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Predicting the per-capita Income of Nepal with the help of the ARIMA Model

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Abstract

Understanding the root causes that affect any given issue, event, or variable in great detail is necessary to forecast it. This is true for estimating Nepal's per capita income. In Nepal, several factors, including employment, international commerce, industrialization, political stability, and productivity, have a significant impact on per capita income. As the nation's per capita income serves as a gauge for its economy, predicting per capita income is therefore not just laborious but also essential. The main objective of this research was to study the trend of per capita income of Nepal and to forecast it for the coming years. In this investigation Three possible ARIMA models were (2,1,0), (1,1,0) and (9,1,0) identified. Out of them based on different popular criteria ARIMA (9,1,0) model was found best-fitted model for the foresting of the per capita income of Nepal Among the three identified models R^2 value of the (9,1,0) model was found greater compared to other models, different kinds of errors value were lesser compared to other models, so based on ARIMA model selection criteria (9,1,0) model was chosen as the best model for forecasting per capita income of Nepal. Five years of per capita income was forecasted by the fitted model. Forecasted per capita income for the years, 2023,2024,2025,2026, and 2027were1274.57,1429.25,1497.33,1587.67and1744.77 (In American dollars) respectively. IBM SPSS,19 version was used to identify the best ARIMA model and foresting per capita income of Nepal. secondary source of data was used in this study. Together 62 observed per capita income values recorded for different years were used to conduct this investigation. The accuracy of these predicted values, however, may be questioned because, frankly speaking, none of the components operate perfectly or in the desired direction; in this case, it might be wise to reevaluate a different forecasting model that would use more data to predict Nepal's per capita income. This is perhaps one of the paper's shortcomings.

Keywords: *ARIMA model, autocorrelation, per capita income, predicting, stationery*

Introduction

The amount of money earned per person in a country or geographic area is measured by its per capita income. The average income per person in a given area is calculated using per capita income, which is also used to assess the population's standard of living and overall quality of life. A country's per capita

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income is determined by dividing its national income by the number of its citizens Kenton, (2024) The phrase "per capita" is mostly used in statistics and economics to describe how various measures relate to a population. It is most frequently used for national indicators and how those measurements relate to that nation's population. The two most popular applications of per capita are income per capita and gross domestic product (GDP) per capita. (Banton, 2022) The entire value is probably interesting for national economic measures, such as gross national product (GNP) or GDP. However, the per capita approach will give the analyst more detailed data and enable more accurate apples-to-apples comparisons between other nations. Banton (2022). The average number of residents in a certain nation or region is per capita. Because it doesn't take statistical outliers into account and encompasses everyone from newborns to senior individuals, it may be deceptive. In this case, any outliers will be factored into the median income.

Based on data from the CIA World Factbook (the most recent version of the CIA website), the gross domestic product (GDP) of the United States was a little over $20 trillion in 2021. Approximately 337.3 million people called the United States home during that same period. A GDP per capita of $59,500 is the outcome (*Instagram*, n.d.). China's economy, which is currently the second largest, is projected to be worth $17.5 trillion in 2021, 12.5% less than that of the US. Nevertheless, China's GDP per capita is only $16,400 due to its far larger population than that of the US. Therefore, despite the aggregate productivity of the nation, the majority of Chinese citizens still earn significantly less than the average American, according to per capita GDP data. Central Intelligence Agency(n.d.). A method of averaging values per person to have a better understanding of how each person contributes to overall statistics is called per capita. In economics, GDP and income per capita are used to determine the average degree of prosperity in a nation and to draw similar comparisons between nations. Measures of non-economic data, like the per capita intake of alcohol or the per capita number of car accidents, can also be used (Banton, 2022d).

China to the north and India to the east, west, and south are the two developing global economic giants that physically encircle Nepal, a landlocked nation in the Himalayas. Due to a special economic deal, India and Nepal essentially enjoy free borders. Since the majority of Nepal's territory is mountainous, it has been extremely difficult to build physical infrastructure, such as roads, bridges, and other constructions, from a financial, environmental, and spatial standpoint. The nation has very little strategic raw material or mineral reserves, making its factor endowment extremely low. The amount of land that can be farmed is very little. Over time, the population's demands on the finite amount of land have increased. Reducing poverty is currently the largest task facing Nepal's policy leaders. In an attempt to lower poverty and inequality, a great deal of time, money, and effort have been directed at various economic sectors. The overall rate of poverty decreased over the past ten years, however the fall varied by geographic area. Regional inequality increased dramatically as a result of this. Rural communities have high rates of poverty, especially in the agricultural sector. Food production has not increased at the same rate as population expansion, even with massive investments in agriculture in the past (Adhikari,2024). In 2023, Nepal's gross domestic product per person was last measured at 1091.90 US dollars. Nepal has a GDP per capita that is 9% higher than the global average. From 1960 to 2023, Nepal's GDP per capita averaged 532.77 USD, with a record low of 321.79 USD in 1973 and an all-time high of 1091.90 USD in 2023 (*Nepal GDP per Capita*, n.d.). Nepal is still among the world's poorest nations despite having a large amount of resources, including natural resources, arable land, and a labor force. According to the most recent Human Development Index, the nation is ranked 207th out of 229 countries in terms of per capita income (based on purchasing power parity) and 157th out of 187 in terms of human development. However, according to the CIA Fact Book (2013), the country ranks 35th for labor force availability and 46th for the amount of arable land. In terms of laborers per hectare, Nepal is in fifth place, needing 3.6 persons to cultivate a hectare of land.

The most well-liked and often applied forecasting model for univariate time series is the Autoregressive Integrated Moving Average (ARIMA) model, which is applied in this study.

