ISSN PRINT 2319-1775 Online 2320-7876, www.ijfans.org
Vol.11, Iss.7, Dec- 2022

UGC CARE Listed (Group -I) Journal

Trends and Prediction of Poverty in Yemen

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Abstract

In this paper, we analyze time series data for trends in poverty rates from 1994 to 2022 issued by the Central Statistical Organization. Then, we present a prediction of the poverty rates for 2023 and 2024 using the Expert Modeler method via SPSS software. Finally, we apply the least-squares method using the Eviews program to verify the model quality used in the prediction. The results revealed increased poverty trends. The prediction model results also predicted an increase in poverty rates in the future. The findings may aid the decision-makers in Yemen in rethinking their poverty-reduction strategies in light of the predicted model. This study provides relevant evidence for new insights into the extent and nature of poverty in least-developed countries, such as Yemen.

Keywords: poverty; forecast; expert modeler method; poverty trends.

1. Introduction

Poverty is measured in different methods as a multidimensional phenomenon [1]. Given the complexity of the issues, the phenomenon's multifaceted nature is the best introduction to measuring poverty and the different concepts [2]; [3]. Many international organizations and researchers deal with different concepts of poverty according to his vision and goals. The definition of poverty differs in developed and developing countries because the individual in developed countries can find a minimum level of needs or a better standard of living than the individual in developing countries [4]. Moreover, this difference in the standard of living creates different concepts of poverty that differ in other societies. Still, there are efforts made by researchers, economists, and sociologists to bridge the differences in conceptions of poverty in different communities. The European Council defined poverty in 1975 as families or individuals whose resources are so limited that they exclude from the lowest acceptable manner of life in the State [5]. The concept was revised in 1985 to emphasize that "the limited resources of families and individuals were not only financial but also social and cultural [6]; [4]. Overall poverty, according to the WSSD, is defined as a lack of productive resources and income that promote sustainable livelihoods; famine and malnutrition; lack of access to education and other fundamental services; ill health; homelessness and insufficient housing; higher mortality from disease; and social exclusion [7]. A lack of involvement in civic, social, and cultural life and decision-making also typifies it [8]. It implies vulnerability to vehemence and often means living in peripheral or fragile environments without access to safe water or sanitation [9]; [10]. The SDG aims to eradicate poverty in all forms and dimensions, posing major challenges for statistical agencies and poverty researchers to collect data to monitor progress [11]. Poverty monitoring is a caution system that demands regular and frequent evaluations of several welfare measures or indicators to identify signs of deterioration in the well-being of people. Thus, the proper authorities can take the necessary and early actions to prevent the situation from worsening [12].

Furthermore, the quest for an optimal global poverty metric is doomed. Nevertheless, a focused search may result in a better, albeit still imperfect, result [13]. The development literature suggests various classes of metrics in response to Amartya Sen's pioneering insights on measuring poverty and inequality [14]. Scientists have recently proposed various alternative approaches for defining and measuring the quality of life [15]. However, most are composite indicators, a highly contentious construction due to the ad hoc selection of component weights and arbitrary choice of criteria [16]. We organize our paper as follows; the methods used in the study are described in Section 2. Section 3 reviews the literature on poverty prediction

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Vol.11, Iss.7, Dec- 2022

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models of poverty. Section 4 describes the results and discussions. Section 5 reports the study's conclusion, major limitations, and future research.

2. Methodology

A series of data on trends in poverty rates were collected and analyzed from official data issued by the Central Statistical Organization from 1994 to 2022 using the descriptive approach. Moreover, poverty rates from 2023 to 2024 were predicted by applying the expert modeler method via SPSS software. In the end, the least squares approach was used via Eviews software to verify the quality of the predictive model.

