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Predicting sales during COVID using Machine Learning Techniques

Sagar Vishwakarma[1], Dr. S. C. Solanki[2]
[1]M.E scholar, Mechanical Engineering(Industrial Engineering and Management),Ujjain Engineering College, Ujjain
[2]Professor, mechanical Engineering, Ujjain Engineering College, Ujjain

Abstract: The purpose of this study is to compare VAR, ARIMA and SARIMA methods in an attempt to generate sales forecasting in Store xyz with high accuracy. This study will compare the results of sales forecasting with time series forecasting model of Vector Auto Regression (VAR), Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA). VAR or ARIMA model still accurate when the time series data is only in a short period, these models is accurate on short period forecasting but less accurate on long period forecasting. Meanwhile Seasonal Autoregressive Integrate Moving Average is more accurate on forecasting seasonal time series data, either it's pattern shows trend or not all three models are compared with forecasting data showing seasonal patterns. The data used is the data of super mart retail store, sales from 2017 to 2022. Accuracy level of each model is measured by comparing the percentage of forecasting value with the actual value. This value is called Mean Absolute Deviation (MAD). Based on the comparison result, the best model with the smallest MAD value is SARIMA model (0,1,0) (0,1,0)12 with MAD value 0.122. From the comparison results can be concluded that the SARIMA model is optimal to be used as a model for further forecasting
Keywords: Machine Learning, sales prediction, ARIMA, SARIMA, VAR, PYTHON, Anaconda navigator, Jupiter notebook.

I. INTRODUCTION

In the strip mall business, it is commonly known that consumer demand is normally very volatile. Before and after the COVID pandemic I have seen a lot of difference, In fact consumer's choice of mart is generally based on price. In this case, to overcome this condition, the managerial store tried to forecast the demand and reduce the price by reducing the cost of maintance or by buying goods directly from the manufacturer or the first party. Where machine learning is an innovative way for sales or demand forecasting. It is one of the effective solutions to prepare a complete data set for eradication of different challenging situations in the organization. In Machine learning system, the uses of different models such as VAR (multivariate forecasting algorithm), ARIMA (non-seasonal time series data), SARIMA (seasonal or non-seasonal time series data) helps to introduce different algorithms to understand the accuracy of business. last few decades for the maintenance of the organization's potentiality in the organization. The uses of artificial intelligence and computer algorithms help to create different programs for autonomous activities in the organization. where python and Jupyter are two innovative software that has been used for sales prediction

The aim of this research paper is to determine the impact of machine learning in sales prediction for the enhancement of business profitability. An authentic data preparation process is essential to determine the sales rate in the same year. The machine learning process is important for the vision of future sales revenues to determine the mart profitability. Moreover, this process is required to generate innovative sales management strategies for future performances .

II. LITERATURE REVIEW

In 2021, DontiReddy et al. [1] discussed about the machine learning is an effective way for sales forecasting. They Implement the Jupiter and Python are two innovative models for introducing different algorithms for secured business profitability. The different models, such as GARCH, SARIMA, SARIMAX helped to promote business profitability for the management. In 2020, Purvika Bajaj et al. [2] discussed about the dimension for predicting the future sales of Big Mart Companies keeping in view the sales of previous years. A comprehensive study of sales prediction is done using Machine Learning models such as Linear Regression, K-Neighbors Regressor, XGBoost Regressor and Random Forest Regressor. In the paper The prediction includes data parameters such as item weight, item fat content, item visibility, item type, item MRP, outlet establishment year, outlet size and outlet location type etc. In 2021, Ashutosh Kumar Dubeya et al. [3] g. discussed about data analytics presented on the collected smart meter measurement and then predicting the energy consumption on a daily basis using ARIMA, seasonal ARIMA, SARIMA and LSTM. The results indicate the feasible method for forecasting energy consumption.