There are many different techniques and methodologies available for forecasting, and whether they work better than one another depends largely on the specific problem being solved. The reason behind selecting this is the way our time series data behaves is the basis for this kind of model. An entire family of models known as Autoregressive Integrated Moving Average (ARIMA) models is proposed by Box and Jenkins (1976). It appears to be appropriate in a broad range of circumstances. Additionally, they have created a workable process for selecting the best ARIMA model from this group of models. Choosing the right ARIMA model, meanwhile, might not be simple. Numerous. According to the literature, creating an accurate ARIMA model is a skill that calls for a great deal of experience and sound judgment.. Autoregressive Integrated Moving Average (ARIMA) models are a family of models that Box and Jenkins (1976) propose. It appears to be appropriate in a broad range of circumstances. Additionally, they have created a workable process for selecting the best ARIMA model from this group of models. Choosing the right ARIMA model, meanwhile, might not be simple. Numerous academic works imply that creating an accurate ARIMA model is a skill that takes a great deal of experience and sound judgment Sarpong, S. A. (2013) ARIMA models work particularly well for forecasting in the short run. This is a result of the model giving the current past a higher priority than the distant past. Because of this focus on the recent past, long-term projections from ARIA models are not as dependable as short-term projections (Pankratz, 1983).

This article attempts to forecast Nepal's per capita income for the five years leading up to it. The Autoregressive Integrated Moving Average (ARIMA) model was created specifically for forecasting purposes. Since Box and Jenkins created this model in 1960, it is also referred to as the Box-Jenkins Model. This model is used to forecast a single variable. The ARIMA model was selected for the forecasting in this study primarily because it assumes and accounts for the non-zero autocorrelation between the time series data's subsequent values (Kumar and Anand,2014).

Nepal GDP Per Capita - Historical Data

Year	**Per capita income in $**	**Per capita income in$**	**Per capita in$**	**Per capita in $**	**Per capita $**
1960	50	1982	147	2004	280
1961	51	1983	146	2005	309
1962	54	1984	151	2006	341
1963	46	1985	149	2007	387
1964	45	1986	159	2008	467
1965	65	1987	161	2009	476
1966	79	1988	186	2010	589
1967	72	1989	184	2011	791
1968	65	1990	185	2012	794
1969	66	1991	195	2013	809

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1970	69	1992	164	2014	828
1971	69	1993	172	2015	882
1972	78	1994	187	2016	880
1973	73	1995	197	2017	1028
1974	89	1996	198	2018	1162
1975	113	1997	212	2019	1229
1976	102	1998	205	2020	1339
1977	95	1999	208	2021	1186
1978	108	2000	224	2022	1162
1979	121	2001	242		
1980	125	2002	239		
1981	142	2003	246		

source: *Nepal GDP Per Capita 1960-2024 | MacroTrend*

Literature Review

One of the main prediction methods for time-dependent variable forecasting is time series analysis. These days, there are numerous uses for time series analysis. To forecast the future, the time series analysis technique with the ARIMA model is applied to per capita disposable income in this paper. The average amount of money each individual has available after income taxes are deducted is known as per capita disposable income. It serves as a gauge for the general health of an economy. Per capita disposable income forecasting is essential because it can assist governments in evaluating their nation's economic standing concerning other nations' economies. Per capita disposable income forecasting could be useful in evaluating inflation and precarious financial situations. A nation's planning commission may utilize the findings of this study to create plans and policies for the future (Sena and Nagwani,2015)

One of the most important measures of a nation's economic health is its GDP per capita. Scholars and policymakers use it frequently to develop both public and private policies. The project's forecast is to determine Bangladesh's actual GDP per capita. The study uses the ARIMA technique to analyze future GDP per capita using annual data for Bangladesh from 1972 to 2019. ARIMA (0, 2, 1) is the suitable model to forecast GDP per capita in Bangladesh, according to the results of the ADF, PP, and KPSS tests. In conclusion, we used the ARIMA model (0,2,1) in our article to project Bangladesh's GDP per capita over the ensuing ten years. Bangladesh's future GDP per capita indicates that living standards will persist. Bangladesh's economy is expanding, in fact, and other developing nations should take note of what Bangladesh has learned. The report provides policy recommendations to assist Bangladeshi policymakers in preserving and advancing sustainable development in their country (Voumik and Smrity,2020)

The Box-Jenkins ARIMA approach is used in this study to examine GDP per capita using annual time series data for Rwanda from 1960 to 2017. According to the ADF tests, the GDP per capita figure for Rwanda is I (1). The study introduces the ARIMA (3, 1, 1) model, which is based on the AIC and Theil's U. The diagnostic tests also demonstrated the reasonableness and stability of the parsimonious model that was presented. According to the study's findings, Rwanda's living conditions will gradually rise over the following ten years. The "middle-income status" aim of Vision 2020 is unlikely to be met,

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although this does not negate Rwanda's remarkable achievement of drastically lowering extreme poverty (Nyoni, T., & Bonga, W. G. 2019).

Rwanda's economy is indeed expanding, and other African nations ought to take note of what Rwanda has learned. The paper provides recommendations for policies to assist Rwandan policymakers in promoting and preserving the needed to determine which model produces a more accurate prediction, we choose the ARIMA model and the Holt-Winters exponential smoothing approach to anticipate the GDP per capita of five EU members that are Balkan nations. To do this, we use Theil's U statistics along with the Root Mean Square Error (RMSE), Mean Actual Error (MAE), Mean Actual Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE) criterion. In four out of the five countries studied, ARIMA is the best forecasting model based on statistical metrics and fitting performance during the studied time. Rwanda achieved steady growth (Dritsaki and Dritsaki, 2021).

