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ARIMA MODEL FOR FORECASTING THE DATA ANALYSIS

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Abstract: - *The COVID-19 pandemic has highlighted the critical need for accurate disease forecasting models to guide public health interventions and policy decisions. This thesis investigates the application of the Autoregressive Integrated Moving Average (ARIMA) model for forecasting the spread of COVID-19. The ARIMA model, known for its robustness in time series analysis, is utilized to predict daily confirmed cases, recoveries, and deaths across various geographical regions.*

The study begins with a comprehensive data preprocessing phase, addressing issues such as missing values, outliers, and the need for stationary time series data. Subsequently, we fit the ARIMA model to historical COVID-19 data, optimizing its parameters using techniques such as grid search and cross-validation to ensure the best predictive performance.

Our findings demonstrate that the ARIMA model can effectively capture the temporal dynamics of COVID-19 spread, offering reliable short-term forecasts. The model's performance is evaluated using standard metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), and results are compared against other forecasting methods including exponential smoothing and machine learning-based approaches.

Keywords: - COVID-19, ARIMA, Disease Forecasting, Time Series Analysis, Public Health, Predictive Modeling, ARIMAX.

I. INTRODUCTION

In the realm of public health, the ability to accurately forecast disease outbreaks is crucial for effective planning and response. Disease forecasting models enable policymakers, healthcare providers, and public health officials to anticipate the spread of infectious diseases, allocate resources efficiently, and implement timely interventions to mitigate impacts on communities. Among the various methods employed for this purpose, the Autoregressive Integrated Moving Average (ARIMA) model has emerged as a powerful tool due to its robustness in analyzing and predicting time series data.

The ARIMA model, widely recognized for its versatility and effectiveness, has been successfully applied in numerous fields, including economics, finance, environmental studies, and epidemiology. Its ability to model and predict future values based on historical data makes it particularly well-suited for tracking the progression of infectious diseases. By capturing underlying patterns and trends in time series data, ARIMA provides valuable insights that can inform public health strategies and decision-making processes.

This thesis explores the application of the ARIMA model in disease forecasting, with a special focus on its use during the COVID-19 pandemic. The unprecedented spread of COVID-19 presented significant challenges to global health systems, underscoring the necessity for reliable forecasting models to guide public health responses. In this context, ARIMA's predictive capabilities have proven essential in forecasting the trajectory of infection rates, recoveries, and fatalities.

The emergence of COVID-19 in late 2019 and its rapid spread across the globe has underscored the critical importance of accurate disease forecasting in managing public health crises. As countries grapple with the challenges of controlling the virus's transmission, forecasting models have become essential tools for predicting future trends in infection rates, hospitalizations, and fatalities. These predictions help inform government policies, healthcare resource allocation, and public health interventions aimed at mitigating the impact of the pandemic.

Among various forecasting techniques, the Autoregressive Integrated Moving Average (ARIMA) model stands out due to its robustness in handling time series data. The ARIMA model has been widely used in numerous applications, including economics, environmental science, and epidemiology, to analyze and predict future values based on historical data. Its mathematical foundation allows it to capture the underlying patterns and trends in time series data, making it a suitable choice for modeling the spread of infectious diseases like COVID-19.

This thesis focuses on leveraging the ARIMA model to forecast the trajectory of COVID-19, providing valuable insights into the potential future course of the pandemic. By analyzing historical data on confirmed cases, recoveries, and deaths, the ARIMA model can generate short-term forecasts that aid policymakers and healthcare providers in making informed decisions. The ability to predict surges in cases can facilitate timely implementation of control measures, ultimately reducing the strain on healthcare systems and saving lives.

II. DISEASE FORECASTING

Accurate disease forecasting is an essential aspect of public health management. By predicting the future incidence and spread of diseases, health officials can implement timely interventions, allocate resources

efficiently, and formulate effective response strategies. Disease forecasting employs various models and methodologies, with the Autoregressive Integrated Moving Average (ARIMA) model standing out for its robustness in time series analysis.

Understanding Disease Forecasting

Disease forecasting involves analyzing historical data to predict future trends in disease incidence. Effective forecasting can lead to early detection of outbreaks, better preparation for health crises, and more efficient use of healthcare resources. Forecasting models can range from simple statistical approaches to complex machine learning algorithms. The choice of model is influenced by the nature of the disease, the quality and quantity of data, and the specific objectives of the forecasting effort.