3. Literature Review on Poverty prediction models

Many studies have used different methods to predict poverty, such as the study by R Aminudin and Putra. Exponential smoothing has been applied to predict poverty lines in West Java, Indonesia. The study relied on data from 2005 to 2017. The forecast was made for 2018-2020, and high poverty lines were noted during the forecast period [17]. Mogull discussed predictors of poverty Incidence and the number of poor individuals in 2015 in California for 11 regions. The study was based on multiple regression models and used the data for 2004-2014 [18]. Parolin and Wimer presented poverty estimates during the Corona epidemic in 2020. The simulation method was applied to predict poverty rates. Poverty rates are expected to increase from 12.4 to 18.9. The expected results showed the correlation of unemployment rates with poverty rates from 2000 to 2018 and that with an increase in unemployment by 10%, poverty rates would rise to 15% [19]. Latreille 2005 set a target for monetary poverty estimation and poverty forecasting in Senegal. The study suggested income inequality and relied on the Senegal National Survey. The poverty forecast for 2003-2004 was presented at the poverty line of $1 for regions and households using a simple simulation model [20]. Reed and Stark examined a prediction method for the Child Poverty Scale in Scotland based on the simulation method in forecasting 2015-2030 in 2018 [21]. Azcona and Bhatt predicted extreme poverty for age and gender using the International Future Model from 2019 to 2022 based on the selected sample from 129 countries [22]. Silalahi made the prediction using SARIMA models in Java Province in Indonesia. The study found a good prediction model based on the poor population's data (2002-2019). Poverty has been forecast for the period (2020-2024) [23]. Warnia aimed to predict the poverty level using the multiple regression model for 2017 in Indonesia. The study relied on the data for the period (2006-2016); the poverty line and the percentage of poor people were used as independent variables, and the number of the poor as a dependent variable. It found that the predicted value amounted to 36.15, as well as an increase in poverty by 3.85 compared to 2016 [24].

4. Results and Discussions

This section discusses some empirical results. First, we present and analyze the descriptive data on the reality of poverty rates [25]. Then we predict poverty prevalence rates in Yemen during future years to work on drawing the attention of decision-makers to reduce poverty.

4.1 Descriptive Data

Table 1 presents the poverty rates in Yemen from 1994 to 2022. We found that the poverty rate fluctuated, increasing from 34.90 in 1994 to 41.80 in 1998 and decreasing in 1999. Then it rose again from 2000 until 2004. After that, it decreased in 2005 and 2006, then increased in 2007 and continued to rise until 2011 due to political unrest and security instability. Additionally, it decreased during the period (2012-2014) due to political stability to some extent, and the poverty rate increased and continued to rise until it reached 61.02 in 2022. In this regard, the rise in poverty rates in Yemen is attributed to many factors, including political unrest, civil wars, inflation, and the decline in the purchasing power of the Yemeni currency against hard currencies. Moreover, the complete interruption of the salaries of state employees, the cessation of most government and private work sectors, corruption, the cessation of public revenues of the state, and thus the weak economic growth are all factors that have contributed to the high poverty rates in Yemen. In general, we found an increase in poverty rates by 74.8% from 1994 to 2022. Figure (1) illustrates this.

ISSN PRINT 2319-1775 Online 2320-7876, www.ijfans.org
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Table 1. Poverty rates in Yemen from 1994 to 2022.

Years	Poverty Rate	Years	Poverty Rate
1994	34.90	2009	48.80
1995	35.59	2010	49.00
1996	37.85	2011	49.85
1997	39.98	2012	47.20
1998	41.80	2013	47.80
1999	40.60	2014	48.60
2000	41.98	2015	52.00
2001	42.18	2016	54.00
2002	42.79	2017	56.89
2003	42.97	2018	57.95
2004	43.00	2019	58.22
2005	42.50	2020	59.15
2006	41.50	2021	60.19
2007	44.50	2022	61.02
2008	47.60		

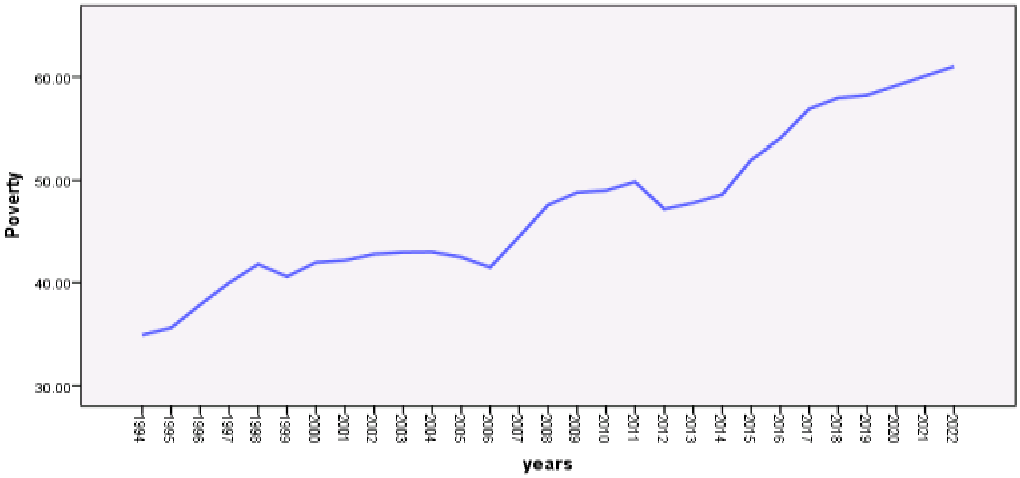

Fig (1). The poverty rates in Yemen from 1994 to 2022.