In 2021, Prabhat sharma et al. this research shows in the tough time of covid-19, what will be the sales trend for various automobile companies will the graph go downward or upward, by various machine learning techniques and the result is project successfully meet its aim. In 2020, Ms. Rachana Mohite et al. [4] . This research discussed the comparison between market basket analysis by using apriori algorithm and market basket analysis without using algorithm in creating rule to generate the new knowledge with the help of these concepts can easily setup his retail shop and can develop the business in future. In 2020, Jiantao Zhao et al. [5] in this paper discussed about combination model is to use prophet and SARIMA model to forecast the sales data respectively, and then weighted combination to get the final forecast results, and the result is combination model which is weighted by two single models is optimal. In 2018, G A N Pongdatu et al. [6] In this study they will compare the results of sales forecasting with time series forecasting model of Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt Winter's Exponential Smoothing method and the result is SARIMA model (1,1,0) (0,1,0)12 . With accurate forecasting results or estimates.

III. DATA AND ANALYSIS

A. Var (Vector Auto Regression)

Vector auto regression (VAR) is a multivariate forecasting algorithm that is used when two or more time series influence each other**.** We set the first estimation period to be 2022:5 and forecast with each VAR recursively, applying 1,6 and 12-month ahead forecasts in each single month of the sample 2017:12 through 2021:12 When factors are extracted from the 55 predictor variables, these are estimated using the same sample period as the VAR

Forecasts are calculated at the end of each sample period,

T = 2017 :12,..., 2022 :05

```
In [2]: df=pd.read_csv('E:/sagar vishwakarma/SARIMA/5 YEAR 2017-2022/book2.csv')

In [3]: df.head()

Out[3]:
```

	Month	GROCCERY	OTHER
0	01-01-2017	8.42	9.70
1	01-02-2017	10.27	8.42
2	01-03-2017	11.18	7.35
3	01-04-2017	11.72	7.52
4	01-05-2017	12.01	6.54

Here we will predict both ‘grocery’ and ‘other’. If we plot them, we can see both will be showing similar trends.

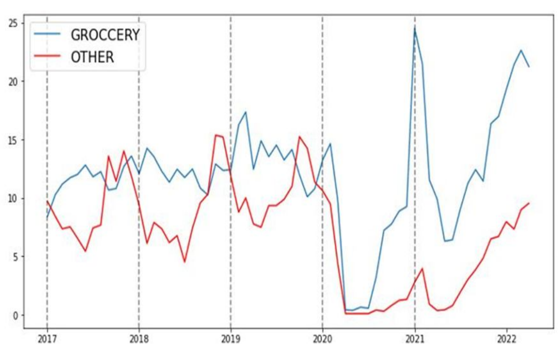

Fig. 1 actual sales

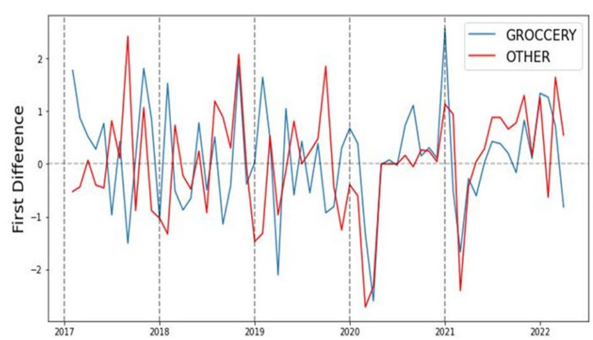

Fig.2 diffrence in sales

VAR Formula for multivariate forecasting.

$$y_{1,t} = c_1 + \phi_{11,1} y_{1,t-1} + \phi_{12,1} y_{2,t-1} + e_{1,t}$$
$$y_{2,t} = c_2 + \phi_{21,1} y_{1,t-1} + \phi_{22,1} y_{2,t-1} + e_{2,t},$$

The VAR model has shown some limitation which are as follows,
Only time series data can be used
It shows error in long time seasonal forecasting

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B. ARIMA (Autoregressive Integrated Moving Average)

Our dataset contained selling data for grocery and other (non-essential items), spanning over five years and 41248 order lines. For all product, we used the sales per month

```
In [50]: df.head()
Out[50]:
```

	Month	sales in lakh
0	2017-01	18.12
1	2017-02	18.69
2	2017-03	18.53
3	2017-04	19.24
4	2017-05	18.55

Pre-processing has to take place in order to convert data to the appropriate format for the ARIMA model. During pre-processing the following steps are taken:

1) Sales data are ordered by date time
2) Data are reduced to one-dimensional information, so extra information like average price and other product attributes are removed.