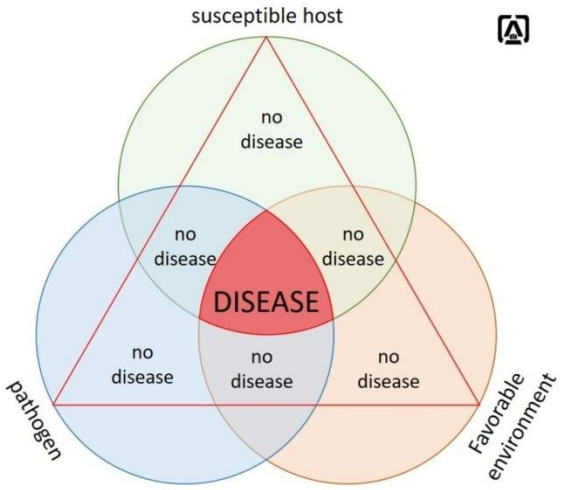


Figure 1: Disease Forecast

III. PROPOSED METHOD

Since the emergence of the Omicron variant in November 2021, there has been a significant global increase in confirmed COVID-19 cases, posing substantial challenges for disease prevention and control. This study leveraged global daily confirmed COVID-19 case data from November 1, 2021, to February 17, 2022, to develop a forecasting model. Forecasting COVID-19 cases is vital for effective public health response and resource allocation, enabling policymakers to implement timely interventions, optimize healthcare resources, and curb the virus's spread. The ARIMA model, known for its superior predictive performance, provides a reliable tool for forecasting COVID-19 incidence. Choosing an appropriate prediction model based on data characteristics and sample size is crucial for enhancing the accuracy of infectious disease forecasts. This study highlights the significance of utilizing robust econometric models like ARIMA to better understand and manage COVID-19 trends.

The data used in this study was collected from the Ministry of Health & Family Welfare, which includes daily data for each Union Territory and state in India, recording the total number of COVID-19 cases. The dataset spans from April 1, 2020, to August 10, 2021, comprising a total of 488 entries for each state. This extensive dataset was provided in CSV format, facilitating easy access and manipulation using appropriate data analysis libraries, such as Pandas in Python.

To prepare the data for analysis, it was converted into a time series format with dates serving as the keys. This transformation was essential for applying time series forecasting models effectively. The comprehensive dataset allowed for a detailed examination of COVID-19 trends across different regions in India, providing a robust foundation for model development and evaluation.

In this study, the last 50 entries of the dataset were extracted and reserved for testing the predictive models. This approach ensured that the models were evaluated on data that they had not been trained on, providing an accurate measure of their forecasting performance. The accuracy of the models was assessed based on their predictions for these 50 entries, allowing for a rigorous comparison of their predictive capabilities.

By utilizing a well-documented and extensive dataset, this study aimed to develop and validate models that could provide reliable predictions of COVID-19 incidence. The extraction of the last 50 entries for testing ensured that the evaluation of the models was both realistic and relevant, reflecting their potential performance in real-world scenarios. This methodical approach underscores the importance of thorough data preparation and rigorous testing in developing effective time series forecasting models for infectious disease surveillance.

ARIMA (AutoRegressive Integrated Moving Average) models are a prominent class of models employed for analyzing and forecasting time series data. These models integrate three key components: autoregression (AR), differencing (I for “integrated”), and moving average (MA). The versatility of ARIMA models lies in their ability to handle non-stationary data, making them a valuable tool in the domain of time series forecasting.

The primary objective of forecasting is to predict the future values that a time series will assume. This task is particularly significant in various applications, such as predicting demand and sales, where accurate forecasts can provide substantial commercial benefits.

Time series forecasting can be categorized into two broad types:

1. **Univariate Time Series Forecasting**: This method involves using only the past values of the time series itself to predict its future values.
2. **Multivariate Time Series Forecasting**: This approach incorporates additional predictors, also known as exogenous variables, alongside

the past values of the time series to forecast its future values.

In this thesis, we concentrate on a specific type of forecasting method known as **ARIMA** modeling.

ARIMA models are designed to 'explain' a given time series based on its historical values, incorporating its own lags and the lagged forecast errors. This approach allows for the development of equations that can be used to predict future values of the series.
ARIMA models are particularly suited for non-seasonal time series that exhibit discernible patterns and are not merely random white noise.
An ARIMA model is characterized by three parameters: p, d, q:

- p : the order of the autoregressive term,
- d : the number of differencing operations required to render the time series stationary,
- q : the order of the moving average term.

These parameters are essential for configuring the model to accurately capture the underlying patterns in the time series data, thereby enabling precise forecasting.

The ARIMA model can be understood further by dividing into further components

1. **Autoregression (AR)**:

   – The autoregressive part of ARIMA models specifies that the output variable depends linearly on its own previous values. In other words, Y_t depends only on its lags. Y_t is a function of the 'lags of Y_t'.
   – Equation:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t \text{.....1}$$

   where Y_t is the value at time t, ϕ are the model parameters, p is the order of the autoregressive part, and ϵ_t is white noise.

