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Original Research Article

Forecasting of neonatal mortality trend at a special new-born care unit in Odisha, India: A time-series analysis

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ABSTRACT

Background: New born mortality is a public health problem in the state of Odisha. Newborn mortality is a dynamic process and variations in mortality are observed temporally and seasonally, and also across health facilities. Prior knowledge of mortality burden can enable health system's readiness in terms of resources allocation and timely intervention, thereby improving the chances of survival of sick newborns admitted in the hospitals. Hence, this study aimed to examine temporal trends of newborn mortality in a Special Newborn Care Unit of Saheed Laxman Nayak Medical College and Hospital (SLNMCH) in Odisha and forecast a short-term monthly projection.

Materials and Methods: The Box-Jenkins approach was used to fit a seasonal autoregressive integrated moving average (SARIMA) model to the monthly recorded mortality among the hospitalized new borns in the SNCU during 2016-2020. The best-fit model for forecasting was found based on the Akaike Information Criterion.

Results: The time-series analysis revealed a modest upward trend in newborn mortality rate among SNCU admitted newborns, with peaks in the late winter and late summer months. The seasonal ARIMA (0,1,1)(1,1,1)12 model offered the best fit for time-series data. This model predicted the monthly percentage of mortality in SNCU admitted newborns in the range of 9% to 35% with respective 95% confidence interval for two years period (2021-2022).

Conclusion : SARIMA models are useful for monitoring newborn mortality and provide an estimate of temporal trends and seasonality. The models are helpful for predicting occurrence of mortality in the SNCU of SLNMCH and could be useful for developing early warning systems. It may help in early detection, timely treatment, and prevention of serious complications in admitted sick newborns.

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1. Introduction

Globally, about 2.4 million children dies each year in the first month of life.[1] The recent global estimate suggests that prematurity, birth asphyxia, and sepsis are the three most common causes neonatal deaths, and 80% of this can be prevented with simple interventions at the appropriate time.[2] Majority of newborn deaths occur in low- and middle-income countries (LMICs) such as India.[3] In India, there has been discernible improvements in reducing new-born deaths in the past decade.[4] Nevertheless, the share of new-born deaths in India is the highest in the world with annual figure of 522 thousand deaths which accounts for 14% of global newborn deaths.[5] This is unacceptably high, and the declining rate continues to remain relatively slow despite discernible progress witnessed in the past decade.

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Thus, new-born mortality continues to be a public health challenge in India. This challenge is further compounded by huge inter and intra-state disparities in new-born mortality rate (NMR) with regard to socio-economic differentials.[6]

As per the Civil Registration System (SRS)-2018, the state of Odisha accounts for nearly 4% of total neonatal deaths in the country.[4] Nearly,0.25 lakh (≈ 24537) neonates died in Odisha in 2018 as against the national figure of 6.07 lakh in year 2016-18,thereby standing at the 3^{rd} position in terms of neonatal mortality rate(NMR) in the country after Madhya Pradesh and Uttar Pradesh. This means, each day around 67 neonates succumb to various causes in the state. The current NMR in Odisha is 31 while the corresponding national figure stands at 23.[4]

The facility-based new-born care has assumed importance to tackle the morbidities burden among new-born babies and has the potential to reduce the NMR up to 50% in different settings.[7] Establishing such neonatal units has been one of the thrust areas of Indian government. One such unit is Special Care Newborn Unit (SCNU) having provision of secondary level care. The SNCUs a reestablished mainly in the district andsub-district government hospitals where the delivery load is more than 3000. Studies suggest that the SNCU has significant potential to reduce hospital neonatal deaths and improve survival rate among admitted sick newborns.

Death of newborn babies admitted in the SNCUsis dynamic and fluctuates from facility to facility. It is also not static temporally as well as seasonally.[8,9] If forecast of deaths among newborns admitted in the SNCUs is available, it could enable suitable allocation of resources, and timely intervention could be planned and implemented effectively. The newborn deaths in SNCUs can be predicted by statistical modelling which could enable the health system's readiness to manage the sick newborns, and thereby will enhance newborn survival. Hence, this study was conducted to examine the trends of inpatient neonatal mortality in one of the SNCU sin Odisha from 2016 to 2020 and a forecast of it was made for years 2021 and 2022.

