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Short Term Nowcasting and Forecasting for COVID-19 Potential Spread in SAARC Country: A Modeling Study Using Machine Learning Approach

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Abstract: Emergence of infectious diseases, such as severe acute respiratory syndrome (SARS) and Zika virus disease have presented a major threat to public health. Despite intense research efforts, when and where new diseases appear are still a source of considerable uncertainty. As the COVID-19 has strike globally and form as a large scale pandemic disease in a very short phase. So understanding the severity of the disease to estimate the case fatality risk is a common epidemiological practice defined as the risk of death among cases. The ongoing COVID-19 pandemic continues to spread globally and stating about SAARC countries, the spread is not that alarming to panic, as several social distancing measures implemented by different SAARC governments, but still it is not in the situation of negligence and slackness. We have used forecast models i.e. ARIMA model and SIR Model to generate the short term forecasts of the COVID-19 spread in SAARC countries i.e. India, Afghanistan, Sri-Lanka, Maldives, Bhutan, Pakistan, Nepal and Bangladesh using daily reported number of case from 22 January, 2020 up to 01 April, 2020, the forecast for each countries have been generated separately but for the validation we have used forecast of whole SAARC and values are really good for prediction as ARIMA(0,2,3) is best fitted for confirmed cases with MAPE of 17.1, similarly ARIMA (0,2,1) for Death cases with excellent MAPE of 5.5 and lastly ARIMA(0,2,1) for Recovery cases with MAPE of 8.1, which is very good, the prediction is shows rise of confirm cases to 35000, death tolls to 600 and recovery to 1600 till 30th April, 2020. For the SIR Model for SAARC, the trend is comes to peak of Infection during 95th to 120th day of the pandemic period with β=0.25 and γ=0.007.

Keywords: ARIMA Model, COVID-19, MAPE, SAARC, SIR Model, β, γ.

I. INTRODUCTION

A large family of diseases, called coronaviruses, are severe pathogens for human beings, which contaminate respiratory, hepatic, gastric, and neurologic diseases. They are distributed among humans, birds, livestock, mice, bats, and other uninhabited animals [1]–[3]. The epidemics of two previous coronaviruses, (SARS-CoV) and (MERS-CoV) in 2003 and 2012, respectively, have approved the spreading from animal to animal, and human to human [4]. In December 2019, the World Health Organization (WHO) received statements from China for many cases of respirational illness that were linked to some people who had visited a seafood marketplace in Wuhan. Presently, Wuhan city writhes from the dissemination of a novel coronavirus, called COVID-19 (previously, it was called 2019-nCoV), which is the currently restrained as the epicenter of the pandemic virus.

The novel coronavirus disease that was seemed in November-December, 2019 (COVID-19) which was initially in Southeast Asia is now spread onto more than 190 countries, and has resulted in a significant number of deaths. To comprehend the harshness of infection, i.e., the virulence of the causative agent of COVID-19 , the communal epidemiological practice is to evaluation the case fatality risk (CFR) as the risk of death amongst cases (for the sake of practical analysis, we refer to it as the case fatality risk rather than the case fatality rate [5]. Depending on the CFR value, the government reaction toward COVID-19 may vary, and approximations of CFR can also influence the strictness of policy judgement and the extent of containment and mitigation measures. For instance, a well-known CFR estimate for severe acute respiratory syndrome (SARS) in Hong Kong in 2003 was approximately 17 % [6], almost indicating that one out of five diagnosed cases would die of the disease. SARS containment measures were implemented as early as possible due to high estimates of CFR. The total volume of deaths, i.e., mortality, is determined by the product of the CFR and the total number of cases; it should be remembered that our perceived severity of the COVID-19 epidemic can be directly influenced by the absolute number of deaths.

As were ongoing epidemic of a novel coronavirus sickness (COVID-19) began at comprehensive wholesale seafood market in Wuhan city of Hubei Province, China in December 2019 and continues to cause infections globally and have become pandemic. In the initial stages of COVID-19, there have been 59,907 collective cases, including 1368 demises, reported globally with 48,206

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cases reported in Hubei alone [7]. To control the pandemic, the Chinese government has endorsed a range of social distancing strategies, such as city-wide lockdowns, transmission measures at trains and airports, active case finding, and isolation of suspected cases and mostly affected countries adopted it. The number of cases and deaths continue to accumulate every day.

The virus of COVID-19, all these aspects have not yet remained fully addressed, even though the global public health community is indulged to continually provoke the pandemic and make political decisions incorporating travel restrictions, containment measures, and mitigation strategies. To undertake the scientific assessment of the brutality and sufficiently understand weakness surrounding the accompanying debates, we object to guide the readers to comprehend the likely severity of COVID-19 and direct the progression of forthcoming research work.

II. STUDY AREA

The South Asian Association for Regional Cooperation (SAARC) is the union of regional intergovernmental organization and geopolitical states in South Asia. The member states are Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan and Sri Lanka. SAARC comprises of 3% of the world's area with 21% of the world's population and 4.21% (US$3.67 trillion) of the global economy until 2019.

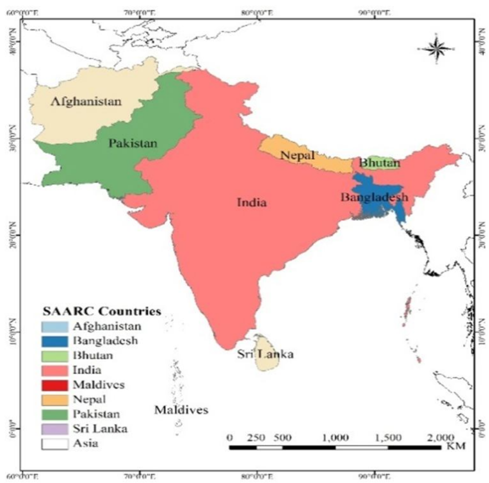

Fig.1. Study Area

III. METHOD AND DATA USED

A. Data

We use the data from the worldometer web portal [7]. which is published by a US-based and American-Owned company which reports the live world real-time statistics on population, Government and Economics, Society and Media, Environment, Food, Water, Energy and Health which provides the cumulative cases of daily based of more than 190 countries and territories around the world recently the current pandemic of Novel-Coronavirus updates and also used the data of John's Hopkins public school Ltd. [8]. we collected reported case data each day as reset after midnight (GMT+0) from the initial date of reporting from 22nd January, 2020 up to 1st April, 2020.We then forecasted the trajectory of the COVID-19 epidemic in SAARC Countries which have exhibited a potential threat in near future.