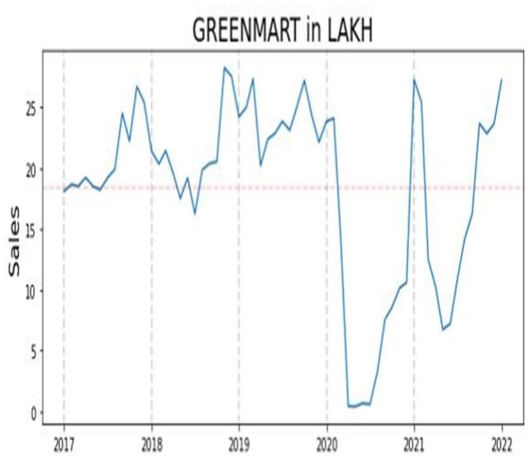

Fig. 3 actual sales

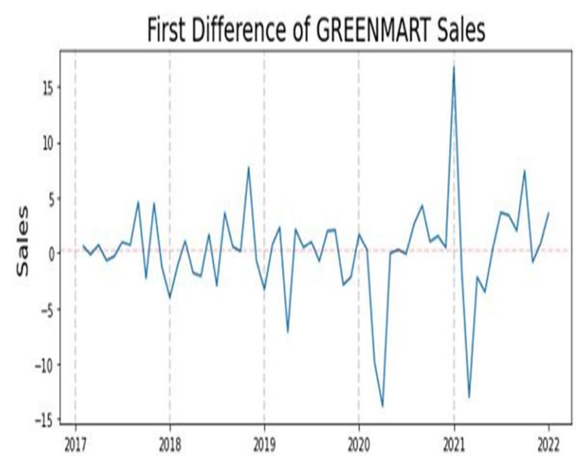

Fig. 4 difference in sales

ARIMA forecasting formula

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

where:

yt−1...yt−p = are the selling quantities where:

et−1...et−q are the moving average parameters.

φ1...φp and θ1...θq are the trained autoregressive parameters and moving average parameters

- Limitation with ARIMA model
    1. It shows poorer result during long forecast
    2. Cannot be used for time series seasonal data

C. SARIMA (Seasonal Autoregressive Integrated Moving Average)

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is ARIMA

p d q P D Q S (, ,)×(, ,)

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with p = non-seasonal AR order,
d = non-seasonal differencing.
q = non-seasonal MA order.
P = seasonal AR order.
D = seasonal differencing.
Q = seasonal MA order.
S = time span of repeating seasonal pattern.

This study collected time series data of green mart and the data is 55 month period from January 2017 to march 2022. The data was obtained from the sales in the mart. The original data is plotted as presented.

In [55]:
```
df.tail()
```

Out[55]:

	Month	Sales
58	2021-11	22.85
59	2021-12	23.66
60	2022-01	27.22
61	2022-02	28.74
62	2022-03	31.62

