendall (M-K) trend:**

We applied weekly cumulative rCFR data and performed the M-K trend test to identify the trend of COVID-19 rCFR.(17)

The M-K method is a non-parametric test that provides an indicator of monotonous trend and also indicate that there is a positive or negative trend.(17). It can calculated ranks and sequences of time series by dealing with non-normally distributed data, censored data, and time series with missing values rather than the original values.(18)

In addition, the Sen’s slope test was exerted to determine the changes in COVID-19 rCFR in both periods.(19) M-K and Sen’s slope trend analysis are using by R package ‘trend’.(20)

**Empirical evaluation**

The ARIMA and Prophet are experimentally evaluated by comparing their outcomes to benchmarks in foreseeing the rCFR. This benchmark allowed us to survey the execution picks up made by their counterparts(21). The SES also allows the most appropriate non-seasonal model for each series, allowing for any kind of error or trend component. Here, we analyse and compare the execution of the considered time arrangement models with a few of the commonly utilized measures to assess the expectation noteworthiness counting coefficient of assurance (R2), root cruel square blunder (RMSE), and cruel outright mistake (MAE).

**Outcome and predictor variables**

We used rCFR as the outcome variable, we also collected and used several factors data from the ….

**Statistical analysis**

Here, we analysed that the rCFR of COVID-19 has changed over time (**Fig. 1**). We also find out that the rCFR reached a peak at 17th epidemiological week (22-28 April 2020, considering 1st January 2020 as the start of epidemiological week) and then the trend turned into decline. Not only used time-series model to identify the reason behind the increasing and decreasing trend of COVID-19 rCFR. We tried to find out the relationship between the rCFR of COVID-19 and country-level explanatory variables vary over time or they remain the same in two period through regression model. We divided this dataset into two half one until it reaches a peak (1-17th week) and termed as “before peak rCFR” or simply as “pre-peak period” and another with 18th – 53rd week (December 29-31, 2020) and termed as “after peak rCFR period” or simply as “post-peak period”. Here, we got the trending of rCFR value is different in both periods, then we applied the beta regression model separately for each dataset to investigate the association between possible explanatory variables and tried to get which variables affecting most in the both periods separately.

**Bayesian Structural Time Series (BSTS):**

Bayesian structural time series (BSTS) model is a statistical technique according to use the time series data, like forecasting, nowcasting, inferring causal impact and other applications(22). The benefit of the Bayesian Structural Time Series (BSTS)model is to understand the causal structure of uncertainties in the data, but the demerit is, it is difficult to

illustrate the time factors in the model. For this studies the R package ‘forecast’ had been using f eliminating or the BSTS model (23).

**Beta regression models:**

As the outcome variable (rCFR) varies in an interval of 0 or 1, here we used beta regression models to find out the relation between possible explanatory variables and the rCFR.(24,25). The benefits of beta-regression model (25) is explanatory variables of two different periods (Pre and post peak)and reported that the incidence rate ratios (IRRs) after adjusting them for population density (per square kilometrer),the prevalence of obesity and the stage of the epidemic in Bangladesh country(26). In this study the beta regression models had been carried out using R package ‘betareg’.(20)

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