B. Models

Forecasting is extremely vital even to get slightest result for multi variables consideration over public health factors, especially pandemic crisis like COVID-19. In this case, forecast from single models is not enough for reliable result and prediction. Therefore here we are using different models integrated for time series analyses. Hence all the different models will be discussed ahead. For this study we will be using two complicated but still effective models for prediction forecast i.e. ARIMA Model and SIR Model. We will further discuss models separately

1) ARIMA Models

a) *Auto-regressive Models (AR):* It is the process where a time series is said to be AR when present value of the time series can be obtained using previous values of the same time series i.e. the present value is weighted average of its past values. Stock prices and global temperature rise and here where our data based on the rise in COVID-19 victims and so can be thought of as an AR processes.

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The AR process of an order p can be written as,

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \ldots + \phi_p y'_{t-p} + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots\ldots + \theta_q y_{t-q} + \varepsilon_t \qquad (1)$$

Where ε_t is a white noise and y_{t-1} and y_{t-2} are the lags. Order p is the lag value after which PACF plot crosses the upper confidence interval for the first time. These p lags will act as our features while forecasting the AR time series. We cannot use the ACF plot here because it will show good correlations even for the lags which are far in the past.

b) Moving Average Models (MA): Moving average (MA) is the process where the present value of series is defined as linear combination of past errors. So assuming the errors to be independently distributed with the normal distribution. The MA process of order q is defined as:

$$y_t = c + \varepsilon_t + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots\ldots\ldots\ldots\ldots\ldots + \theta_q y_{t-q} \qquad (2)$$

Where ε_t is a white noise and y_{t-1} and y_{t-2} are the lags. Order q of the MA process is obtained from the ACF plot, this is the lag after which ACF crosses the upper confidence interval for the first time. As we know PACF captures correlations of residuals and the time series lags, we might get good correlations for nearest lags as well as for past lags [9].

c) Auto-Regressive Integrated Moving Average Model (ARIMA): Now, here we combine differencing with auto-regression (AR) and a Moving Average models (MA). The full model can be written as:

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \ldots + \phi_p y'_{t-p} + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots\ldots + \theta_q y_{t-q} + \varepsilon_t \qquad (3)$$

Where, y'_t is the differenced series. The "predictors" on the right hand side include both lagged values of y_t and lagged errors. We call this an ARIMA (p,d,q) model, where,

p=order of the autoregressive part;

d=degree of first differencing involved;

q=order of the moving average part.

The same stationary and invariability conditions that are used for autoregressive and moving average models also apply to an ARIMA model[10] . For our study, after the pre-processing method of data smoothening and testing the database for stationary and further for prediction modeling. Therefore as there is multi-variate database for COVID-19. And after different iteration methods, we put the model with double differencing and as per lags, ACF correlation is find more suited for the database and therefore, the model we made for prediction of death, confirm and recover variable separately is ARIMA (2,1,2).

2) SIR Model: The SIR model is one of the simplest and smartest compartmental models for epidemiology like COVID-19. The model is composed of three compartments that represent different categories of individuals within a population; the susceptible (S), infected (I), and removed (R), hence it is called as SIR Model. Here susceptible is meant by people exposed to this COVID-19, infected comes after COVID-19 is confirmed in a person and removed means that either the person is recovered or death due to COVID-19 [11]. Mathematical it is determined with respect to time i.e. days here and given by:

$$dS/dt = -\beta SI$$
$$dI/dt = \beta SI - \gamma I$$
$$dR/dt = \gamma I$$
$$\beta = cp \qquad (4)$$

Where,

S – proportion of susceptible individuals in total population

I – proportion of infected individuals in total population

R – proportion of removed individuals in total population

β – transmission parameter (rate of infection for susceptible-infected contact)

c – number of contacts each host has per unit time (contact rate)

p – probability of transmission of infection per contact (transmissibility)

γ – recovery parameter (rate of infected transitioning to recovered).

This model is very basic and has important assumptions. The first being the population is closed and fixed, in other words – no one it added into the susceptible group (no births), all individuals who transition from being infected to removed are permanently resistant to infection or are dead because of the disease and there are no deaths. Second, the population is homogenous (all individuals are the same) and only differ by their disease state. Third, infection and that individual's "infectiveness" or ability to infect susceptible individuals, occurs simultaneously[12].

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C. Short-Term Forecast

To calibrate the model to the daily cases counts reported for South Asian Countries. Short-term forecasts generated from such models can be useful to guide the allocations of resources that are critical to bring the epidemic under control. In this paper, we use dynamic model called (ARIMA mode) to generate, The data from 22nd January up to 1st April with One month ahead forecasts of the cumulative reported cases in the SAARC Countries

IV. DATA USED

The main dataset of our study i.e. regarding the spreading of COVID-19 was mainly collected from official web portal of Worldometer. It is run by an international team of developers, researchers, and volunteers with the goal of making world statistics datasets regarding population, financial updates etc. Currently, they have made datasets for COVID-19 available freely to a wide audience around the world. Respective information and more details of the day-wise scenario has been taken from WHO official website portal for Novel Coronavirus. It contains the daily confirmed cases in SAARC countries from 22nd January to 1st April, 2020 as, confirmed, death and recovered cases.

V. RESULT AND DISCUSSION

A large outbreak of Covid-19 occurred on a cruise ship. Estimating the incidences, the peak time of infection was shown within the time period of 22nd January to 1st April the outbreak was since Start in 10th January in Wuhan City, china the first case was declared by World Health Organisation (WHO). The procedure adopted in this research work forms the basis for deriving the ARIMA model to generate the forecasts of cumulative reports of COVID-19 within SAARC Countries. And then generating SIR model for prediction of the spread extension of the COVID-19. Further the spatial distribution of the Corona spread till 1st April, 2020 is shown for South Asian countries.