The orginal data plotted graph is shown in Figure.5

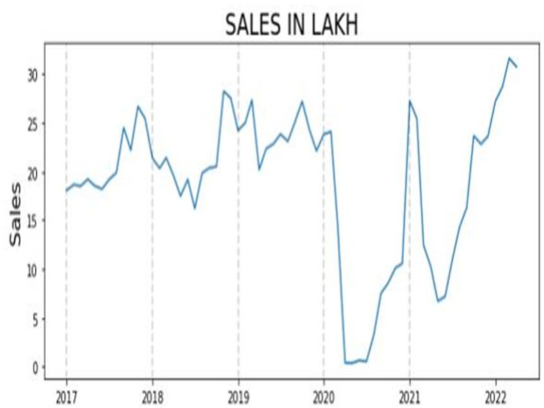

Fig. 5 actual sales

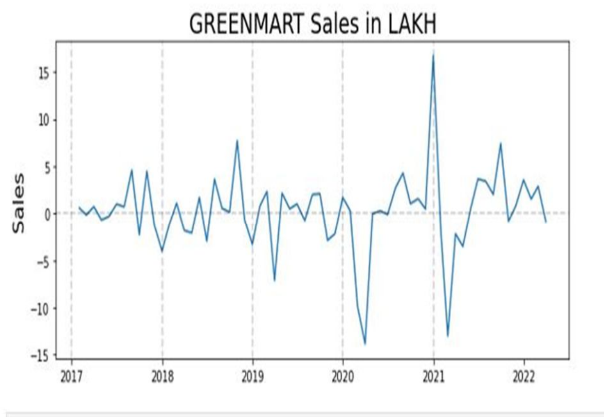

Fig. 6 sales fluctuation

Since time series plot of the historical data exhibited the seasonal variations which present similar trend every year, then SARIMA was chosen as the appropriate approach to develop a model prediction.

SARIMA formula used for forecasting
The general form of seasonal model SARIMA(p, d, q) (P, D, Q)s is given by:

$$s\ D\ d\ s\ P\ s\ t\ Q\ t\ \Phi\ \phi\ \nabla\ \nabla = \Theta\ \theta\ (B\ )\ (B)\ x\ (B\ )\ (B)w$$

IV. RESULT AND DISCUSSION

A. VAR

In this method, the selected months sales separated for the period of Jan 20017 to march 2022, have been used as the basis on daily scale. But to get the maximum explorative information and reduction of volatility, the data have been transformed to the monthly scale. Data from January 2017 to march 2022 are used in-sample estimation and from April 2022 to December 2022 are used for the out-of-sample forecasting purposes.

From Figure 5, it has been observed that each study variable, except grocery and other non-essential product and the forecasting result as shown below.

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Month	GROCCERY	OTHER	GROCCERY_annual_vol	OTHER_annual_vol	GROCCERY_month_avg	OTHER_month_avg
2017-02-01	1.771532	-0.524707	0.214149	0.560100	1.012638	-0.577486
2017-03-01	0.871402	-0.438622	0.214149	0.560100	-0.241141	-0.441414
2017-04-01	0.517096	0.069688	0.214149	0.560100	-1.025799	-0.553271
2017-05-01	0.277700	-0.401729	0.214149	0.560100	0.012697	-0.191163
2017-06-01	0.766068	-0.455019	0.214149	0.560100	0.209811	0.175312
...	...	...	...	...	...	...
2021-12-01	0.102468	0.157016	1.220766	0.292455	0.195611	-0.401019
2022-01-01	1.337081	1.256625	0.351213	0.232044	0.709606	-0.101936
2022-02-01	1.261177	-0.633260	0.351213	0.232044	1.012638	-0.577486
2022-03-01	0.712332	1.642518	0.351213	0.232044	-0.241141	-0.441414
2022-04-01	-0.817430	0.544208	0.351213	0.232044	-1.025799	-0.553271

