# Rose Wine Sales Forecast

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# 1. DATA OVERVIEW

## CONTEXT

As an analyst at ABC Estate Wines, we are presented with historical data encompassing the sales of different types of wines throughout the 20th century. These datasets originate from the same company but represent sales figures for distinct wine varieties. Our objective is to delve into the data, analyse trends, patterns, and factors influencing wine sales over the course of the century. By leveraging data analytics and forecasting techniques, we aim to gain actionable insights that can inform strategic decision-making and optimize sales strategies for the future.

## OBJECTIVE

The primary objective of this project is to analyse and forecast wine sales trends for the 20th century based on historical data provided by ABC Estate Wines. We aim to equip ABC Estate Wines with the necessary insights and foresight to enhance sales performance, capitalize on emerging market opportunities, and maintain a competitive edge in the wine industry.

- Shape: This dataset has 185 entries with dates ranging from Jan 1980 to July 1995. After missing value treatment, there are 187 entries.

- Basic Info:

**Fig.1 Basic info**

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 187 entries, 1980-01-31 to 1995-07-31
Freq: M
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Rose    187 non-null    float64
dtypes: float64(1)
memory usage: 2.9 KB
```

- First Few rows:

**Fig.2 First 5 rows**

| | Rose |
|---|---|
| **1980-01-31** | 112.0 |
| **1980-02-29** | 118.0 |
| **1980-03-31** | 129.0 |
| **1980-04-30** | 99.0 |
| **1980-05-31** | 116.0 |

- Plotting the Time Series:

**Fig.3 Time Series Plot (Before Missing value treatment)**

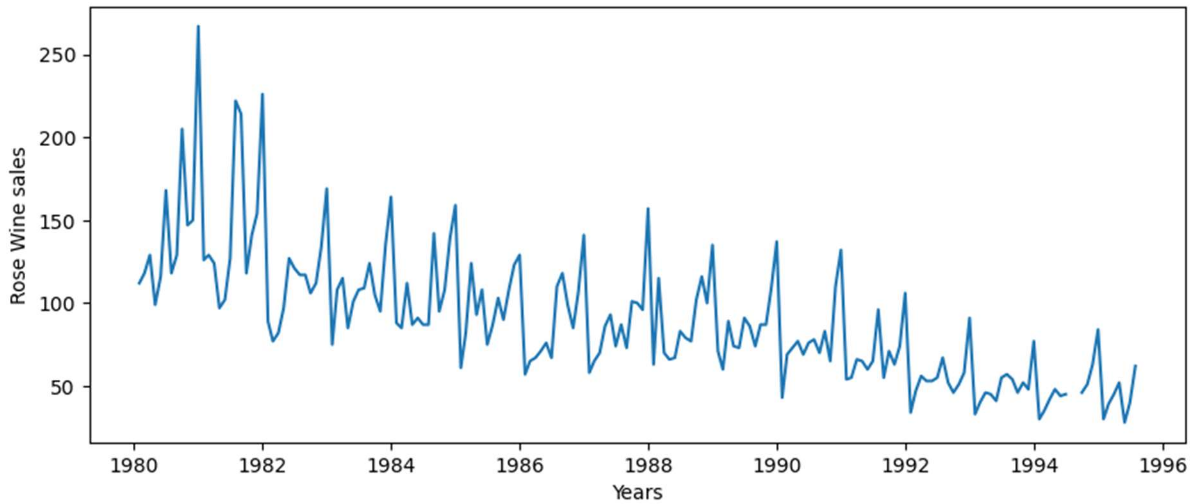