4.2 Prediction Strategies

The Expert Modeler is a time series models ad hoc procedure used by SPSS for prediction [26]. It attempts to automatically construct a useful predictive model with one or even more series of endogenous variables. If exogenous variables are related to the endogenous variable, the Expert Modeler method automatically selects just the statistically significant exogenous variables. The Expert Modeler, by default, deems both ARIMA and exponential smoothing methods. Nevertheless, the Expert Modeler Procedure can be restricted to only looking at exponential smoothing or ARIMA methods.

Moreover, it is simple to implement and aids in quickly determining the most suitable models that meet the required criteria, thus making it simpler to obtain forecasts quickly. [27]; [28]. Many time series models can be used to forecast the behaviour and trends of phenomena through time in various sciences, including economic and medical fields, climate sciences, epidemiology, engineering, and others [29]; [30]. Recently, many researchers have presented and used these models for modelling and predicting the behaviour of phenomena, including poverty. The models utilized in time series include conducting four basic steps: defining the model, estimating unbeknown parameters, the diagnostic process, and finally, the prediction process [31]; [32]. In this manner, Some models are utilized to analyze and forecast time series data, such as (ARIMA, ARCH, ARMA, GARCH, AR and MA) [33]. In addition, the exponential function and linear regression models are also used in the forecasting process [34]. In this context, many

ISSN PRINT 2319-1775 Online 2320-7876, www.ijfans.org
Vol.11, Iss.7, Dec- 2022
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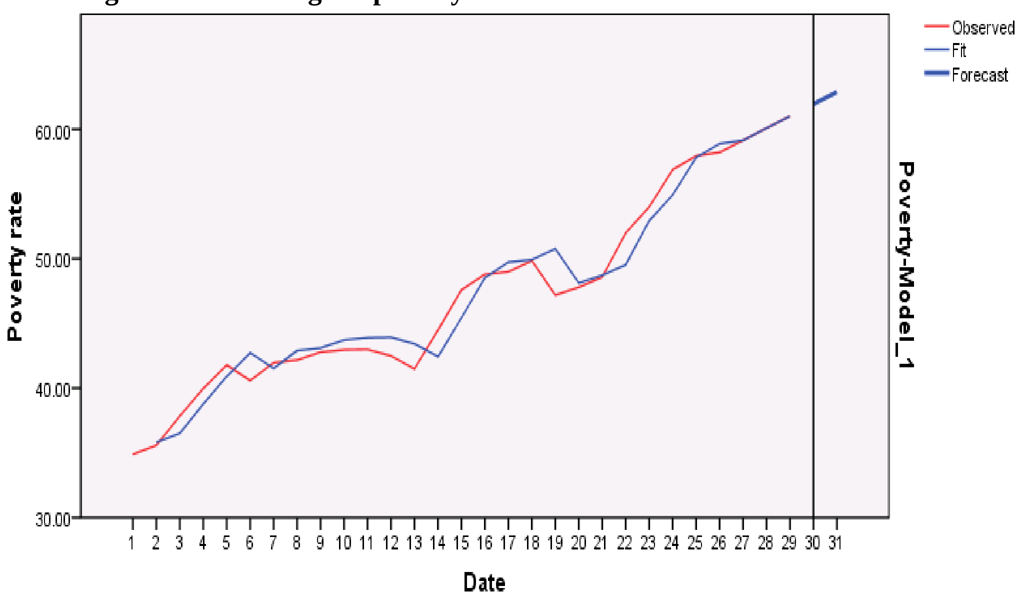
transformations, like a natural log and first- and second-degree differences, are required to transform the initial data of the unstable time series into a stable time series that can be used for prediction. The nature of the original data for the poverty time series during the period (1994-2022) was verified. The stability of the poverty data series was tested by drawing it as shown in Figure 1, which indicates a general trend in the data. Here, we processed the actual data, and the poverty data series stabilized after taking the first difference to be used in the prediction process, as in Figure 2. We found an increase in poverty rates (61.95 and 62.88) for 2023 and 2024, respectively, as depicted in Figure (3) and Table (2).