Tab 1. Annual volume and monthly average

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Tue, 12, Apr, 2022
Time:                     08:47:01
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                    1.50165
Nobs:                     50.0000    HQIC:                  0.223027
Log likelihood:          -73.8106    FPE:                   0.735865
AIC:                    -0.563331    Det(Omega_mle):        0.310282
--------------------------------------------------------------------
```

Where:

OLS = Ordinary least squares
BIC = Significant autocorrelation for Consumption
HQIC = Estimate of the deviance of the model fit
FPE = The function returns information criteria

In the result the standard error is 45% for grocery and 41% for other

B. ARIMA

Here, the data is predicted from the taken dataset by first converting the data into stationary. To make stationary we have to find the difference on mean of Number of sales. The final graph is plotted for the best fit ARIMA model of number of sales next following years. The following is the output with forecasted values of grocery sales in blue. Also, the expected error is displayed with orange lines on either side of predicted blue line.

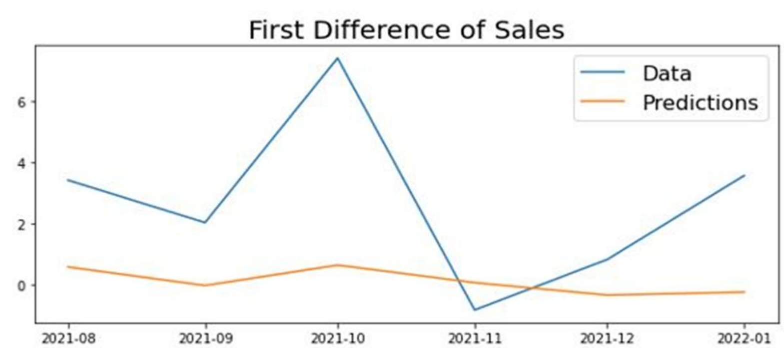

Fig. 7 forecast error

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Volume 10 Issue IV Apr 2022- Available at www.ijraset.com

Dep. Variable:	sales in lakh	No. Observations:	54
Model:	ARMA(4, 1)	Log Likelihood	-152.461
Method:	css-mle	S.D. of innovations	3.972
Date:	Tue, 12 Apr 2022	AIC	318.921
Time:	06:58:27	BIC	332.844
Sample:	02-01-2017 - 07-01-2021	HQIC	324.291