A. Confirmed, Death and Recovered Case

The confirmed cases from 22nd January to 1st April, 2020. Total confirmed case are 4184 in SAARC countries in which Afghanistan 185, India 1451, Pakistan 2337, Sri Lanka 129, Bhutan 4, Nepal 6, Maldives 20, and Bangladesh 51, whereas Pakistan has the highest confirmed case with 2337 in the SAARC Countries and Bhutan has the lowest confirmed case with only 4 in the SAARC Countries (Fig.2). The Death cases from 22nd January to 1st April, 2020, within this period, the total death case are 80 in SAARC Countries, in which, Afghanistan 04, India 40, Pakistan 29, Sri Lanka 2, Bhutan 0, Nepal 0, Maldives 0 and Bangladesh 5. In which, highest death 40 in India and 0 death in Nepal, Bhutan and Maldives (Fig.3). The recovery cases from 22nd January to 1st April, 2020, during this period, total recovered case are 354 in SAARC Countries. In which, Afghanistan 06, India 189, Pakistan 107, Sri Lanka 17, Bhutan 01, Nepal 01, Maldives 13 and Bangladesh 21 (Fig 4).

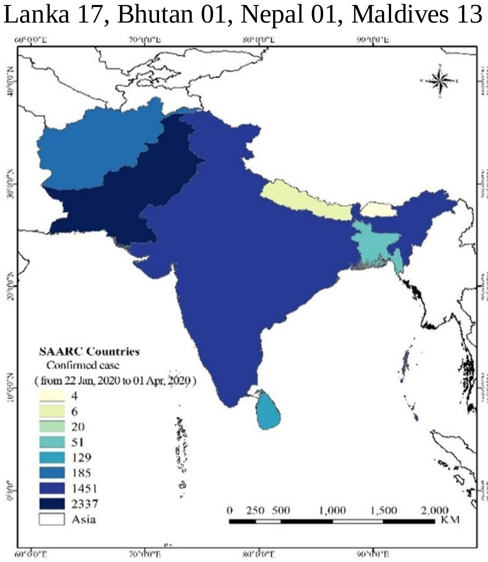


Fig 2. Spatial Distribution of Confirmed Cases

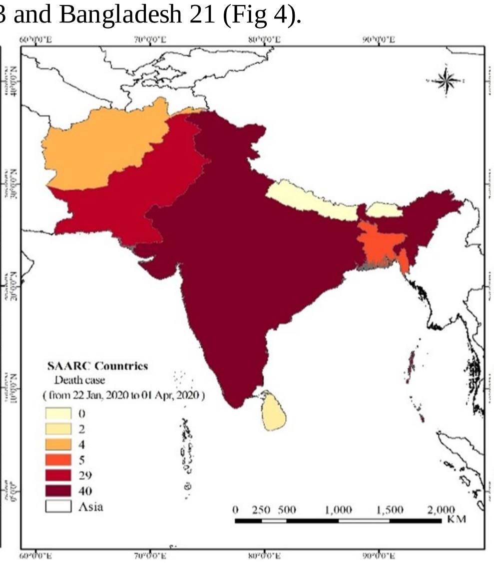


Fig. 3. Spatial Distribution of Death Cases

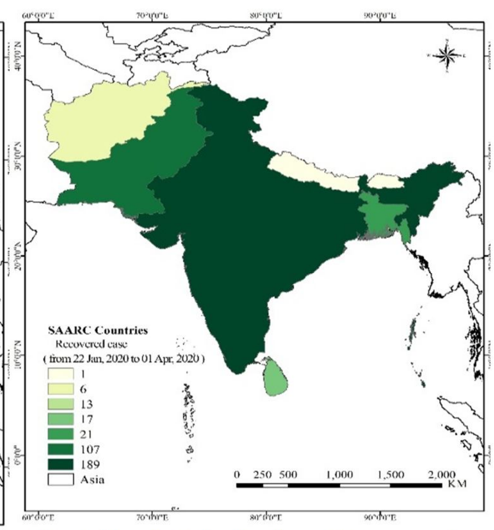


Fig.4. Spatial Distribution of Recovered Cases

The daily Dataset from 22nd January to 1st April, 2020 of the COVID-19 of SAARC Countries, the Confirmed, Deaths and Recovery cases assembled in the Table. I

TABLE I. Dataset Of The COVID-19 In SAARC Countries

Country	Confirmed Cases	Death Cases	Recovery Cases
Afghanistan	185	4	6
Bangladesh	51	5	21
Bhutan	4	0	01
India	1451	40	189
Maldives	20	0	13
Nepal	6	0	1
Pakistan	2337	29	107
Sri Lanka	129	2	17
Total	4184	80	354

B. Graphical Representation of COVID-19

Here the daily wise spread of Corona virus is shown graphically where spread can be interpreted for Confirmed, Death and Recovered cases in South Asian countries. Firstly the confirmed cases for the eight countries is shown below in Fig.5-7. As we can observe and interpret from the graphs that India and Pakistan are showing higher number of confirm, death and recovery cases as compared to other South Asian countries. It can be due to higher migration of Indian and Pakistani population to highly affected countries in the world and causing higher spread in their respective countries. But one interesting factor which can be observed is that all factors are gaining high number from 15th March, 2020 onwards and it is shown for all SAARC countries. One of the major cause of spreading within India and Pakistan is due to higher population density. But we can't just assume statistical parameter but also economical and government actions taken for the control of the spreading.