2. Materials and Methods

2.1. Study area

Saheed Laxman Nayak Medical College and Hospital , commonly known as SLNMCH, is a government medical college and tertiary care hospital located at the heart of Koraput town, the headquarter of administrative district-Koraput in southern part of the state of Odisha, India. It caters to the health needs of more than 1.38 million population. Patients from neighbouring districts and states such as Andhra Pradesh and Chhattisgarh are also dependent on it for tertiary care health services.SNCU data in this hospital show that the annual admission of sick new-born babies in its SNCU of paediatric department are reported to be over 2000.

2.2. Data sources and data description

We acquired the SNCU admission and outcome data of the SLNMCH for the period of 2016 to 2020 from the department of family welfare, government of Odisha, which were routinely captured through its facility-based new-born care database, developed for real-time monitoring of sick neonates. The final data frame consisted of variables of new admissions and corresponding outcome, i.e. discharges and deaths only, occurred in each month during the above-mentioned period. In this study we excluded those admissions, the outcomes of which were either referrals or LAMA (left against medical advice). The SNCU admissions of new-borns from districts other than Koraput, as well as from other states were also not taken into consideration. The monthly frequency data of admissions and discharges on all—cause mortality was converted into deaths rates (rounding off the decimals) per 100 admissions using the number of SNCU mortalities in each month as the numerator and admissions in the same month as the denominator.A sequence of 60 monthly neonatal mortality rates was obtained and studied for temporal variations. Our data were taken in time with the same interval of one month and consisted of a sequence of observations, thereby justifying our choice of using a time series model. The time-series data used in the analysis were in identified form and contained no personal information of the study subjects, i.e., SNCU admitted sick new-born babies.

2.3. Time series modelling

In this study, we applied autoregressive Integrated Moving Average (ARIMA)model. ARIMA model is a form of regression analysis which is commonly used to develop short-term forecasting model with the help of univariate time series data containing ordinary or seasonal trends. It was first presented by Box and Jenkins in 1976. Stationary of time series data is prerequisite for developing and testing an ARIMA model.[10] A time series is said to be stationary if its mean, variance, and auto correlation do not change over time and remain constant or unchanged. In the ARIMA model, the non-stationary time series is made stationary to study its behaviour over the period under consideration and for the purpose of forecasting. Usually, the ARIMA model is represented as ARIMA (p, d, q) where p is the autoregression, d is the number of non- seasonal differences, and q is the order of moving average, i.e., number of lagged forecast errors. The ARIMA (p, d, q) is represented in a general form as follows:

$$yt = \mu + \varphi 1yt - 1 + ... + \varphi pyt - p - \theta 1et - 1 - .... - \theta qet - q + et \quad (1)$$

Where yt is the value at time t, φ is the AR parameter, θ is the MA parameter and e is the error term.

In case of no seasonality, the ARIMA model would be the preferred forecasting method. However, if evident seasonality in the data existed, the seasonal ARIMA(SARIMA) represented by [p, d, q][P,D,Q]s model is considered as the appropriate method. Analogous to the simple ARIMA parameters, these are: Seasonal autoregressive (P), seasonal differencing (D), and seasonal moving average parameters(M); s defines the number of time periods until the pattern repeats again. In this study, the "s" is 12, the time series data used for the study being monthly in nature. By summing above parameters with non-seasonal ARIMA model, the seasonal ARIMA model can be written as a linear equation as follows:

$yt = \mu + \varphi 1ydt - 1 + \varphi pydt - 2 + ... + \varphi nydt - n + \theta 1et - 1 + \theta qet - q + et$ (2)

The four key steps that we adopted for the ARIMA modelling were- Model Identification, Estimation of Parameters of the chosen model, Diagnostic Checks, and Forecasting.

2.4. *Statistical analysis*

While the time series data frame was built by using Excel 2016, R statistical software (version 4.1.1) was used to perform the statistical analyses. A collection of extended packages (forecast, ggplot2, fpp2, tydiverse and ggfortify) were used throughout the analysis. A significance level of0.05 was set for hypothesis tests.