According to the result the standard error is shown in the table

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.2074	0.119	-1.737	0.082	-0.441	0.027
ar.L1.sales in lakh	1.0255	0.133	7.714	0.000	0.765	1.286
ar.L2.sales in lakh	-0.3784	0.188	-2.013	0.044	-0.747	-0.010
ar.L3.sales in lakh	0.2813	0.186	1.512	0.130	-0.083	0.646
ar.L4.sales in lakh	-0.1933	0.131	-1.471	0.141	-0.451	0.064
ma.L1.sales in lakh	-1.0000	0.063	-15.770	0.000	-1.124	-0.876

Roots

Tab. 2 between coefficient and standard error

	Real	Imaginary	Modulus	Frequency
AR.1	1.2641	-0.4557j	1.3437	-0.0551
AR.2	1.2641	+0.4557j	1.3437	0.0551
AR.3	-0.5366	-1.6052j	1.6925	-0.3013
AR.4	-0.5366	+1.6052j	1.6925	0.3013
MA.1	1.0000	+0.0000j	1.0000	0.0000

Root Mean Squared Error: 35%

C. SARIMA

-The final SARIMA model (0,1,0)(1,0,1)12 was used to forecast the values of the 55 months-ahead are presented in Table 2. While, the whole forecasting plot is shown in Fig. 8

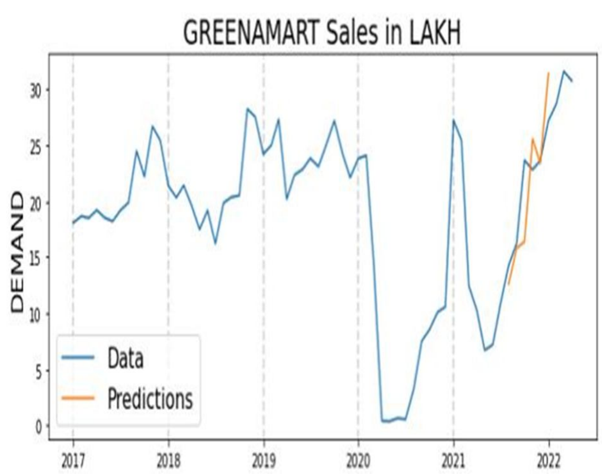

Fig.8 demand

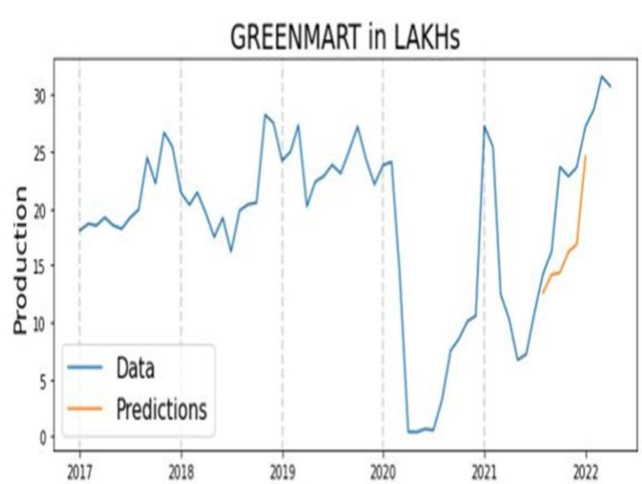

Fig.9 production

1) Error Check

The accuracy of the forecasting can be evaluated using error measures. It is achieved by comparing the original data and the forecast values In this paper, Mean Absolute Percentage Error was used as the error measure. The result showed MAPE value for the selected model was 12.2%. Thus, the empirical result indicated that the model was able to accurately represent the covid sales historical dataset

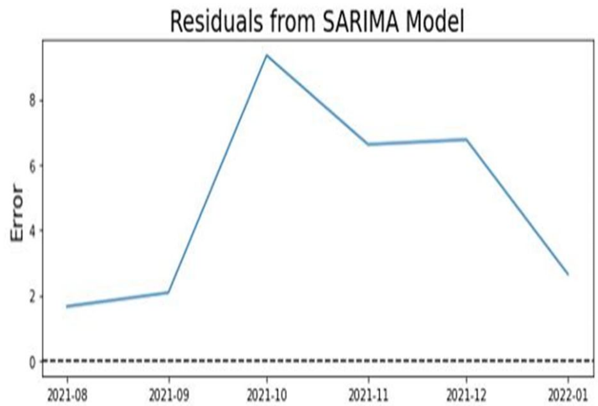

Fig. 10 Residual error

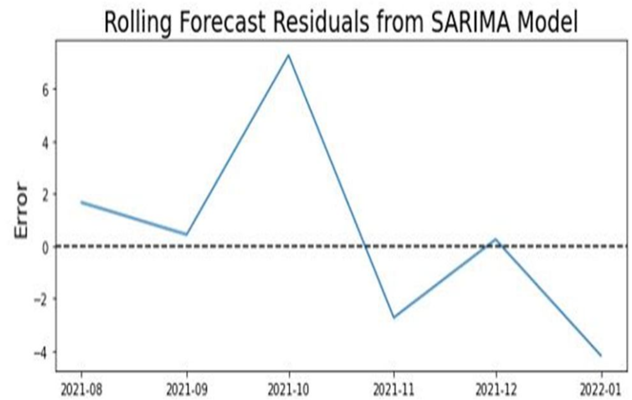

Fig. 11 Rolling forecast residuals error

Different model fit for check the feasible result as shown below