This study examined annual GDP data for Kenya from 1960 to 2012, which were gathered from the Kenya National Bureau of Statistics. Using the Box-Jenkins approach to estimate the GDP, a class of ARIMA (autoregressive integrated moving average) models were constructed using the statistical tools Gretl and SPSS 21. Based on the recognition rules and the stationary test of time series under the AIC criterion, the ARIMA (2, 2, 2) time series model was found to be the most effective for modeling the GDP of Kenya. An in-sample forecast's findings indicated that the relative and anticipated values fell between 5% and 6%, indicating that this model's forecasting ability was comparatively sufficient and effective in simulating the Kenyan GDP's yearly returns (Musonda et al. 2016)

The practical steps that must be examined to anticipate the overall health expenditures for the United States as a percentage of GDP using autoregressive integrated moving average (ARIMA) time series models are presented in this study. Finding the right kind of model using the Box-Jenkins methodology is the goal of this study. Specifically, we utilize the static one-step forward forecasting technique on the annual data from 1970 to 2015. The study's findings demonstrate that the ARIMA (0,1,1) model is the most suitable model for projecting US health spending throughout this time (Klazoglou, and Dritsakis, 2018).

With an eye toward the future, this study forecasts GDP (Gross Domestic Product) per capita in India while also looking at historical and contemporary patterns. The purpose of this study is to use ARIMA to anticipate India's GDP per capita over ten years, from 2021 to 2030. A study indicates that over the past ten years, India's GDP per capita has increased, and this trend is probably going to continue over the next ten years (Sharma et al. 2022)

The Box – Jenkins ARIMA technique is used in this study to examine GDP per capita utilizing annual time series data on GDP per capita in Botswana from 1960 to 2017. The GDP per capita statistics for Botswana is I, according to diagnostic criteria like the ADF tests (1). The study introduces the ARIMA (3, 2, 3) model based on the AIC. The diagnostic tests additionally demonstrate the suitability and stability of the model that is supplied. The study's findings suggest that during the coming ten years, living conditions in Botswana will undoubtedly continue to rise. Botswana is indeed a success story. In an attempt to assist Botswana's policymakers in advancing and preserving the urgently needed higher living standards for all Batswana, the report makes four policy recommendations (Nyoni and Muchingami, 2019).

After consulting different literature, it is clear that no research has been conducted based on predicting the per capita income of Nepal by applying the ARIMA model. So this is the research gap of this investigation.

Methods and Materials

Data: In this investigation, secondary data was obtained from the secondary source MacroTrands website Nepal GDP Per Capita 1960-2024 | MacroTrends.Data from 1960-2022,61 years of time series data were used for short-term prediction of the per capita income of Nepal. Researchers did not spend much time collecting this set of data which was easily available on the website.

Predicting Model

In this research, the ARIMA model was used for predicting the short-term per capita of Nepal. The Autoregressive (AR) model and the Moving Average (MA) model are two univariate time series models that are combined to form the ARIMA model. These models are used to predict future values for a time series by using its historical data. When a series is stationary, the ARIMA model is used for forecasting the value of the variable. At least 50 data sets for the period must be required to apply the ARIME model otherwise accuracy cannot be obtained. However, an integrated stationary process can benefit from the use of the ARMA model through an initial differencing step, which corresponds to the "integrated" component of the model. The
The abbreviation ARIMA represents "Auto-Regressive Integrated Moving Average." Time series that require a difference to become stationary are referred to as "integrated" versions of stationary series; lags of the differenced series that show up in the forecasting equation are called "auto-regressive" terms; lags of the forecast errors are called "moving average" terms. Classified as a "ARIMA (p, d, q)" model, a non-seasonal ARIMA model has p as the number of autoregressive terms, d as the number of non-seasonal differences, and q as the number of lagged forecast errors (moving average) in the prediction equation. All values in the model are greater than or equal to zero (Hurvich and Tsai, 1989; Pfaff, 2008; Kleiber and Zeileis, 2008; Pankratz, 1983; Kirchgässner and Wolters, 2007).

Methodology

A four-step sequential modeling process is proposed by Box and Jenkins (1976) and includes the following steps: model identification, model parameter estimates, model checking (goodness of fit), and forecasting. Depending on the collection of data being studied, the four iterative phases take the form of a continuous path rather than being straightforward steps. The stages below form the foundation of the Box-Jenkins methodology, which is used to create ARIMA models: Model identification, parameter estimation and selection, diagnostic checking (also known as modal validation), and model application are the first four steps. Finding the orders (p, d, and q) of the AR and MA components of the model is necessary for model identification. In essence, it looks for solutions to the questions of whether data is stationary or not. What is the differentiation order (d) that causes the time to become stationary?

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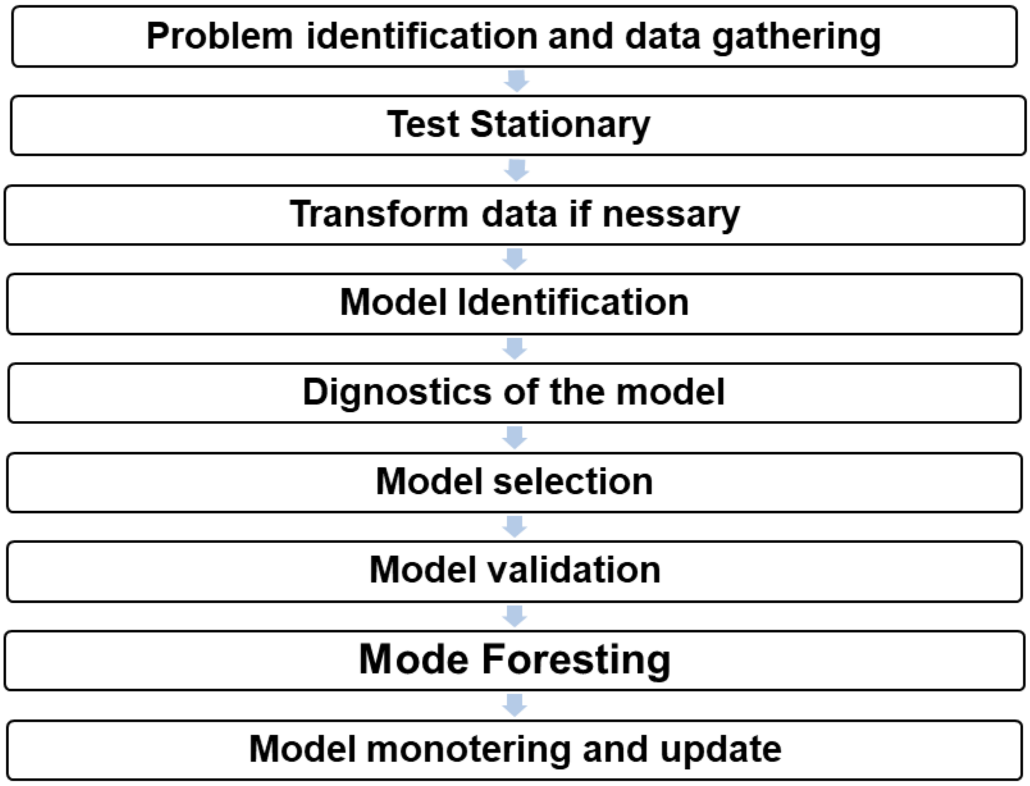
Flow- Chart of ARIMA model conducting process