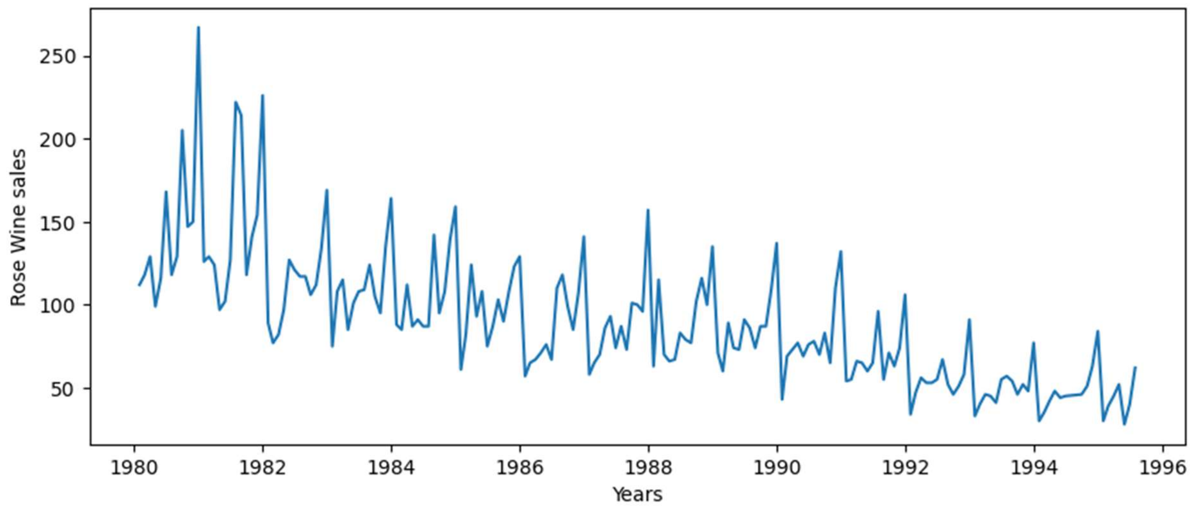



**Fig.4 Time Series Plot (After Missing value treatment)**



# 2. EXPLORATORY DATA ANALYSIS

## 2.1 TIME SERIES DATA PLOTS:

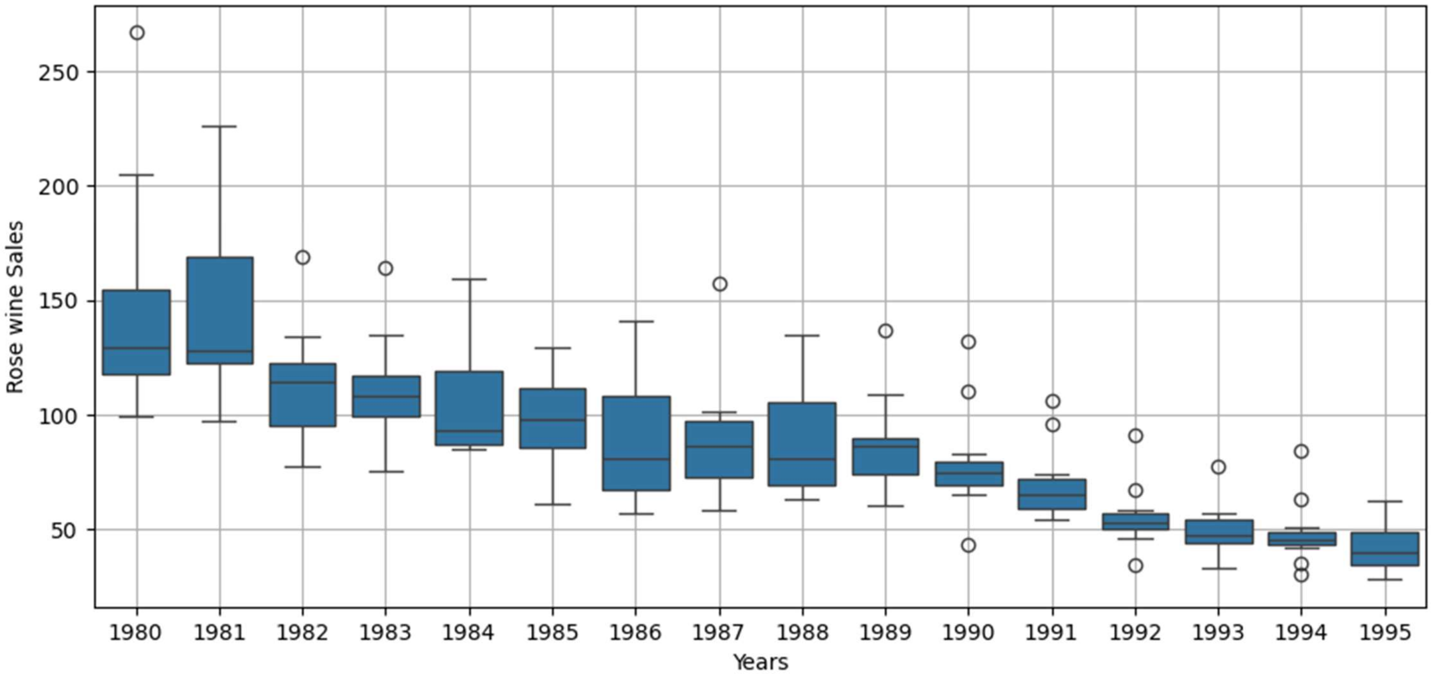
**Fig.5 Numerical Statistics**

| | Rose |
|---|---|
| **count** | 187.000000 |
| **mean** | 89.914439 |
| **std** | 39.238325 |
| **min** | 28.000000 |
| **25%** | 62.500000 |
| **50%** | 85.000000 |
| **75%** | 111.000000 |
| **max** | 267.000000 |

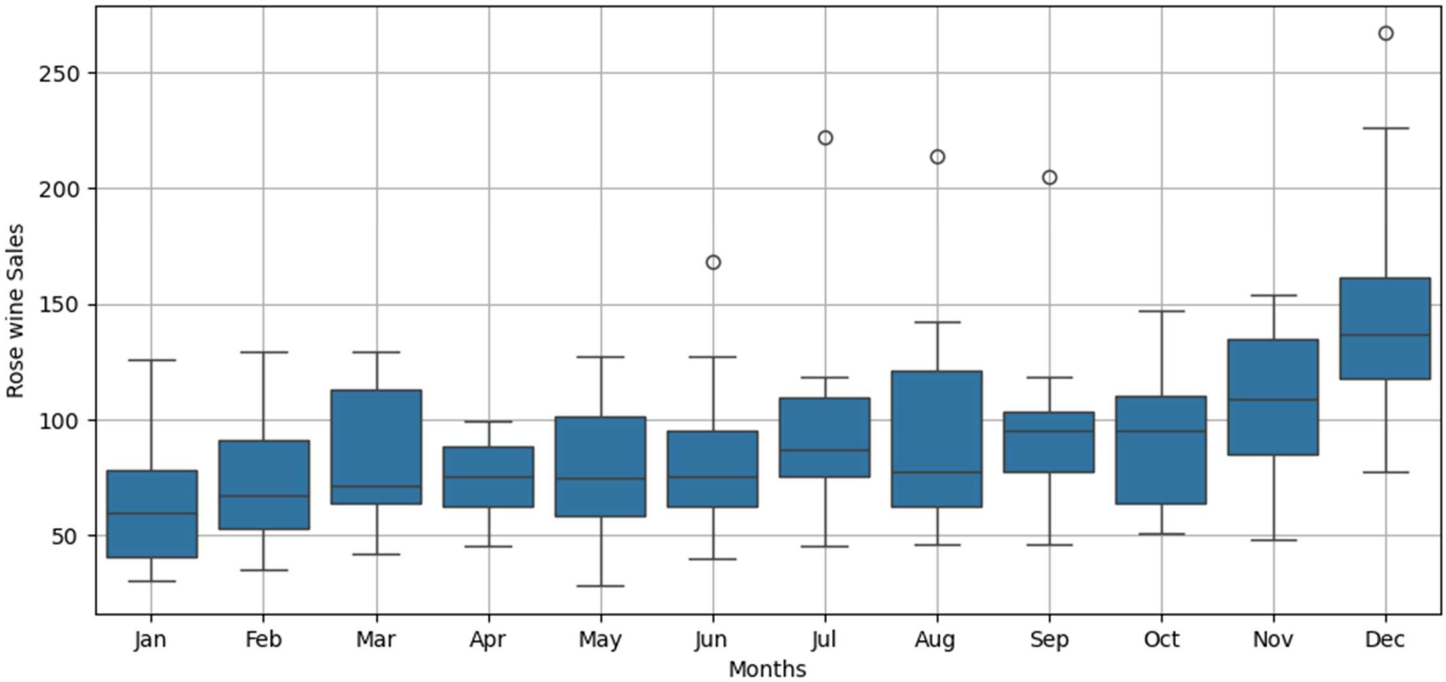