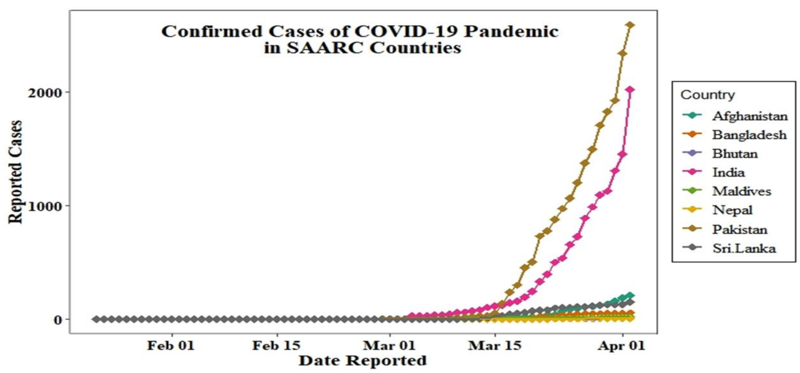


Fig.5. Graphical representation of Confirmed cases

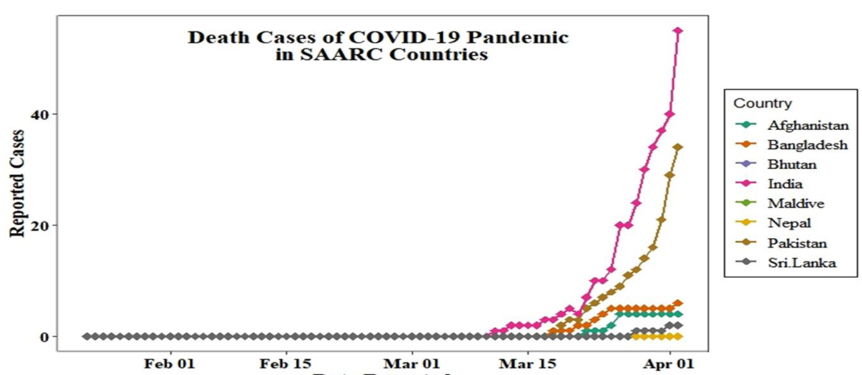


Fig.6. Graphical representation of the death cases

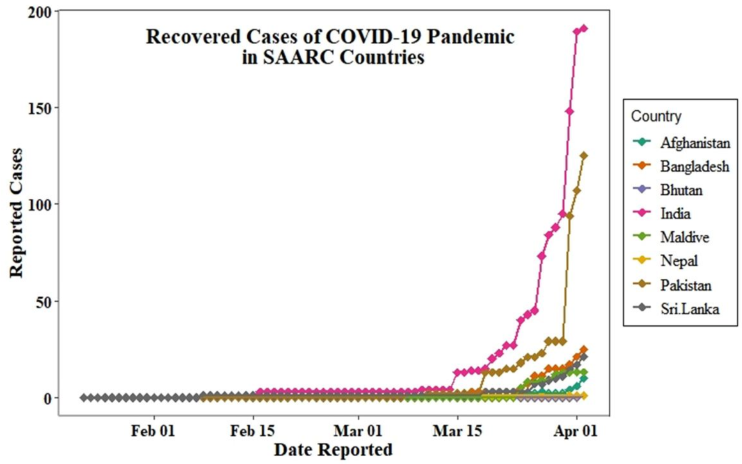
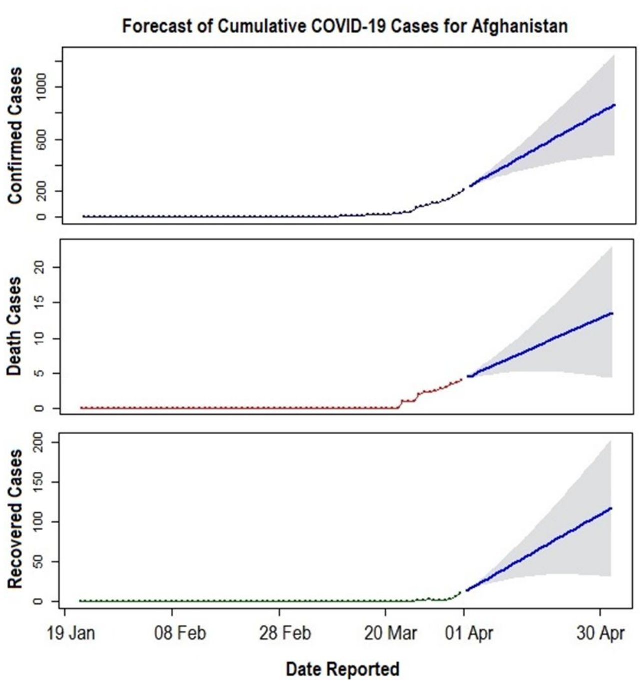


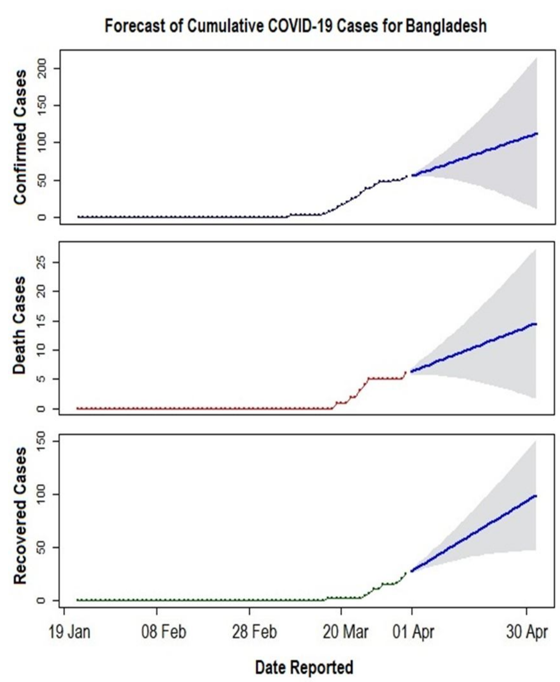
Fig.7. Graphical representation of recovered cases.