Analysing Time Series and Constructing ARIMA

A set of data in Table No. 1 is used to plot a time series graph, which is later used for predicting the per capita income of Nepal.

Representing the time and per capita point line graph of Nepal from 1960 to 2022

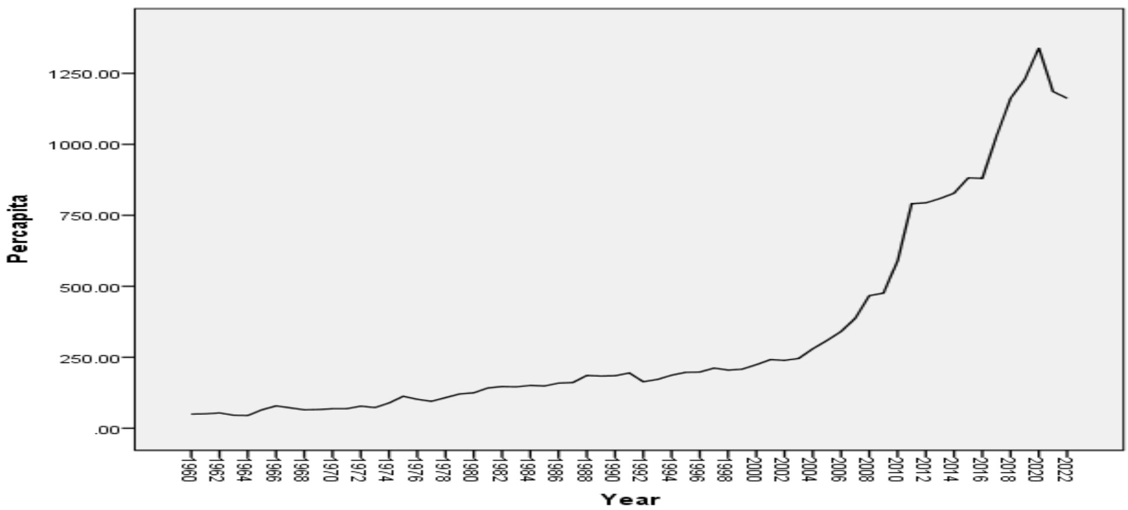


Figure No. 1

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Now according to above mentioned different steps of ARIMA analysis we should proceed analysis as follows

Model Identification

Finding out if the variable being forecasted is stationary in the time series is the first step in creating an ARIMA model. By stationary, we imply that the variable's values fluctuate over time within a fixed mean and variance. Picture 1 above's time plot of the per capita income data makes it abundantly evident that the data is not stationary. It is not possible to construct the ARIMA model until this series is stationary. To create a stationary series and an ARIMA (p,d,q) model with 'd' as the order of differencing, we must first differentiate the time series 'd' times. When differencing, exercise caution because too much difference tends to raise rather than lower the standard deviation. Starting with the lowest order differencing (of the first order, d=1) is the recommended course of action when testing the data for unit root issues. As a result, we were able to construct a first-order differencing time series. The line plot of the first-order differenced per capita income data is shown in Figure 2

Figure 1First-order point line graph of time series data

From the above Figure No. 2, it is clear that time series data becomes stationary at both its mean and variance. Before doing further analysis we have to check different time series data for stationary by applying the augmented Dickey-Fuller test.

Augmented Dickey-Fuller (ADF) Test.

Stationarity Tests

Augmented Dickey-Fuller t	-4.324	3	0.010	[a] Non-stationary
Phillips-Perron regression coefficient ρ	-30.262	3	0.010	[a] Non-stationary
Phillips-Perron studentized τ	-4.512	3	0.010	[a] Non-stationary
Kwiatkowski-Phillips-Schmidt-Shin Level η	0.163	3	0.100	[b] Level stationery
Kwiatkowski-Phillips-Schmidt-Shin Trend η	0.073	3	0.100	[b] Trend stationery

We are applying the PP and ADF tests to determine whether a time series is non-stationary. The series has a unit root, indicating that it is non-stationary, which is the null hypothesis of the tests. Given that the series is stationary, we can reject the null hypothesis that the series is 1% significance level stationary, according to the low p-values (0.010) for both tests. Alternatively, the null hypothesis that a series is stationary around a mean or a linear trend is tested with the KPSS test. The p-values in this instance are 0.100, which is not low enough to rule out the stationarity null hypothesis. The series is assumed to be in a stationary trend or level state.