```
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

for param in pdq:
    for sales_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(train,
                                            order=param,
                                            seasonal_order=param_seasonal,
                                            enforce_stationarity=False,
                                            enforce_invertibility=False)

            results = mod.fit()

            print('ARIMA{}x{}12 - AIC:{} - BIC:{}'.format(param,
                                                         sales_seasonal,
                                                         results.aic,
                                                         results.bic))


        except:
            continue
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:232.02550567294801 - BIC:236.22909781793447
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ARIMA(1, 1, 1)x(1, 0, 0, 12)12 - AIC:181.10721895598476 - BIC:187.7682415068608
ARIMA(1, 1, 1)x(1, 0, 1, 12)12 - AIC:181.10721895598476 - BIC:187.7682415068608
ARIMA(1, 1, 1)x(1, 1, 0, 12)12 - AIC:181.10721895598476 - BIC:187.7682415068608
ARIMA(1, 1, 1)x(1, 1, 1, 12)12 - AIC:181.10721895598476 - BIC:187.7682415068608
```

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                        sales in lakh   No. Observations:                 55
Model:             SARIMAX(0, 1, 0)x(1, 0, [1], 12)   Log Likelihood                -153.056
Date:                              Tue, 12 Apr 2022   AIC                            312.112
Time:                                      06:43:10   BIC                            318.079
Sample:                                  01-01-2017   HQIC                           314.413
                                       - 07-01-2021
Covariance Type:                                opg
==============================================================================


                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.S.L12       0.0675      0.615      0.110      0.913      -1.138       1.273
ma.S.L12       0.4238      0.656      0.646      0.518      -0.862       1.710
sigma2        16.0121      2.201      7.275      0.000      11.699      20.326
===================================================================================
Ljung-Box (L1) (Q):                   0.19   Jarque-Bera (JB):                32.25
Prob(Q):                              0.66   Prob(JB):                         0.00
Heteroskedasticity (H):               7.85   Skew:                             0.21
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.76
===================================================================================
```

Mean Absolute Percent Error: 0.1222
Root Mean Squared Error: 3.67004542635048

V. CONCLUSION

In our case study, we considered different machine-learning approaches for time series forecasting.. The use of SARIMA algorithm for sales forecasting can often give us better results compared to ARIMA and VAR. in this research paper we use 5 year data in which both seasonal and non-seasonal data set are present. The aim of this research paper finding the optimal method between them. The uses of different algorithm and software made huge changes in the conduction of effective resource plans in the organization. A secondary data collection method has been used to identify the impact of machine learning . by the application of this method we were able to get mean standard error between 12 to 12.5 % in other models this error get so high

The model can hence provide following benefits to the greenmart company if the results of this research paper are adopted.

1) Accurate sales prediction before upcoming pandemic because we all know that what decision get taken by the government
2) Stock maintenance get easy
3) It helps to increases customer satisfaction because demand and sale are both interconnected to each

REFERENCES

[1] DontiReddy Sai Rakesh Reddy, Katanguru Shreya Reddy, S. Namrata Ravindra B. Sai Sahithi., (2021), " Prediction and Forecasting of Sales Using Machine Learning Approach " International Research Journal of Engineering and Technology (IRJET), vol. 8, pp.377

[2] Purvika Baja1, Renesa Ray, Shivani Shedge, Shravani Vidhate, Prof. Dr. Nikhilkumar Shardoor., (2020) "SALES PREDICTION USING MACHINE LEARNING ALGORITHMS", "International Research Journal of Engineering and Technology (IRJET), vol. 7 issue 6 pp 380

[3] Ashutosh Kumar Dubeya, Abhishek Kumara, Vicente García-Díazb, Arpit Kumar Sharmac, Kishan Kanhaiyad., (2021) "Study and analysis of SARIMA and