C. Forecasting of COVID-19 using ARIMA model

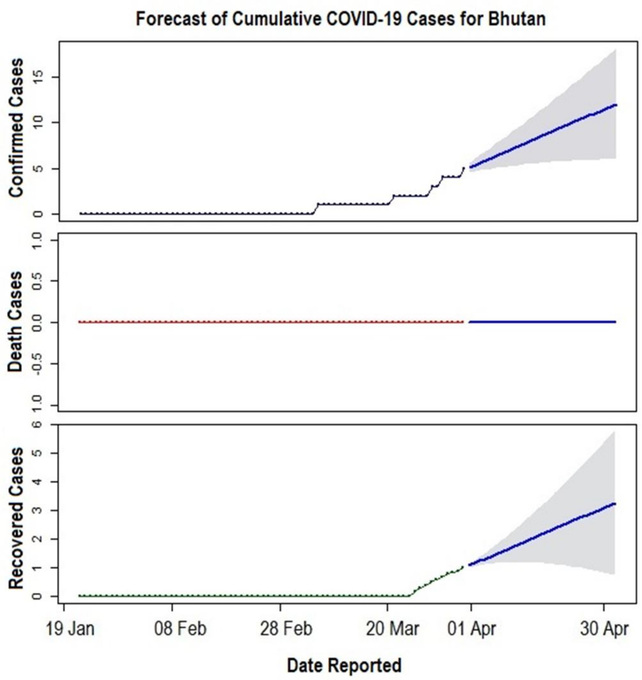
After generating the models for prediction of COVID-19, it has been analysed and observed that ARIMA model with double differencing, double PACF correlation and single ACF correlation has been evolved for all the prediction outputs i.e. we have used ARIMA Model (2,2,1) which fit, best for the forecasting. From the output has come near to accuracy as validation. The prediction has been made from 2nd April, 2020 to 30th April, 2020 i.e. 30 days forecast. As we can see from the output below that there is numbers of infected cases rises for predicted maximum cases for Pakistan among SAARC countries. The rise of confirm, death and recovered cases are spontaneous for India and Pakistan, as confirm cases rises to 12500 for India and 11000 for Pakistan, but forecasts for like Sri Lanka, Bangladesh shows slower rate in spreading of virus, whereas countries like Bhutan, Nepal and Maldives predict for least number of cases. As shown in the figure below the prediction value is given by solid blue line starting from 1st April till 30th April, 2020 and blue buffer is representing the high and low predictive range of 85%. As speaking of relevance with the reality at the ground level, it would possibly give positive response and also good correlation with the predicted outcomes (Fig 8a-h).



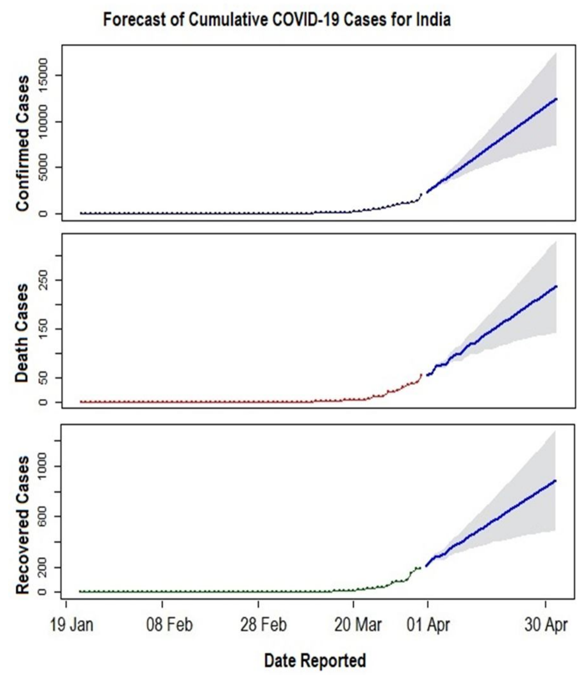
(a)



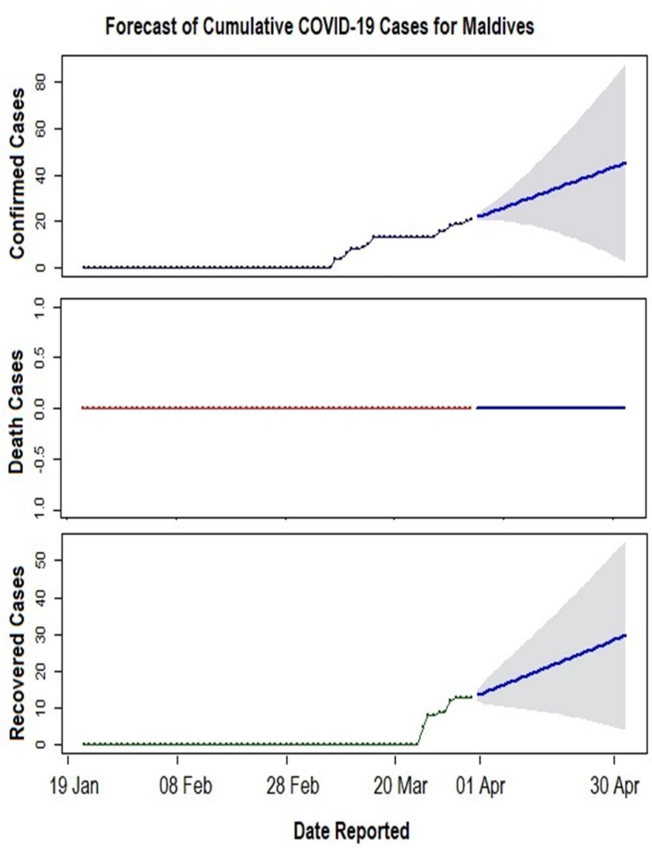
(b)


Forecast of Cumulative COVID-19 Cases for Bhutan
Confirmed Cases
Death Cases
Recovered Cases
19 Jan
08 Feb
28 Feb
20 Mar
01 Apr
30 Apr
Date Reported