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Stationarity Tests

First-order point line graph of time series data

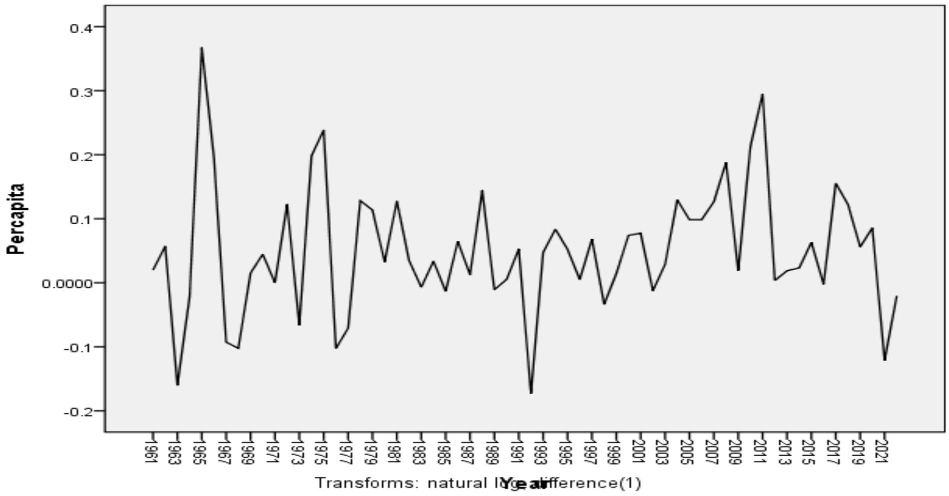

Figure No.2

From the above Figure No. 2, it is clear that time series data becomes stationary at both its mean and variance. Before doing further analysis we have to check different time series data for stationary by applying the augmented Dickey-Fuller test.

Augmented Dickey-Fuller (ADF) Test.

Stationarity Tests	Statistics	df	p-value	H_o
Augmented Dickey-Fuller t	-4.324	3	0.010	[a] Non-stationary
Phillips-Perron regression coefficient ρ	-30.262	3	0.010	[a] Non-stationary
Phillips-Perron studentized τ	-4.512	3	0.010	[a] Non-stationary
Kwiatkowski-Phillips-Schmidt-Shin Level η	0.163	3	0.100	[b] Level stationery
Kwiatkowski-Phillips-Schmidt-Shin Trend η	0.073	3	0.100	[b] Trend stationery

After one differencing time series graph looks like a stationary. It is further valid by drawing a correlogram. After studying patterns of ACF and PACF, PACF at second lag is significant, and the ACF graph shows exponential character, which means the model is AR(2), MA(0), and d(1)

i.e. ARIMA (2,1,0). But this is not all in all. Other possible models may be ARIMA (1,1,0), and ARIMA (9,1,0). We should choose the best model based on different criteria.

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Graphs representing correlograms

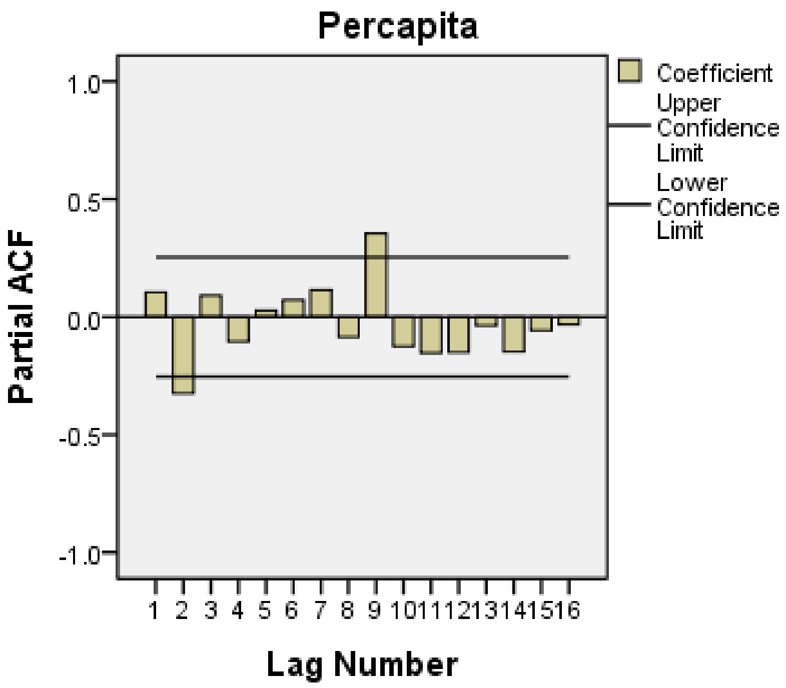

Figure No. 3

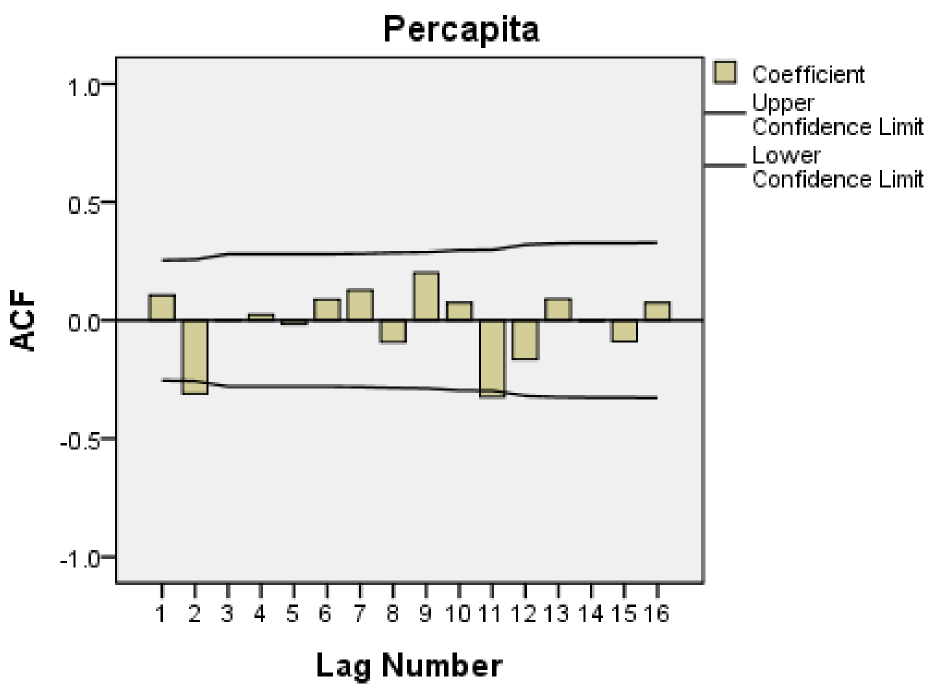

Figure No. 4

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The following table represents the best model-selecting criteria