**Fig.6 Sales Pivot Table**

| | Apr | Aug | Dec | Feb | Jan | Jul | Jun | Mar | May | Nov | Oct | Sep |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1980** | 99.0 | 129.000000 | 267.0 | 118.0 | 112.0 | 118.000000 | 168.0 | 129.0 | 116.0 | 150.0 | 147.0 | 205.0 |
| **1981** | 97.0 | 214.000000 | 226.0 | 129.0 | 126.0 | 222.000000 | 127.0 | 124.0 | 102.0 | 154.0 | 141.0 | 118.0 |
| **1982** | 97.0 | 117.000000 | 169.0 | 77.0 | 89.0 | 117.000000 | 121.0 | 82.0 | 127.0 | 134.0 | 112.0 | 106.0 |
| **1983** | 85.0 | 124.000000 | 164.0 | 108.0 | 75.0 | 109.000000 | 108.0 | 115.0 | 101.0 | 135.0 | 95.0 | 105.0 |
| **1984** | 87.0 | 142.000000 | 159.0 | 85.0 | 88.0 | 87.000000 | 87.0 | 112.0 | 91.0 | 139.0 | 108.0 | 95.0 |
| **1985** | 93.0 | 103.000000 | 129.0 | 82.0 | 61.0 | 87.000000 | 75.0 | 124.0 | 108.0 | 123.0 | 108.0 | 90.0 |
| **1986** | 71.0 | 118.000000 | 141.0 | 65.0 | 57.0 | 110.000000 | 67.0 | 67.0 | 76.0 | 107.0 | 85.0 | 99.0 |
| **1987** | 86.0 | 73.000000 | 157.0 | 65.0 | 58.0 | 87.000000 | 74.0 | 70.0 | 93.0 | 96.0 | 100.0 | 101.0 |
| **1988** | 66.0 | 77.000000 | 135.0 | 115.0 | 63.0 | 79.000000 | 83.0 | 70.0 | 67.0 | 100.0 | 116.0 | 102.0 |