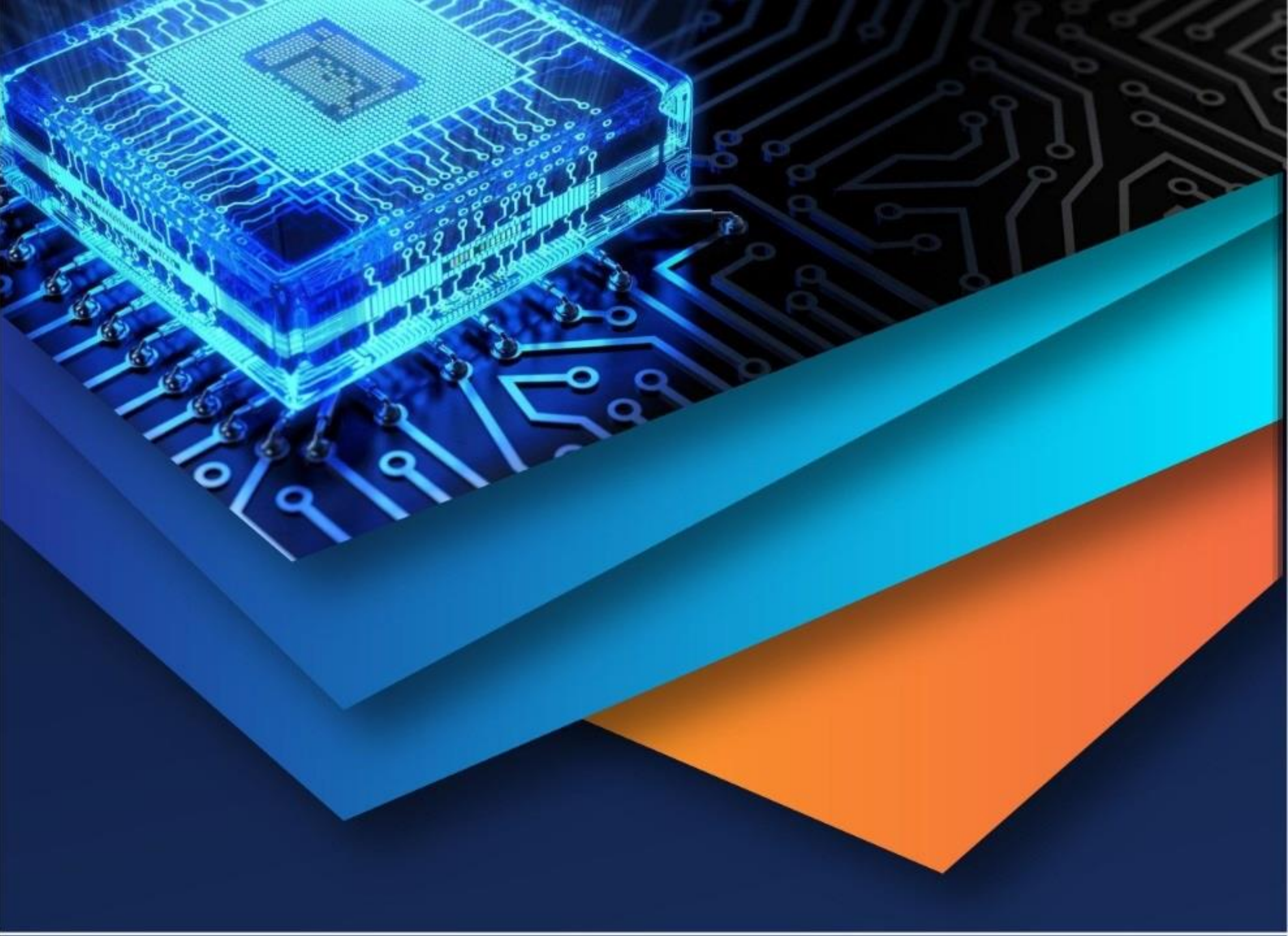
LSTM in forecasting time series data" "ELSEVIER" , vol.47

[4] Ms. Rachana Mohite, Mr. Kevin Shah, Mr. Gaurav Kolhe, Mrs. Madhura Mokashi, Mrs. Prajakta Rokade (2020) "Sales Prediction of Market using Machine Learning" "International Journal of Engineering Research & Technology (IJERT)" vol.9

[5] Jiantao Zhao, Chunwei Zhang (2020) "Research on Sales Forecast Based on Prophet-SARIMA Combination Model" "Journal of Physics: Conference Series" doi:10.1088/1742-6596/1616/1/012069

[6] G A N Pongdatu and Y H Putra (2018) "Seasonal Time Series Forecasting using SARIMA and Holt Winter's Exponential Smoothing" "IOP Conference Series: Materials Science and Engineering" doi: :10.1088/1757-899X/407/1/012153

[7] M'Amanja, Daniel; Lloyd, Tim; Morrissey, Oliver (2005) "Fiscal aggregates, aid and growth in Kenya: A vector autoregressive (VAR) analysis" "The University of Nottingham, Centre for Research in Economic Development and International Trade (CREDIT)" vol. 05.07



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