Table 2. Poverty forecasts with (95%) confidence intervals (CIs) for 2023 and 2024.

Model		2023	2024
Poverty rate-Model_1	Forecast	**61.95**	**62.88**
	UCL	64.76	66.86
	LCL	59.14	58.91

Fig 2. Transforming the poverty rate data to the first difference.



ISSN PRINT 2319-1775 Online 2320-7876, www.ijfans.org
Vol.11, Iss.7, Dec- 2022

UGC CARE Listed (Group -I) Journal

Figure 3. Poverty forecasts with (95%) confidence levels (CIs).

Table 3 illustrates the model statistics results; the R-squared value of 0.964 is close to 1, which is the best possible value and denotes the goodness of the poverty rate model used for forecasting and represents this data appropriately and ideally. It also notes the Ljung-Box Q(18) test outcome, which examines the residual randomness of the model, and that the Ljung-Box statistic (22.073) and the value of ($Sig.$ = 0.229) is statistically significant because it is greater than (0.05), meaning that there is no problem in the used model and follows the distribution of random.

Table 3. Results Model Statistics

Model	Model Fit Statistics			Ljung-Box Q(18)		
	R-squared	RMSE	Normalized BIC	Statistics	DF	Sig.
Poverty rate	0.964	0.370	0.748	22.073	18	0.229

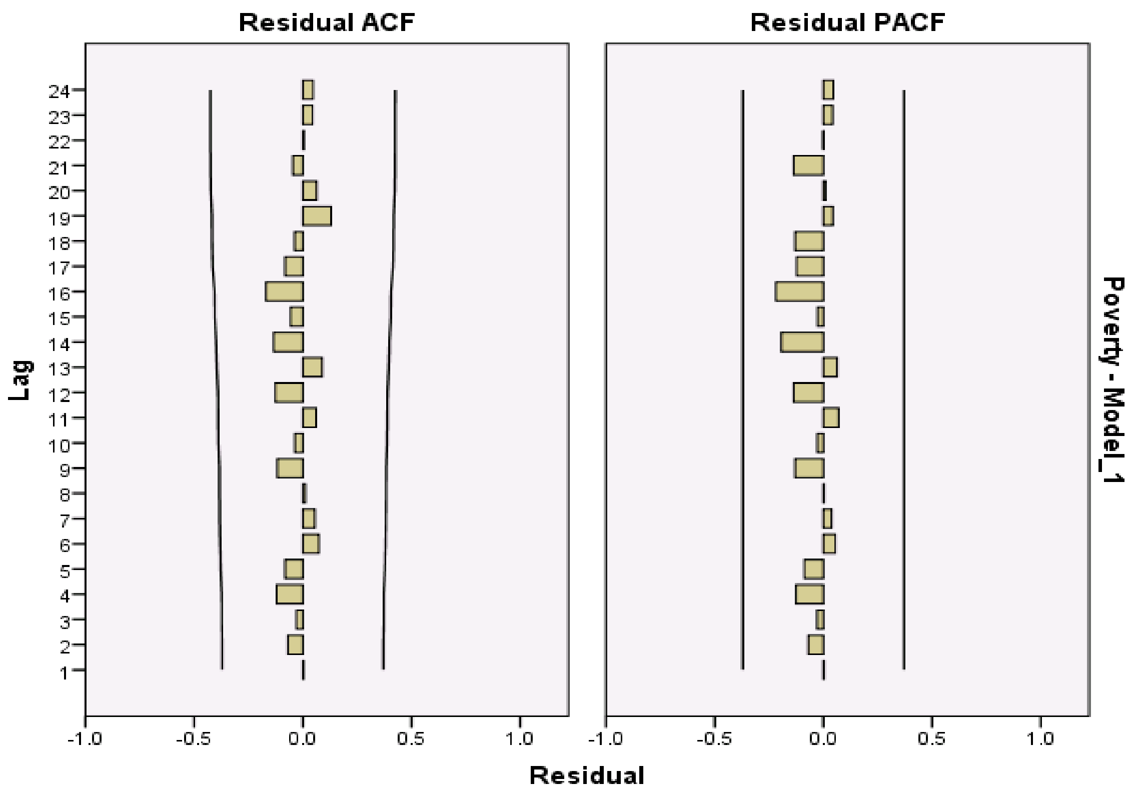


Figure 4 illustrates that there is no auto-correlation between errors. Thus, auto-correlation and partial auto-correlation are all within confidence limits and indicate that the prediction model is good, and the residuals of the poverty prediction model can be considered white noise.