Initially, we conducted a descriptive analysis followed by plotting the time series graph associated with the percentage of monthly new-born mortality in the SNCU to visually inspect the non-stationarity of the data. Thereafter, we performed Augmented Dickey–Fuller (ADF) statistic, to formally test the non- stationarity, i.e., a trend in change over time. The ADF statistic showing no statistical difference would indicate a non-stationary time series. The "decompose" function using additive model was used to decompose the seasonal trend of the sequence. Next, in the event of non-stationary series, the time-series was subjected to differencing until a stationary series was obtained. In the model identification stage, instead of visually examining the auto correlation function (ACF) and partialACF (PACF) graphs of the differenced time series to identify values for AR and MA components, we used the 'auto.arima()' function in the 'forecast' library which have an ability to automatically identify the best-performing ARIMA model by considering the goodness of fit measures such as a larger value of R-squared (R^2), a lowest value of normalized Akaike information criterion (AIC) and the appropriate ACF and PACF graphs of the errors. In this analysis, we used both these parameters to determine the best model. Non-seasonal differencing (d) term and seasonal differencing (D) were also applied in the event of non-stationary series. Prior to using the model for forecasting, we checked for its adequacy, i.e., the residuals leftover after fitting the model are simply white noise. For this, we examined the ACF and PACF of the residual series that the best fitting ARIMA model produced and applied Ljung-Box Q test to provide an indication of whether the model was correctly specified. The Ljung-Box Q test statistic providing p-value greater than 0.05, would mean that the residuals behaved like a white-noise series. The Shapiro-Wilk test was also conducted to test the normality of the residuals. On passing all the required assumptions checking, the finally selected model was used for out-of-sample forecasting for the period of January 2021to December2022. Forecast accuracy was assessed by computing the mean absolute percentage error (MAPE).

3. Results

3.1. *Trend of the monthly percentages of SNCU admitted new-born mortality*

The sick-new-born admissions load and new-born mortalities in the SNCU of SLNMCH, Koraput during the five-year period of 2016-2020 were reported to be 8417 and 1395, respectively. In every 100 SNCU admissions, there were 17 new-born deaths (Supplement-1) occurred during the said period. The monthly time series data used for the analyses are presented in Table 1.

The monthly time series plot of the new-born mortality in the SNCU displayed a slightly increasing tendency and seasonal pattern (Figure 1). The seasonal fluctuations were roughly constant in size over time and did not seem to depend on the level of the time series. The random fluctuations also seemed to be roughly constant in size over time. Thus, we described using an additive model. The decomposition plot of the series suggested an obvious trend and seasonality (Table 2). Therefore, it was likely to be non-stationary. While mortality cases were recorded throughout the year, a seasonal periodicity with a major peak was observed between December and January, i.e., during the winter. The conclusion of non-stationarity observed from the time series plot was confirmed by the ADF test which returned a p-value of 0.06579. Since the p-value obtained was more than 0.05, we accepted the null hypothesis that the data were not stationary. Hence, there was a need for differencing to make it stationary (Table 2).

Being a seasonal time series, our data consisted of a trend component, a seasonal component, and an irregular component. Decomposing the time series separated and estimated these three components. The estimated trend component showed, a small drop in mid-2017 followed by avery minimal but steady increase from then on.

The seasonal factors were estimated for the months from January to December. The largest seasonal factor was for January (about 3.52), and the lowest was for June (about -2.30), indicating that there seems to be a peak in deaths in January and a trough in deaths in June each year in the

Table 1: New-born mortality per 100 SNCU admissions grouped by month, 2016-2020

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2016	16	7	11	11	16	14	16	13	8	16	18	13
2017	20	13	9	10	13	13	9	6	18	14	15	15
2018	17	16	14	18	19	19	16	21	16	17	18	22
2019	21	20	16	16	20	14	18	24	20	15	9	26
2020	20	15	17	21	17	12	13	21	27	24	24	13

Table 2: Augmented dickey- fuller test

Test	Test Statistic	P- value
Dickey-Fuller	-3.541	0.06

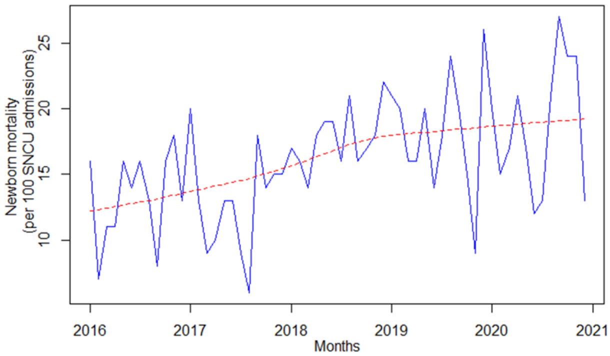

Figure 1: Monthly time series of SNCU admitted new born mortality, 2016-2020

SNCU mortality figures.