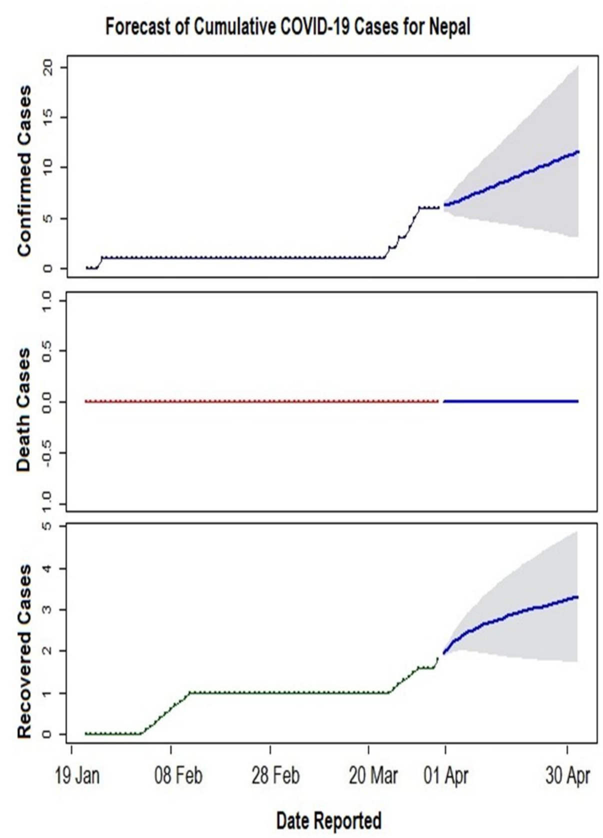
(c)


Forecast of Cumulative COVID-19 Cases for India
Confirmed Cases
Death Cases
Recovered Cases
19 Jan
08 Feb
28 Feb
20 Mar
01 Apr
30 Apr
Date Reported

(d)


Forecast of Cumulative COVID-19 Cases for Maldives
Confirmed Cases
Death Cases
Recovered Cases
19 Jan
08 Feb
28 Feb
20 Mar
01 Apr
30 Apr
Date Reported

(e)


Forecast of Cumulative COVID-19 Cases for Nepal
Confirmed Cases
Death Cases
Recovered Cases
19 Jan
08 Feb
28 Feb
20 Mar
01 Apr
30 Apr
Date Reported

(f)

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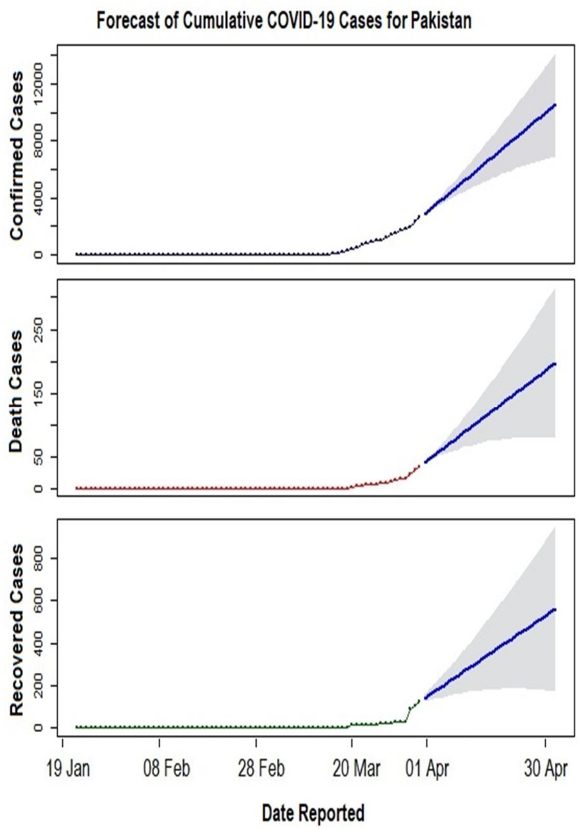
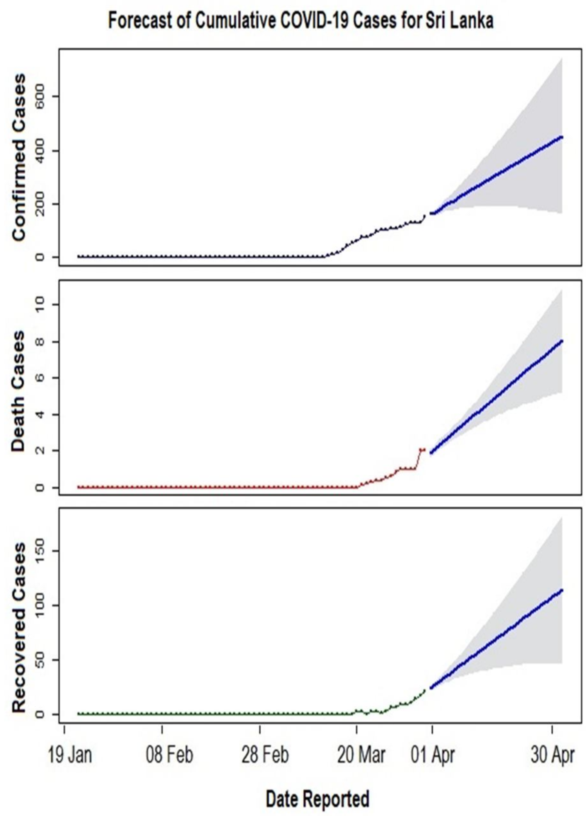


(g)



(h)

Fig.8. (a-h). Representing graphically the forecast of spread of COVID-19 for SAARC Countries

D. Validation and Statistical Analysis

Prediction is defined as statistical assumption and can't be concluded as the validated hypothesis, so for that we are putting some validation for the overall prediction for SAARC countries as a whole. Where the number as obviously changed to be taken as whole, given as total confirmed as 4184, Death tolls to 80 and Recovered cases are 354 till 1st April, 2020. The prediction is validation are given by statistical parameter here taken as Mean Error (ME), Root Mean Squared Error (RMSE), Mean Average Error (MAE), Mean Percentage Error (MPE), Mean Average Percentage Error (MAPE), Mean Averaged Scaled Error (MASE) and ACF (Auto Correlation Forecast (ACF1), all these parameter are showing good values for the forecast, where most importantly MAPE is showing the value less than 20, which is assumed to be believed as good prediction for such short term forecast. The Models shown in Table II is the best fitted models used for the forecast given in term with ARIMA (p,d,q) explained in eq. 3., for such authentication, dick fuller test is also implemented on the given models where the p value or predicted value is coming approx. 0.01 which is very good as p-value is assumed to be under 0.05, here dick fuller test is a null hypothesis test, which is used for determining the time series to be stationary or non-stationary. The best fitted model is determined by Akaike Information Criterion (AIC), which determine the order of an autoregressive model, Corrected Akaike Information Criterion (AICc), when the AIC does not provide then efficient order of model selection, then AICc is used for determining the order, Normalized Bayesian Information Criterion (BIC), it is used to proof that this model is superior to Box and Jenkins Model, these parameters shows whether the model used is best fitted for the forecast, and as we can see from Table III, the values are lower from 900, i.e. it is showing the model used is the best fitted and in the correct order for any forecast. The prediction is showing rise of confirm cases to 35000, death tolls to 600 and recovery to 1600 till 30th April, 2020 for SAARC countries (Fig.9).