Table No. 2

Table No. 3

Autocorrelations

Series:Percapita

			Box-Ljung Statistic		
Lag	Autocorrelation	Std. Error[a]	Value	df	Sig.[b]
1	.106	.124	.731	1	.393
2	-.310	.123	7.100	2	.029
3	.002	.122	7.101	3	.069
4	.023	.121	7.137	4	.129
5	-.017	.120	7.157	5	.209
6	.088	.119	7.703	6	.261
7	.127	.118	8.862	7	.263
8	-.092	.117	9.478	8	.304
9	.201	.116	12.515	9	.186
10	.074	.114	12.933	10	.227
11	-.324	.113	21.115	11	.032
12	-.164	.112	23.260	12	.026
13	.091	.111	23.927	13	.032
14	-.001	.110	23.927	14	.047
15	-.090	.109	24.610	15	.055
16	.075	.108	25.091	16	.068

At lags 2, 11, and 12, there is a significant negative autocorrelation signal.
Except at lag 13, when it already shows positive autocorrelation, there is no discernible autocorrelation. Beyond these lags, the majority of other lags show no substantial autocorrelation, suggesting that the series is essentially independent.
The series has some autocorrelation up to lag 14 according to the Box-Ljung test, but it also gradually decreases after that.
These findings imply that, despite some notable autocorrelations at particular lags, the aggregate series may have properties akin to white noise after these points. Therefore, to improve the forecast's accuracy, it might be crucial to think about modeling that includes the considerable lags that were found.

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Table No 4

Partial Autocorrelations

Series:Percapita

Lag	Partial Autocorrelation	Std. Error
1	.106	.127
2	-.325	.127
3	.091	.127
4	-.105	.127
5	.028	.127
6	.072	.127
7	.115	.127
8	-.086	.127
9	.355	.127
10	-.126	.127
11	-.153	.127
12	-.150	.127
13	-.037	.127
14	-.149	.127
15	-.057	.127
16	-.032	.127

The link between a time series and its lags, net of the series' effect at all intermediate lags, is provided by the partial auto-correlation function, or PAF. Lastly, the explanation of the outcomes is as follows:

There is a large negative partial autocorrelation at the lag 2.
Large positive partial autocorrelation is present at lag 9.
Differently, because the values of the partial autocorrelation at delays other than 1, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, and 15 are less than the standard error, they are not statistically significant.

Large partial autocorrelations at lag 2 and 9 indicate that an ARIMA model for the per capita income series should incorporate these lags:
Lag 2:This negative partial autocorrelation at lag 2 shows that the current value is directly impacted negatively by the value of a series two periods ago.
Lag 9: The extremely significant partial autocorrelation at lag 9 now indicates that the series' value from nine periods ago had an immediate beneficial impact on its current value.
Add lags 2 and 9 to the ARIMA model's AR terms.
Make sure there is no significant autocorrelation left by performing diagnostic checks on residuals after the original model has been fitted.
The ARIMA model can produce more accurate projections by taking into account these notable lags, which helps it better represent the underlying trends in the per capita income series.

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Comparison between criteria of ARIMA model.

ARIMA (p, d, q)	ARIMA (1, 1, 0)	ARIMA (2, 1, 0)	ARIMA(9,1,0)
R^2	.984	.984	.987
BIC	7.795	7.887	8.217
MSE	46.112	46.69	43.533
MAPE	7.524	7.053	6.452
MAXAPE	27.362	27.763	6.452
MAE	23.611	23.182	20.606
MAXAE	234.933	235.182	191.644

From table no. 2,

The (9,1,0) variant of the ARIMA models has the greatest BIC but is also the most accurate in terms of R2, MSE, MAPE, MAE, MAXAPE, and MAXAE. As a result, it merely highlights the complexity of the model—especially if the main considerations are handling extreme values and prediction accuracy. In this case, ARIMA (9, 1, 0) can be considered the best. However, ARIMA (1, 1, 0) is the best option based on BIC, which is lower in the first example, if the focus is on model conciseness and parsimony.

Model Statistics

Model	Number of Predictors	Model Fit Statistics: Normalized BIC	Ljung-Box Q(18): Statistics	Ljung-Box Q(18): DF	Ljung-Box Q(18): Sig.	Number of Outliers
Percapita-Model_1	0	8.213	10.468	9	.314	0

When looking for autocorrelation in the model's residuals, the Ljung-Box Q statistic is used. At the 0.05 level, a Q (18) value of 10.468 with nine degrees of freedom is not significant (p-value = 0.314). As a result, we can conclude that there is no discernible autocorrelation in the residuals, indicating a satisfactory model fit.

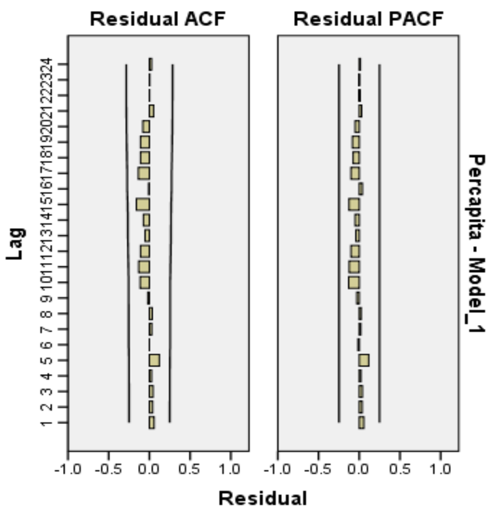

Figure No. 6

Interdisciplinary Journal of Management and Social Sciences (IJMSS)
Vol. 5, No. 2, July 2024. Pages: 83-101
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
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The autocorrelations present in the residual series at various delays are quantified by the ACF plot of the residuals. The autocorrelations of the residuals for a well-fitting ARIMA model should ideally be closest to zero and within the 95% confidence interval bounds (typically indicated by dashed lines). The graph suggests that most residual autocorrelations are inside the confidence ranges, indicating residuals that are roughly white noise.