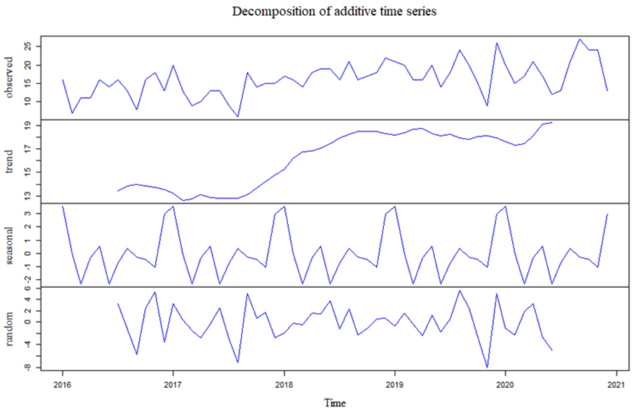

Figure 2: Decomposition of time series data, 2016-2020

3.2. Model identification

Before developing the ARIMA model, we transformed the raw time-series data by differencing to induce stationarity. To make the mean and variance stationary, first order differencing was used. After the first differencing, it appeared to be stationary in mean and variance, as the level of the series along with the variance stayed roughly constant over time. As shown in Figure 2, the stationarity after first order of differencing for both the temporality and seasonality suggested that d and D in the seasonal ARIMA $(p,d,q)(P,D,Q)_{12}$ would be 1 and 1, respectively. Hence, a SARIMA model of (p,1,q) $(P,1,Q)_{12}$ was selected as the basic structure ofthe candidate model. Next, we examined whether there was correlations between successive terms of this irregular component in order to make a predictive model for the SNCU monthly mortality rate. The auto-correlogram showed no spikes exceeded the significance bounds. For the partial correlogram, the partial auto correlations at lags 1 and 2 exceeded the significance bounds and were negative which slowly decreased in magnitude with increasing lag. The partial auto correlations tended to tail off to zero after lag 2.

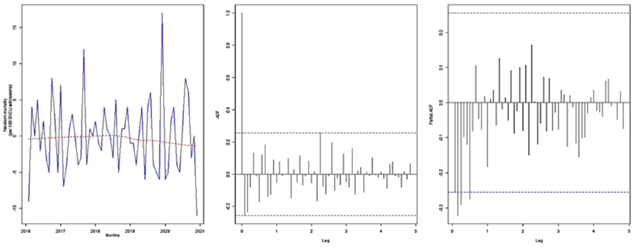

Figure 3: Transformed series with first order of temporal and seasonal differencing

3.3. Model estimation and diagnosis

Applying the “auto. arima” function we found the best possible model for the seasonal ARIMA model with statistically significant parameters. According to the goodness-of-fit test statistics, the seasonal ARIMA $(0,1,1)(1,1,1)^{11}$ model was confirmed to be the optimal model. The coefficient associated with the AR component (1) wassar1 = -0.0798 (SE = 0.3550), the coefficients associated with the MA component (1) were ma1 =–0.9477 (SE = 0.1886) and sma1 = -0.7566 (SE = 0.0.6909). The lowest AIC and BIC values of this model were 296.44and 303.84, respectively.

The Ljung–Box test (Q statistic 10.437 and P-value 0.316) suggested that there was no significant autocorrelation between residuals at different lag times and the residuals were white noise. This was further corroborated by plotting the ACF of the residuals. Form Figure 4, the ACF of the model showed that the auto correlations of the residual were all close to zero which meant they were uncorrelated, hence the residual assumed mean of zero and constant variance. A plot of the residual histogram showed no volatility clustering and so assumed the residuals were homoscedastic. The model explained 56.1% (stationary R^2)of the variance of the series.