Figure 4. ACF and PACF of the poverty prediction model residuals

The linear model was estimated using the least-squares method via the Eviews program to test the extent of the model used to predict the future by considering the estimated values as the predictor variable and the real values as the predicted variable. It was noted that the estimated parameter was close to one, indicating that the estimated figures are almost identical to the actual. Table 4 exhibits the results of the quality and ability of the model to estimate because the estimated value is near one, and the value of ($prob$ = 0.000 < 0.05) is statistically significant.

ISSN PRINT 2319-1775 Online 2320-7876, www.ijfans.org
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Table 4. Results of linear model's ability to predict the poverty rate.

Dependent Variable: POVERTY_RATE				
Method: Least Squares				
Sample (adjusted): 1994 - 2022				
Included observations: 29				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.65048	2.1243	3.13057	0.0045
PREDICTED	0.972309	0.0052	19.1167	0.0000
R-squared	0.967919	Mean dependent var		47.25207
Adjusted R-squared	0.967919	SD dependent var		7.519030
SE of regression	1.346755	Akaike info criterion		3.467147
Sum squared resid	50.78494	Schwarz criterion		3.514295
Log-likelihood	-49.27363	Hannan-Quinn criteria.		3.481913
F-statistic	35.1689	Durbin-Watson stat		1.901384
Prob(F-statistic)	0.000000			

5. Conclusions and future research directions

5.1 Conclusion

This study served two purposes: First, non-monetary poverty measures were estimated in Yemen in 2022. Second, poverty trends from 1994 to 2022 were collected and analyzed. Besides, the Expert Modeller method predicted poverty rates for 2023 and 2024. The study's results revealed a significant increase in non-monetary measures of poverty and an increase in the poverty rate by 74.8% during the study period. The prediction model results also predicted an increase in poverty rates in the future. The findings may aid policymakers in developing programs and policies to alleviate poverty in Yemen.

5.2 Future research directions

The limitations of this study are that there is no data series for non-monetary measures such as human poverty, capability poverty, and multidimensional poverty. The study suggests future work that could be done, such as more research into the factors contributing to poverty in Yemen. In addition, the study suggests conducting research on monetary and non-monetary indices of poverty and analyzing poverty data using cutting-edge statistical techniques. Finally, an investigation of poverty trends across Yemen's governorates can be carried out to identify areas that require additional attention and resources and assess the effectiveness of poverty alleviation programmes.

References

1. T. Nawab, S. Raza, M. S. Shabbir, G. Yahya Khan, and S. Bashir, “Multidimensional poverty index across districts in Punjab, Pakistan: estimation and rationale to consolidate with SDGs,” Environ. Dev. Sustain., vol. 25, no. 2, pp. 1301–1325, 2023.
2. K. M. Chen, C. H. Leu, and T. M. Wang, “Measurement and Determinants of Multidimensional Poverty: Evidence from Taiwan,” Soc. Indic. Res., vol. 145, no. 2, pp. 459–478, 2019, doi: 10.1007/s11205-019-02118-8.
3. L. Middlemiss, P. Ambrosio-Albalá, and A. Emmel, Nickod, “Energy poverty and social relations: A capabilities approach,” Energy Res. Soc. Sci., vol. 55, pp. 227–235, 2019.
4. M. Pomati and S. Nandy, “Measuring Multidimensional Poverty According to National Definitions: Operationalising Target 1.2 of the Sustainable Development Goals,” Soc. Indic. Res., vol. 148, no. 1, pp. 105–126, 2020, doi: 10.1007/s11205-019-02198-6.
5. C. Decision, “75/458/EEC of 22nd July 1975—Concerning a programme of pilot schemes and studies