The partial autocorrelations of the residual are computed at different lags and are displayed on the residual PACF graphic.
The residuals should show no significant partial autocorrelations, just like the ACF plot did. Additionally, the majority of the partial autocorrelations in the plot above fall inside the confidence intervals. Therefore, the residuals show very little meaningful partial autocorrelation.

Graph representing observed, estimated, and forecasted per capita income

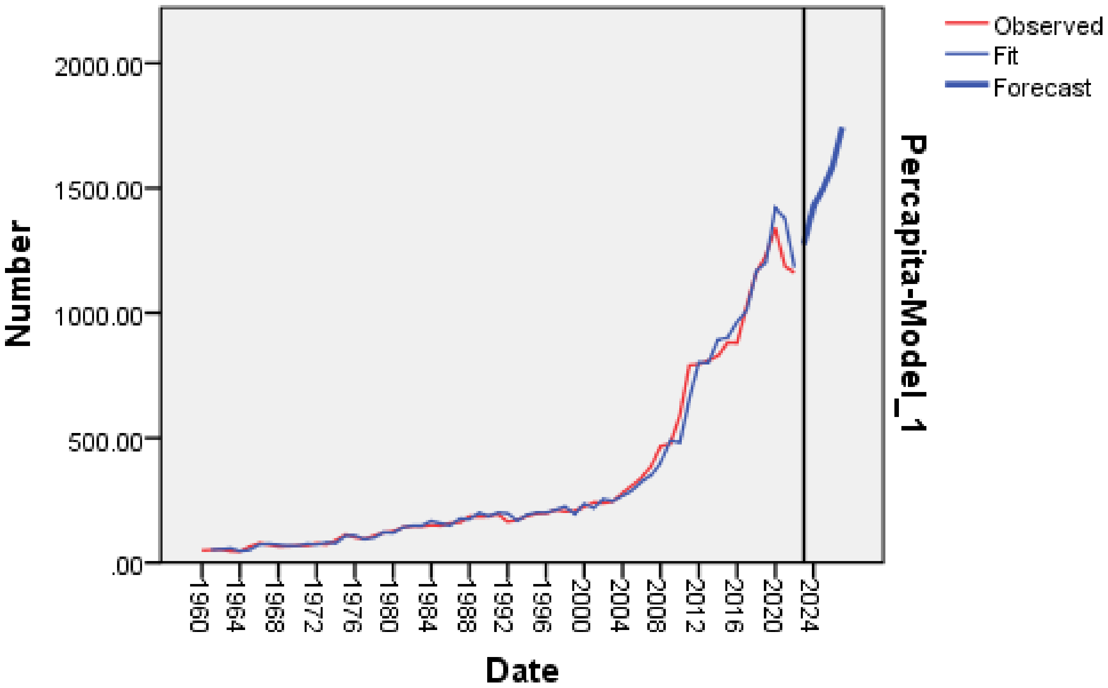

Figure No 7

Forecast Table

Model		2023	2024	2025	2026	2027
Percapita-Model_1	Forecast	1274.57	1429.25	1497.33	1587.67	1744.44
	UCL	1523.67	1886.90	2047.97	2228.95	2515.17
	LCL	1057.40	1060.52	1066.15	1096.06	1166.33

Table No. 8

Vol. 5, No. 2, July 2024. Pages: 83-101
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
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Forecast tendency: From 1274.57 in 2023 to 1744.44 in 2027, there is a definite increase tendency, based on the forecast.

Uncertainty: The 2023 model's prediction intervals begin modestly and gradually get wider over time, reflecting the slight increase in uncertainty that comes with looking ahead. And this range will be between 1166.33 and 2515.17 by 2027.

Discussion and Conclusion

Using 62 years' worth of time series data, the study's most appropriate model, ARIMA (9,1,0), was chosen to forecast Nepal's per capita income for a maximum of five years, or until 2027. Because ARIMA can forecast time series data with any type of pattern and autocorrelations between the time series' subsequent values, it was chosen for this purpose. Additionally, the study employed statistical testing and validation to establish that there was no correlation between the successive residuals (prediction errors) in the fitted ARIMA time series. The residuals appeared to be normally distributed, with mean zero and constant variance. Thus, we may say that the chosen ARIMA (9,1,0) appears to offer a sufficient predictive model for Nepal's per capita income. According to the ARIMA (9,1,0) model, predicted per capita income in 2023, 2024,2025,2026 and 2027were 1274.57, 1429.25, 1497.33, 1587.67 and 1744.77 (In $) respectively. All forecasted values for foresting years belong to confidence intervals, it was concluded that every year per capita income of Nepal will increase. The ARIMA (9, 1, 0) model was shown to be the most suitable model for forecasting Nepal's future per capita income. The model was used to forecast per capita income for the ensuing five years and met all requirements for a high-quality ARIMA model. The issue of per capita income has long been crucial to the advancement of human society. The forecast of a nation's per capita income statistics for the next years will not only be crucial for the economic and social advancement of the area, but it will also offer a scientific foundation for assessing pertinent policies. Nepal, being a country with limited economic development, must quickly recognize the trend in its per capita income. Analyzing the nation's per capita income has the potential to significantly advance the ARIMA model has been extensively documented in several nations for its use in forecasting economic indices, including GDP per capita and per capita disposable income. As a result, by using an ARIMA model for the first time to predict Nepal's per capita income, this study will add to the body of literature. Experiments from several nations demonstrate how well the ARIMA model captures time-varying factors and, hence, provides useful information about future economic conditions, and the economic and living standards of its citizens.