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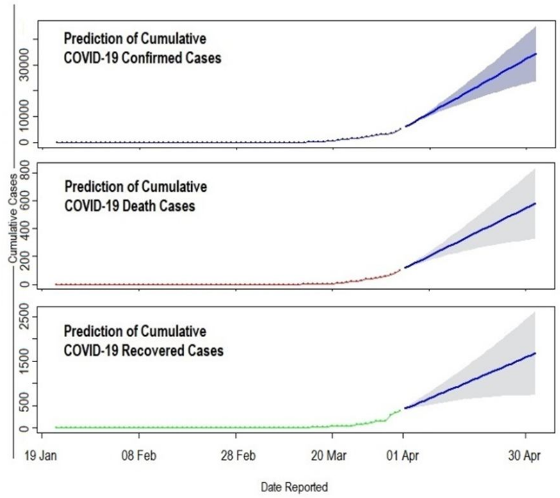

Fig.9. Representing graphically the forecast of spread of COVID-19 for oveall SAARC Countries.

TABLE II
Statistical Accuracy Assessment Of Arima Model For Overall Saarc Countries

Sr. No.	Forecast	ARIMA Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
1	Confirmed	ARIMA (0,2,3)	9.112098	18.68659	27.52437	0.7772725	17.11945	0.3865553	-0.01497629
2	Death	ARIMA(0,2,1)	0.3733494	1.997898	0.7604909	1.647857	5.501815	0.5372622	-0.01866556
3	Recovered	ARIMA(0,2,1)	2.110796	14.2299	3.591102	2.304261	8.023562	0.6596849	0.02145308

TABLE III
Summary And Statistical Parameters For Each Model

Forecast	AIC	AICc	BIC
Confirmed	781.46	782.07	790.45
Death	301.66	301.84	306.15
Recovered	577.03	577.21	581.53

E. Forecasting of COVID-19 using SIR model:

After the prediction and analysis from ARIMA model, we will be using SIR model for much better prediction and spreading of COVID-19. There is a long tradition of apply deterministic models to the study of infectious disease, these models become important and have huge impact in population and in the health systems content with human and material resources. But, to be infected with a virus of such massive magnitude as COVID-19 causing epidemic, such model fails drastically. However, the rise of new technologies and the growth of interdisciplinary, the luxury of epidemiological models comes as a saviour for the researcher to apply in fields such as COVID-19 epidemic. In this paper the selection of SIR models comes as exposition and not exhaustion. The rise of recent event and the effects it has on the planet, the development of such epidemiological mathematics becomes the possible response to describe the reality[11].Before interpreting the results, we would like to discuss about the parameters apart from susceptibility, infected and removed/recovered (discussed earlier), which been used for the generation of the epidemic model and how it effects the result for longer duration of time.

Firstly, the results shows the population affected and non-affected in proportion, which represent not the actual numbers, but the magnitude of effect on the population. It ranges from 0 to 1 where, 1 implies as maximum possibility, for example taking susceptible, which means population exposed to virus, here 1 indicates the likelihood of expose is 100 percent, similarly, 0 implies as least possibility which means the minimum chance of the occurrence of any event. Now coming to the sub-parameters or we can say multiplier, and they have drastic effects on the final outputs. First is β which is called as transmission parameter means the rate of transmission by the infective to susceptible, and after further study, we come to an assumption that it not only depends on

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population density of the country but also on the government action taken for reduction of transmission. Next parameter γ called as removed parameter or we can say the rate of infected person to recover or die from disease, it is also derived from the product of two more factors i.e. c termed as number of contacts each infected person has per unit time also called as contact rate and p termed as probability of transmission of infection per contact (as given in eq. 4). After further study we can understand that it directly related to number of deceased and infected population, so therefore finding the rate of infection and dead by the disease will clearly to some extent determine γ i.e. removed parameter[12]. Further the following Table 3, will give us better indication of the above parameters and how significantly they affect the output.

Table.IV
Mathematical parameterization of the SIR Model for SAARC Countries.

Sr. No.	Country	Population Density (perkm^2)	Current Removed Rate	β	γ
01	SAARC Countries	303	056	0.25	0.007

Further is the graphical representation of the forecast model SIR for SAARC Countries, which shows peak time to be predicted between 85th to 110th days of Novel Coronavirus transmission which originated at Wuhan city, Hubei-province of China, where first case comes up on 10th January, 2020. The recovery of Case Fatality Risk (CFR) rate initially rises from 50th day but it catches pace till 120th day and reaches maximum in the 90th day. It gradually decline from the 120th day and SAARC country till 250th day of the COVID-19 existence.