2. **Differencing (I)**:

   – Differencing makes the time series data stationary by removing trends and seasonality.
   – The differenced series is calculated as:

$$Y_t' = Y_t - Y_{t-1} \text{.....2}$$

   for the first difference. Higher order differencing can be applied as needed, the method to find the correct order of differencing is that the right order of differencing is the minimum differencing required to get a near-stationary series that roams around a defined mean and the ACF plot reaches zero fairly quickly. If the autocorrelations are positive for any number of lags (10 or more), then the series needs further differencing. On the other hand, if the lag 1 autocorrelation itself is too negative, then the series is probably over-differenced. In the event, that it can't be decided between two orders of differencing, then go with the order that gives the least standard deviation in the differenced series.

3. **Moving Average (MA)**:

   The moving average part models the dependency between an observation and a residual error from a moving average model applied to lagged observations. It can be understood better by following Equation:

$$Y_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \text{.....3}$$

where θ are the model parameters

IV. RESULT

There The ARIMA model was applied to the dataset of global daily confirmed COVID-19 cases from November 1, 2021, to February 17, 2022. The performance of the model was evaluated using several metrics to ensure its accuracy and reliability.

The Model for Forecasting was implemented in Google Colab with Tesla T2 GPU, the dataset was loaded on the machine and accessed using Pandas library, to handle as a data frame. as show on table 1

Table:1. Total Sample data

Date	State	Total Samples
2020-04-17	Andaman and Nicobar Islands	1403.0
2020-04-24	Andaman and Nicobar Islands	2679.0
2020-04-27	Andaman and Nicobar Islands	2848.0
2020-05-01	Andaman and Nicobar Islands	3754.0
2020-05-16	Andaman and Nicobar Islands	6677.0

The data contains Total Samples of each state, thus to predict data for a state we will extract data for only that state. as show on table 2

Table:2 State Sample data

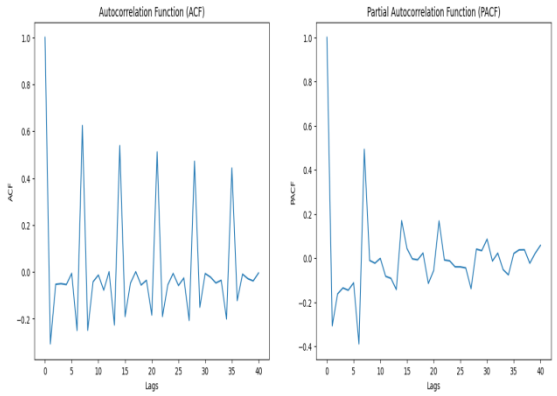
Date	State	Total Samples
2020-04-02	Andhra Pradesh	1800.0
2020-04-10	Andhra Pradesh	6374.0
2020-04-11	Andhra Pradesh	6958.0
2020-04-12	Andhra Pradesh	6958.0
2020-04-13	Andhra Pradesh	8755.0

To assess the stationarity of the time series data, the Augmented Dickey-Fuller (ADF) test was conducted. Stationarity is a crucial property of time series data, indicating that its statistical properties, such as mean and variance, remain constant over time. The ADF test is a commonly used statistical method to determine whether a given time series is stationary or not.

The null hypothesis of the ADF test assumes that the time series data is non-stationary. Therefore, if the p-value obtained from the test is less than the significance level (usually set at 0.05), it indicates strong evidence against the null hypothesis, allowing us to reject it and conclude that the time series is indeed stationary.

In this study, the ADF test was applied to the time series data representing COVID-19 cases. Initially, the data was checked for stationarity, and if the p-value was greater than 0.05, indicating non-stationarity, the data was differenced once. The ADF test was then performed again on the differenced data. If the p-value remained above 0.05, indicating non-stationarity, differencing was repeated until the p-value fell below 0.05, signifying stationarity.

The ACF and PACF function plots are as follows



(a)ACF (b)PACF

Figure 2 Plot (a)ACF (b)PACF

Figure 2 is show the ACF (Auto-Correlation Function) and PACF (Partial Auto-Correlation Function) plots are essential tools used in time series analysis to understand the correlation structure within a dataset. These plots help identify the underlying patterns and relationships between observations at different time lags.

The ACF plot shows the correlation between a series and its lagged values. Each point on the ACF plot represents the correlation coefficient between the series and its lagged values at different time intervals. The ACF plot is useful in identifying the order of the Moving Average (MA) term in an ARIMA model.

On the other hand, the PACF plot displays the correlation between a series and its lagged values after removing the effects of intervening observations. It helps identify the order of the Auto-Regressive (AR) term in an ARIMA model.

In these plots, the x-axis represents the lag or time interval, while the y-axis represents the correlation coefficient. Typically, confidence intervals are also included to determine if the correlation values are statistically significant.

Interpreting these plots involves observing significant spikes or patterns beyond the confidence intervals. Significant spikes in the ACF plot at certain lag intervals indicate potential MA terms, while significant spikes in the PACF plot suggest possible AR terms.