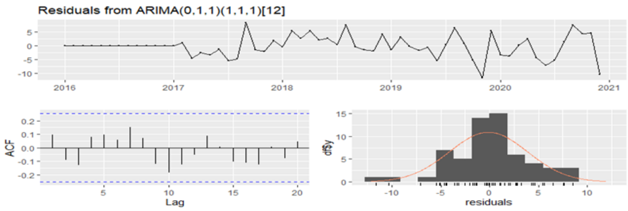

Figure 4: Correlogram, histogram and density plots for model diagnosis

The Q-Q plot in Figure 5 showed the model residuals were normally distributed as most of the residual points were close to the normal line. The Shapiro-Wilk statistics for our time series was 0.96549. Null hypothesis for Shapiro-Wilk test is that the data follows normal distribution. The p-value for the test on the time series is 0.0925 indicating that the null hypothesis is accepted. Thus, the time series data are normally distributed. Thus, the selected model seasonal ARIMA (0,1,1)(1,1,1)[11] satisfied all the model assumptions.

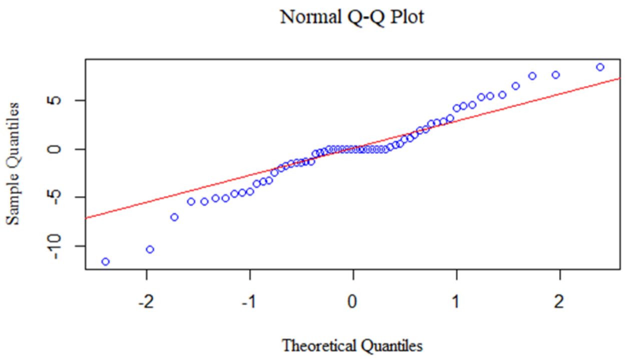

Figure 5: Q-Q plot for diagnosing normality of the distribution of residual errors

3.4. *Model forecasting using ARIMA (0,1,1)(1,1,1)[11]*

The monthly (January–December) forecast of SNCU admitted new-born mortality cases per 100 admissions for the year 2021 and 2022could range from 9 % to 35% with their respective 95% confidence interval. The monthly forecasted SNCU mortality depicted a minimal rise in the new-born death cases for the year 2022 as shown in the line of the shaded region in Figure 6.

Table 3: Monthly forecast of new-born deaths per 100 SNCU admissions in SLNMCH, 2021-2022

Year	Month	Point Forecast	95% CI	
			Lower Limit	Upper Limit
2021	Jan	23	14	33
2021	Feb	19	10	29
2021	Mar	18	9	28
2021	Apr	20	11	29
2021	May	22	12	31
2021	Jun	19	10	28
2021	Jul	19	10	28
2021	Aug	22	13	32
2021	Sep	23	13	32
2021	Oct	22	12	31
2021	Nov	21	11	30
2021	Dec	23	13	32
2022	Jan	25	15	35
2022	Feb	21	11	30
2022	Mar	20	10	30
2022	Apr	22	12	32
2022	May	23	13	33
2022	Jun	20	10	30
2022	Jul	20	10	30
2022	Aug	24	14	34
2022	Sep	25	15	35
2022	Oct	24	14	33
2022	Nov	23	13	33
2022	Dec	24	14	34

The morality cases showed a similar seasonality in year 2021, with a peakin the month of January similar to previous years with an estimated 23%of total admiited cases (95% CI 14–33). For the year 2022,it was no different with 25% of total admissions (95% CI 10-35).

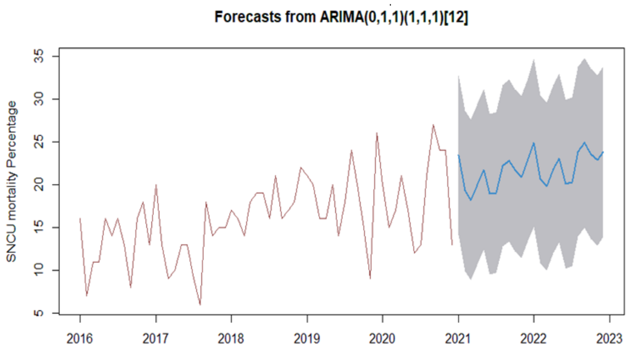

Figure 6: Forecasted values for the year 2021 and 2022

4. Discussion

ARIMA is a useful tool for interpreting surveillance data for disease prevention and control. For mortality forecasting ARIMA models are considered to be one of the most appropriate tools. Our study provides an example of a seasonal ARIMA model to forecast the inpatient newborn mortality rate per 100 admissions in the SNCU. Although there are few studies available in India forecasting neoantal mortality by using these models,[12] to the best of our knowledge such analysis taking the real-time data of inpatient newborn mortality has not been undertaken anywhere in an Indian context before.