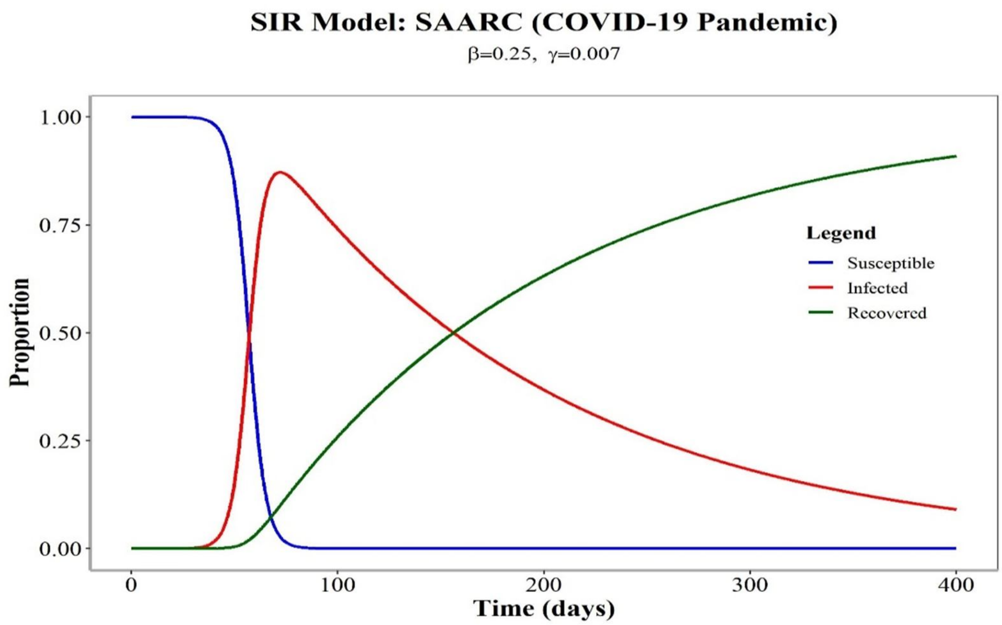

Fig.10. Graphical representation of the SIR Model for SAARC Countries

VI. CONCLUSION

The prediction and forecast only run by the input of the statistical data in the model, but the actually reality sometime can vary from the prediction. Here by using different models, we can give a better idea and also a future blueprint that what measures should be taken to control such pandemic. The government policies with bold economic decisions are likely to be having great impact in the outcome of this virus. The predictions are alarming for the SAARC countries and also goes same for the rest of the world. Therefore, the government of every SAARC country should take strict and major actions to keep up with the control of the infection. We have discussed earlier, the prediction is always made with respect to statistical data itself but the socio-economic decision of the respective countries make high impact on the final outcome and can make prediction a complete nuisance, as we have taken these factors also in the consideration, we can hope to get recovery and also the prediction to be relevant with the realistic scenario.

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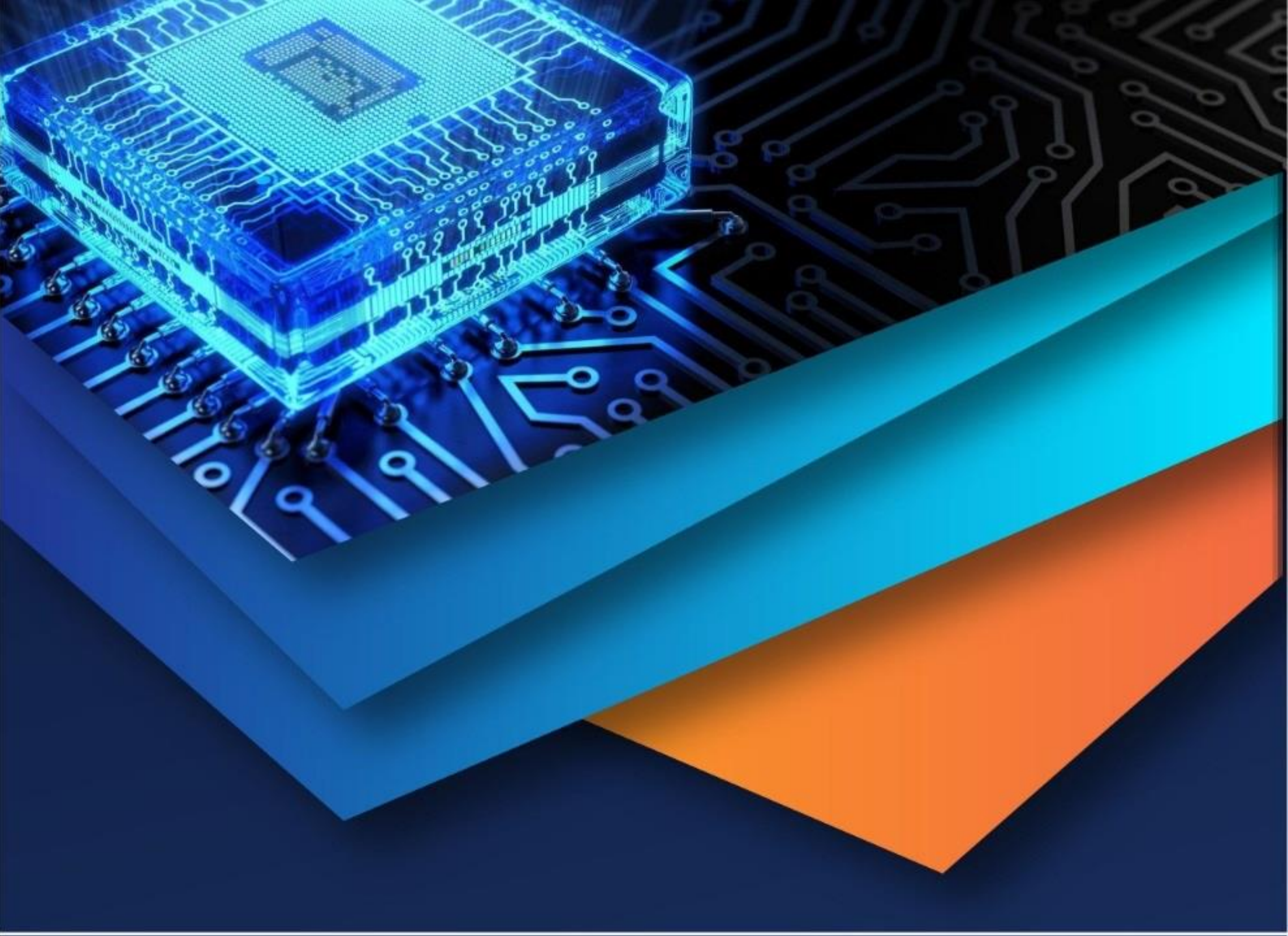

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IMPACT FACTOR: 7.429

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