In several nations, the ARIMA model has been extensively studied about many economic metrics, including GDP per capita and per capita disposable income. By using an ARIMA model—which has never been done for Nepal—to predict per capita income, this study will close a gap in the literature. The outcomes obtained from these diverse nations serve as more evidence of the ARIMA model's effectiveness in capturing time-dependent variables, and thus, provide invaluable insights into future economic circumstances.

The analyzed studies show that the model produces relevant and accurate projections when it is adequately stated. For example, (Voumik & Smrity, 2020) discovered that an ARIMA of order (0, 2, 1) was good for predicting GDP per capita in Bangladesh, whereas (Nyoni & Bonga 2019) found that an

ARIMA of order (3, 1, 1) was suitable for (Rwanda). These models helped these nations' politicians make well-informed choices about economic planning and policy development.

To determine the proper sequence for the model parameters, however, extensive testing is necessary before applying this model. Similar diagnostic tests, like the ADF, PP, and KPSS tests, will be carried out in this study to guarantee the precision and dependability of the ARIMA model used to extract per capita income data for Nepal.

The literature review also makes clear that ARIMA models have been applied and used with some success in other contexts outside GDP per capita, such as the United States, where Klazoglou and Dritsakis (2018) projected health expenditures, and Kenya, where Musonda et al. (2016) examined overall economic health, applications that demonstrate the ARIMA model's adaptability in economic forecasting.

Even though the ARIMA model has a long history of being highly effective for economic indicators, this study would nonetheless take into account a few limitations:
The availability and calibre of previous data have a major impact on how accurate the ARIMA forecasts are. The historical per capita income data series for Nepal may have had gaps or inconsistencies, which would have impacted the model's performance. This now entails figuring out an ARIMA model's appropriate parameters. Erroneous forecasts will result from misspecification. Therefore, to identify the ideal model parameters for the data in Nepal, the study will need to conduct extensive diagnostic testing. Because ARIMA models are univariate, they exclude outside variables that might have an impact on per capita income.

For instance, the ARIMA model does not take into consideration the effects of natural disasters, political unrest, and global economic conditions on Nepal's economy. The ARIMA model assumes that historical data patterns will probably continue to exist in the future. However structural shifts in the economy, including significant policy shifts or significant economic reforms, are likely to veer from the established patterns and hence impair the precision of the projections.
In general, ARIMA models are more effective for short- to medium-term forecasting. Because forecast errors tend to compound over time, long-term projections may have a lower accuracy rate. This research focuses on a single model, even though in some of the studies, this ARIMA model has been compared to other forecasting techniques, like Holt-Winters exponential smoothing. Additional values could be added to the model's relative performance through a comparative analysis. This is an attempt to provide a trustworthy estimate of Nepal's per capita income while taking into account the aforementioned constraints and doing comprehensive diagnostic testing to provide essential information to decision-makers for the next economic planning and policy development.

Suggestions for Future Research

In light of the results and the inadequacies that have been pointed out, the following suggestions might be made to future researchers who might want to use the ARIMA model or any other time series technique in their future research.

Data quality and pretreatment:

Provide comprehensive and high-quality data sets. This could entail working with governmental organizations or even the Bureau of Statistics to obtain the most accurate and recent data.

Vol. 5, No. 2, July 2024. Pages: 83-101
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DOI: 10.3126/ijmss.v5i2.69448

Before training any model, make sure the data is consistent and free of outliers and missing values. This will maximize the fit of the model.

Comparing Models:

Comparative studies can be conducted using a variety of forecasting model classes, including Holt-Winters Exponential Smoothing, SARIMA, ARIMA, and even machine learning models like LSTM. Finding out what functions best in a specific dataset and context may be greatly aided by doing this. Theil's U-statistic, RMSE, MAE, and MAPE can all be used to evaluate and compare models. Exogenous Variable Incorporation: Techniques such as ARIMAX and VAR may be used to include these exogenous variables. This is how the model will lessen the influence of external factors—political events, natural disasters, or even patterns in global economic activity—on the variable that is being anticipated. Regime shifts and structural breaks: Define and explain if significant policy changes or economic reforms have resulted in regime shifts or structural breaks. Techniques like the Bai-Perron test, which finds many structural breakdowns in time series data, are used to test for significant disruptions. Create models that adjust to shifting economic circumstances so that predictions are accurate even in the face of such changes.

Long-term forecasting:

Although ARIMA models work incredibly well for short- to medium-term forecasting, researchers must employ models made expressly for long-term projections; these models may be hybrids, combining the best features of several forecasting approaches. It is necessary to do sensitivity analysis on the decline in forecast accuracy with a longer forecast horizon and to design mitigation solutions.

Implications for Policy:

Work together with the decision-makers to comprehend the real-world effects of the forecasts' outcomes. This could be useful in developing policies that adapt to anticipated patterns.
Based on the forecast's findings, offer concrete suggestions that highlight the areas that require attention in order to produce the intended economic effect.

Technological Advancements:

Process greater data volumes and more complex models by taking advantage of improvements in computer power and software. More complex modeling can be aided by tools like R, Python, and specialized time series analysis packets.
To create timely and appropriate precasts, big data analytics and real-time data streams should be investigated.

Multidisciplinary Methods:

To create more comprehensive forecasting models, include knowledge from computer science, statistics, and economics. Multidisciplinary cooperation may result in even more creative solutions and enhance model functionality. To gain a more comprehensive understanding of the issue at hand, consider incorporating the socio-economic environment and additional qualitative aspects that could account for changes in the target variable.

By implementing the above suggestions, future researchers will be in a better position to advance the body of knowledge already in existence, solve present issues, and produce more precise and trustworthy projections that will assist in the development of economic strategies and public policy.

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