to combat poverty," Eur. Comm., 1975.
6. EEC, "On specific community action to combat poverty',(Council decision of 19 December 1984) 85/8," Off. J. EEC, vol. 2, no. 24, 1985.
7. N. United, "The Copenhagen declaration and programme of action: world summit for social development 6–12 March 1995," New York United Nations, vol. 1995, 1995.
8. J. Wolff, "Beyond poverty," Dimens. Poverty Meas. Epistemic Injustices, Act., pp. 23–39, 2020.
9. D. Gordon, "Indicators of Poverty & Hunger," Expert Gr. Meet. youth Dev. Indic., no. December, pp. 12–14, 2005.
10. M. Gosseslin, "What Is Poverty," Economic and Social Inclusion Corporation, 2009. http://www.worldbank.org/en/topic/poverty.
11. C. Lakner, D. G. Mahler, M. Negre, and E. B. Prydz, "How much does reducing inequality matter for global poverty?," J. Econ. Inequal., pp. 1–27, 2022.
12. S. Sumarto, D. Suryadarma, and A. Suryahadi, "Predicting Consumption Poverty using Non-Consumption Indicators: Experiments using Indonesian Data," Soc. Indic. Res., vol. 81, no. 3, pp. 543–578, 2007, doi: 10.1007/s11205-006-0023-x.
13. S. Alkire and U. Kanagaratnam, "Revisions of the global multidimensional poverty index : indicator options and their empirical assessment," Oxford Dev. Stud., vol. 49, no. 2, pp. 169–183, 2021, doi: 10.1080/13600818.2020.1854209.
14. S. Alkire, C. Oldiges, and U. Kanagaratnam, "Examining multidimensional poverty reduction in India 2005 / 6 – 2015 / 16 : Insights and oversights of the headcount ratio," World Dev., vol. 142, p. 105454, 2021, doi: 10.1016/j.worlddev.2021.105454.
15. E. Diener and E. Suh, "Measuring quality of life: Economic, social, and subjective indicators," Soc. Indic. Res., pp. 189–216, 1997.
16. D. G. Petróczy, "An alternative quality of life ranking on the basis of remittances," Socioecon. Plann. Sci., vol. 78, p. 101042, 2021.
17. R. Aminudin and Y. H. Putra, "Poverty Line Forecasting Model Using Double Exponential Smoothing Holt's Method," IOP Conf. Ser. Mater. Sci. Eng., vol. 662, no. 6, 2019, doi: 10.1088/1757-899X/662/6/062007.
18. R. G. Mogull, "Forecasting State Demographic Poverty: The Case of California," J. Soc. Serv. Res., vol. 41, no. 1, pp. 1–5, 2015, doi: 10.1080/01488376.2014.902786.
19. Z. Parolin and C. Wimer, "Forecasting estimates of Poverty during Covid-19 Crisis," Poverty Soc. policy Br., vol. 4, no. 6, pp. 1–18, 2020.
20. T. Latreille, "A POVERTY FORECASTING TOOL A Case Study of Senegal Jumbo :," Econ. Outlook, no. January, pp. 1–15, 2005.
21. H. Reed and G. Stark, "Forecasting Child Poverty in Scotland," Landman Econ. Graham Stark, Virtual Worlds Res., no. April, pp. 1–7, 2018, [Online]. Available: https://www.gov.scot/publications/tackling-child-poverty-delivery-plan-forecasting-child-poverty-scotland/#res-1.
22. G. Azcona and A. Bhatt, "Estimates and forecasts of extreme poverty by sex and age using the International Futures Model," UN Women, UNDP Frederick S. Pardee Cent. Int. Futur., 2020.
23. D. K. Silalahi, "Forecasting of Poverty Data Using Seasonal ARIMA Modeling in West Java Province," JTAM | J. Teor. dan Apl. Mat., vol. 4, no. 1, p. 76, 2020, doi: 10.31764/jtam.v4i1.1888.
24. W. Nengsih and J. N. Sari, "Forecasting Analysis Using Poverty Level Multiple Regression Analysis," Proceeding 7th Annu. Basic Sci. Int. Conf., 2017.
25. CSO, "Series of Statistical Yearbook for the years (1994-2022),Central Statistical Organization, Ministry of Planning and International Cooperation, Republic of Yemen." Sana'a, 2022.
26. M. Fayaz, G. Meraj, S. A. Khader, and M. Farooq, "ARIMA and SPSS statistics based assessment of landslide occurrence in western Himalayas," Environ. Challenges, vol. 9, p. 100624, 2022.
27. P. Sarla, S. H. Priya, G. Ravindran, and A. Reddy, "Sustainable Concrete Strength Prediction Using ARIMA Model," Tailored Funct. Mater. Sel. Proc. MMETFP 2021. Singapore Springer Nat. Singapore, vol. 15, pp. 1–23, 2022.
28. J. Zhang, F. Chen, Y. Guo, and X. Li, "Multi-graph convolutional network for short-term pas