Bydecomposing the mortly mortality rate among the newborns admitted in SNCU of the SLNMCH, we found that the monthly occurrence of mortality sequence had obvious trends and seasonality.It seeemed to be low in July and peak in December to January. However, the mortality rate has remained relatively consistent after 2017 when a significant reduction was observed. Post 2017, there was a very low up ward pattern of temporal trend of monthly mortality until 2020. Advanced care available for the sicknewborns in the SNCU though had kept the monthly rate of newborn deaths under control, it, however, needed to give itself a little push to prevent the deaths rate to show further increase after 2017. This findingis consistent with Thompson et al which found that greater resources for neonatal care alone could not result in optimal neonatal health outcomes,[11] and probably equal focus on sociodemographic factors is also crucial.[13] Therefore, community-based interventions need to be further strengthened in those areas and populations with larger contribution to the SNCU admission load.

We also found that in late winter period of January month, there was more SNCU deaths in comparison to other months. High frequencies of neonatal morbidities are known to be significantly associated with seasonal variations.[14] Scientific evidences suggest that, winter newborn babies in developing countries are predisposed to several infections such as sepsis during the winter period.[15] Likewise,cold season is likely to increase the risk of hypothermia which has been recognized as a contributing cause of mortality and morbidity among both low birth weight and normal weight babies.[16] Another study conducted in India showed that respiratory distress, hypothermia, skin infection and umbilical infection morbidities among the newborn babies were higher in winter.[17] The newborns' increased susceptibility to various infections in winter season and resulting admission overload could make the neonatologists and staffs in the SNCUs face a greater challenge for timely diagnosis and management of admitted sick neonates,[18] which is likely to adversely impact the SNCU admission outcome as seen in our study. To address such challenges and minimise deaths inside the SNCU, ensuring the health system's readiness especiallyon three critical components-infrastructure, human resources, and procurement of medicines and medical equipment is of paramount importance.[19] Periodical examination and forecasting of SNCU data in the light of local parameters such as delivery load, SNCU admission load, prevalence of low-birth-weight babies and average length of stay could go a long way in making sure the system's readiness as mentioned earlier.

The results of our best-fit predictive model SARIMA (0, 1, 1) (1, 1, 1)12 shows the 95% CIs of the forecast values in this paper containing all of the real time data, which is a good match between the observed value and the fitted value. The occurrence of mortality in 2021and 2022 peaked from December to January but showed a decreasing trend after June, as seen in the previous years. Thus far, in terms of inpatient mortality forecast, the SARIMA model has good results in predicting monthly death rate of the newborn babies admitted in the SNCU. This study can well be replicated in other SNCUs to have a good short-term predictive result. It can provide early warning to the clinicians and neonatologists for formulation of appropriate plans and clinical management of sick newborns accordingly to increase their survival rate in the SNCUs.

Finally, despite applying widely used statistical models and accurate forecasting, our study has several limitations which should be considered when interpreting our findings. Since, secondary database was used for our analysis, there could be chances of minor capture errors at the source itself. TheSARIMA (0,11) (1,1,1)12 model did forecast future mortalityof newborns reliably, but only for a short period. We only considered variations in mortality with time and did not take into account the other impacting factors such as age, gender, socio-economy, environment, and politics. Thus, any structural changes could not be analysed. Since it was a single-centre study in a tertiary care hospital, the results cannot be generalized to other facilities with similar units of care, however, its methodology and analyses could be used to improve decision-making, proper allocation and use of health resources to further reduce the rate of deaths in the SNCU sexisted in other health facilities.

5. Conclusions

The forecast based on seasonal ARIMA modelling of monthly admission and mortality data of newborns admitted in the SNCU indicates a slightly upward trend in monthly mortality rate with a peak in January. This might continue till 2022, even though any surge seems to be unlikely. The key points for future consideration regarding newborn care include management of infections, birth asphyxia and preterm/low birth weight among newborns along with well-designed, community specific preventive measures by taking the socio-economic factors into account. Our study suggests that the seasonal ARIMA models constructed and evaluated with their respective prediction intervals can serve as an adequate tool for future monitoring of the SNCU deaths.

6. Source of Funding

None.

7. Conflict of Interest

None.

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