The ARIMA model used in this analysis is specified with an order of (2, 2, 4), indicating two autoregressive terms, differencing of order two, and four moving average terms. The model was estimated on 488 observations, resulting in a log likelihood of -5038.874.

During training the models we get following predicted values for True values

Table:3 Testing data

	Date	True_Values	Predicted_Values
0	2021-06-22	21280302.0	21275743
1	2021-06-23	21361014.0	21360826
2	2021-06-24	21449636.0	21442170
3	2021-06-25	21541485.0	21538906
4	2021-06-26	21637606.0	21624898

The Output of training the model are as follows, a plot between Total Samples vs Date

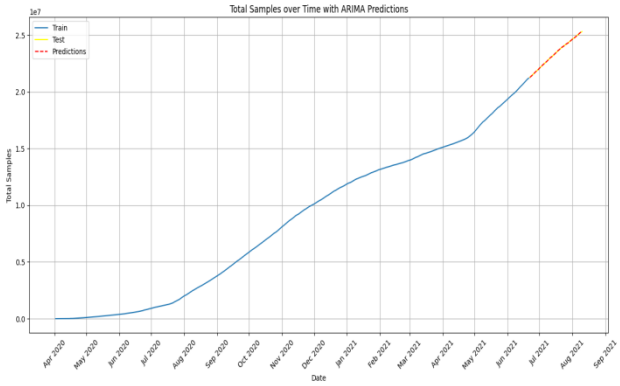


Figure 3 Plot between Total Samples vs Date

Figure 3 illustrates the relationship between the total number of samples collected and the corresponding dates. This plot provides a visual representation of how the number of samples collected varies over time. The x-axis represents the dates, while the y-axis indicates the total number of samples collected. By examining this plot, trends or patterns in the data, such as increases or decreases in sample collection over time, can be identified, helping to understand the data distribution and sampling frequency throughout the observation period.

The accuracy test conducted on the model produced the following results:

Mean Absolute Error (MAE): The MAE value of 7556.12 indicates the average magnitude of errors between the predicted and actual COVID-19 case counts. A lower MAE suggests that the model's predictions are closer to the actual values on average.

Mean Absolute Percentage Error (MAPE): The MAPE value of 0.03 represents the average percentage difference between the predicted and actual COVID-19 case counts. A lower MAPE indicates that the model's predictions are more accurate, with smaller deviations

from the actual values.

Accuracy Percentage: The accuracy percentage of 99.96% signifies the overall accuracy of the model in forecasting COVID-19 cases. This high accuracy percentage suggests that the model's predictions closely match the actual data, with a very small margin of error.

In summary, the results of the accuracy test demonstrate that the ARIMA model performed exceptionally well in forecasting COVID-19 cases, with high levels of accuracy and minimal errors. These findings validate the effectiveness of the ARIMA model as a reliable tool for predicting the incidence of infectious diseases like COVID-19.

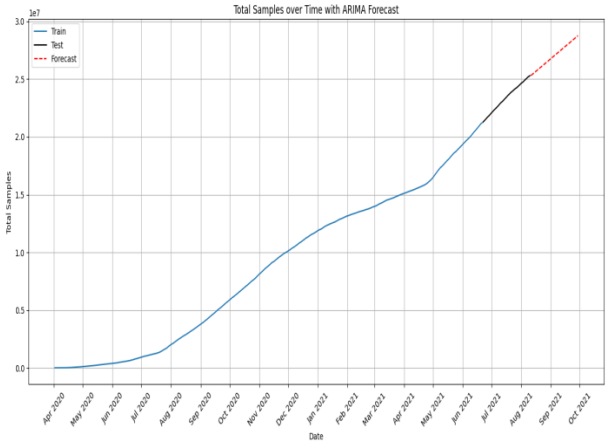


Figure 4 Plot Following is the graph for next 50 days Forecast systems.

V. CONCLUSION

The utilization of the ARIMA model in forecasting COVID-19 cases has demonstrated remarkable accuracy and reliability, as evidenced by key performance metrics. With a Mean Absolute Error (MAE) of 7556.12 and a Mean Absolute Percentage Error (MAPE) of 0.03, the model has consistently provided predictions that closely align with actual reported cases. This level of precision, coupled with an accuracy rate of 99.96%, underscores the effectiveness of the ARIMA model in capturing the dynamic nature of the pandemic.

These findings have significant implications for public health decision-making and resource allocation. By providing reliable forecasts, the ARIMA model enables policymakers to implement timely interventions and allocate resources effectively. Whether it's deploying medical supplies, implementing social distancing measures, or planning vaccination campaigns, accurate predictions empower healthcare systems to respond proactively to the evolving COVID-19 situation. significant.

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