| **1989** | 74.0 | 74.000000 | 137.0 | 60.0 | 71.0 | 86.000000 | 91.0 | 89.0 | 73.0 | 109.0 | 87.0 | 87.0 |
| **1990** | 77.0 | 70.000000 | 132.0 | 69.0 | 43.0 | 78.000000 | 76.0 | 73.0 | 69.0 | 110.0 | 65.0 | 83.0 |
| **1991** | 65.0 | 55.000000 | 106.0 | 55.0 | 54.0 | 96.000000 | 65.0 | 66.0 | 60.0 | 74.0 | 63.0 | 71.0 |
| **1992** | 53.0 | 52.000000 | 91.0 | 47.0 | 34.0 | 67.000000 | 55.0 | 56.0 | 53.0 | 58.0 | 51.0 | 46.0 |
| **1993** | 45.0 | 54.000000 | 77.0 | 40.0 | 33.0 | 57.000000 | 55.0 | 46.0 | 41.0 | 48.0 | 52.0 | 46.0 |
| **1994** | 48.0 | 45.666667 | 84.0 | 35.0 | 30.0 | 45.333333 | 45.0 | 42.0 | 44.0 | 63.0 | 51.0 | 46.0 |
| **1995** | 52.0 | NaN | NaN | 39.0 | 30.0 | 62.000000 | 40.0 | 45.0 | 28.0 | NaN | NaN | NaN |

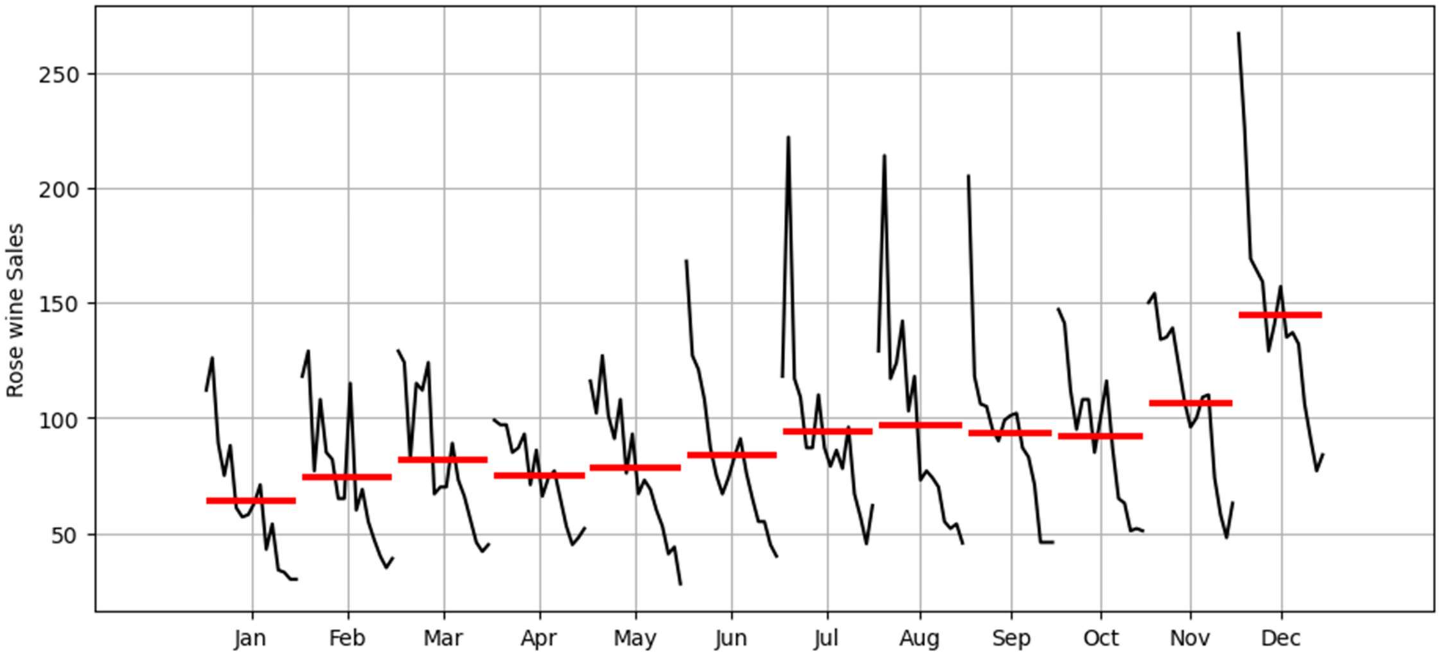
## Fig.7 Yearly boxplot



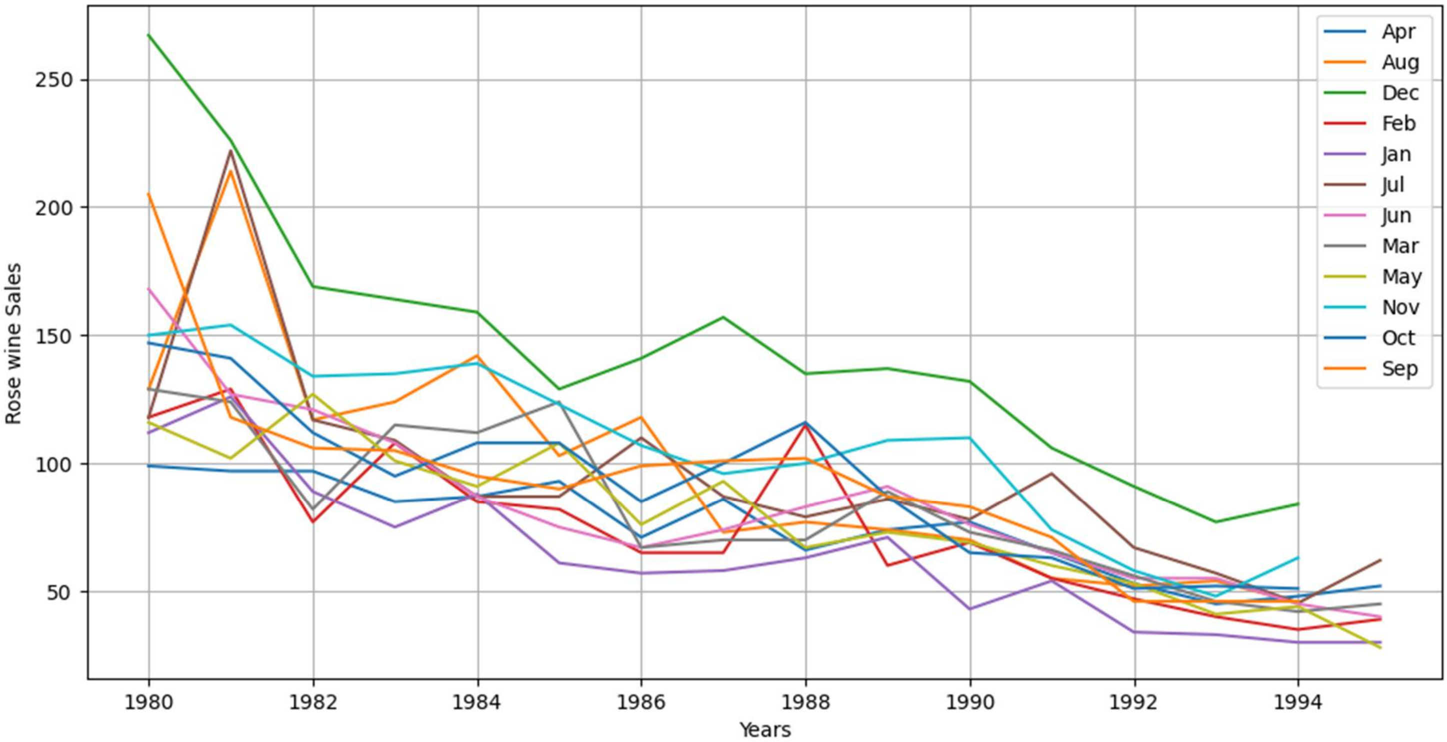

## Fig.8 Monthly boxplot



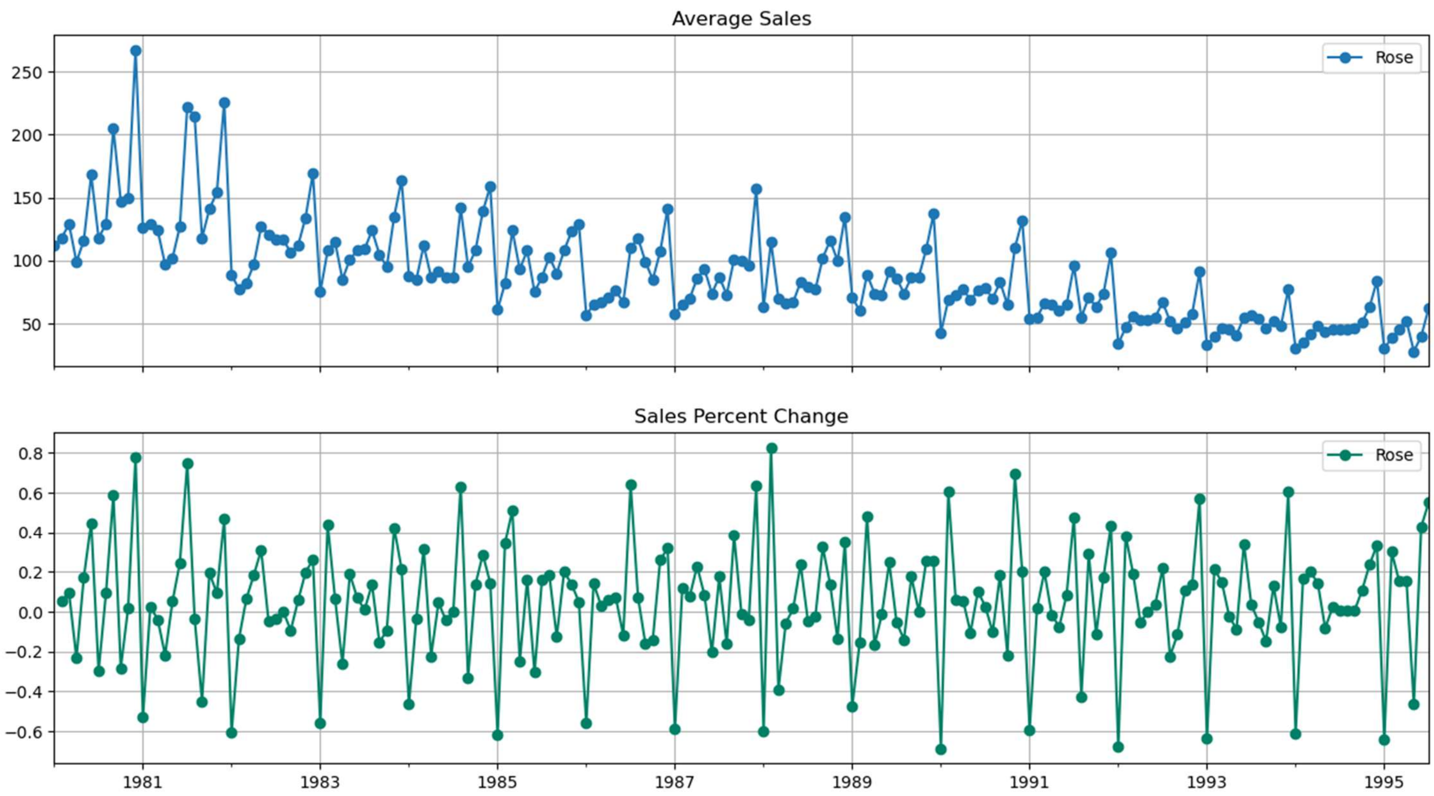
## Fig.9 Month plot



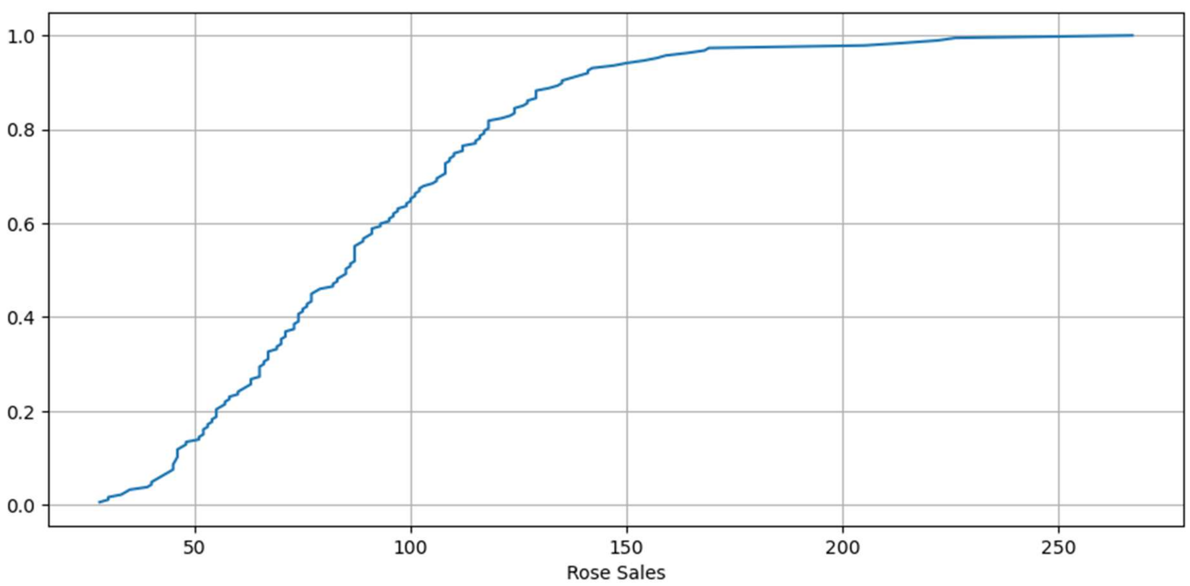

## Fig.10 Monthly sales across years (plot)



## Fig.11 Average Sales and Percent change



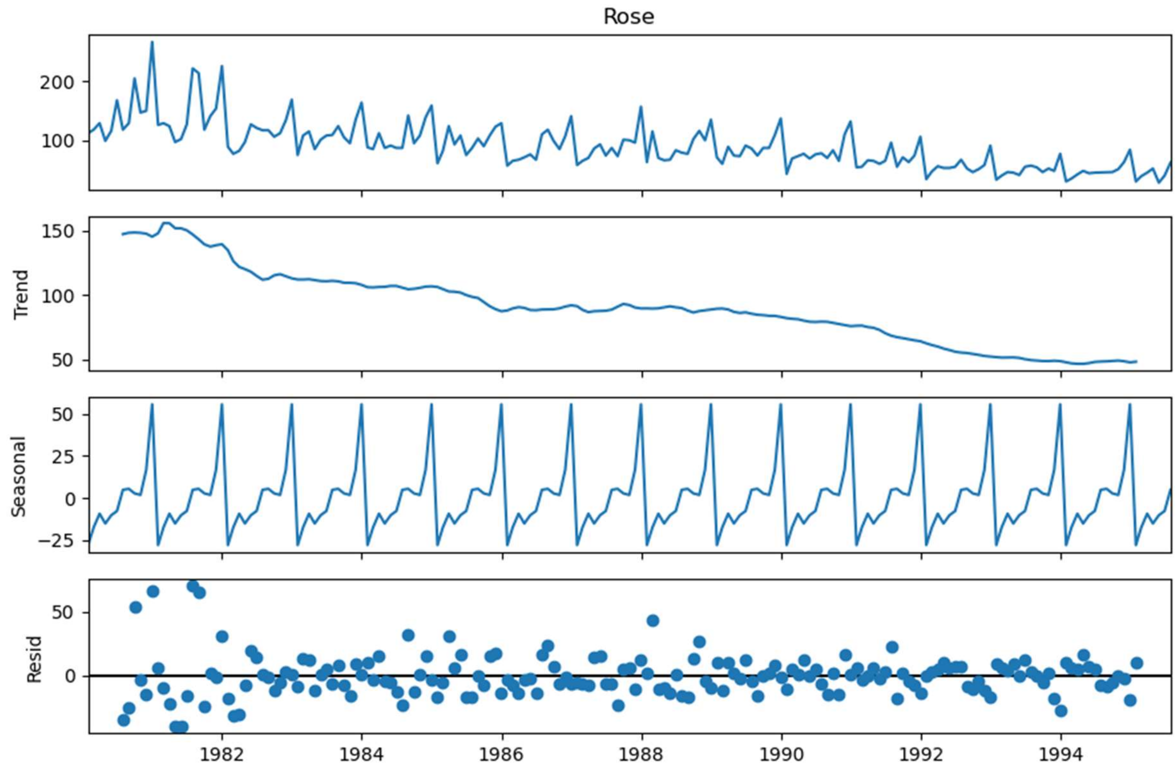

## Fig.12 Empirical Cumulative Distribution



## 2.2 TIME SERIES DECOMPOSITION

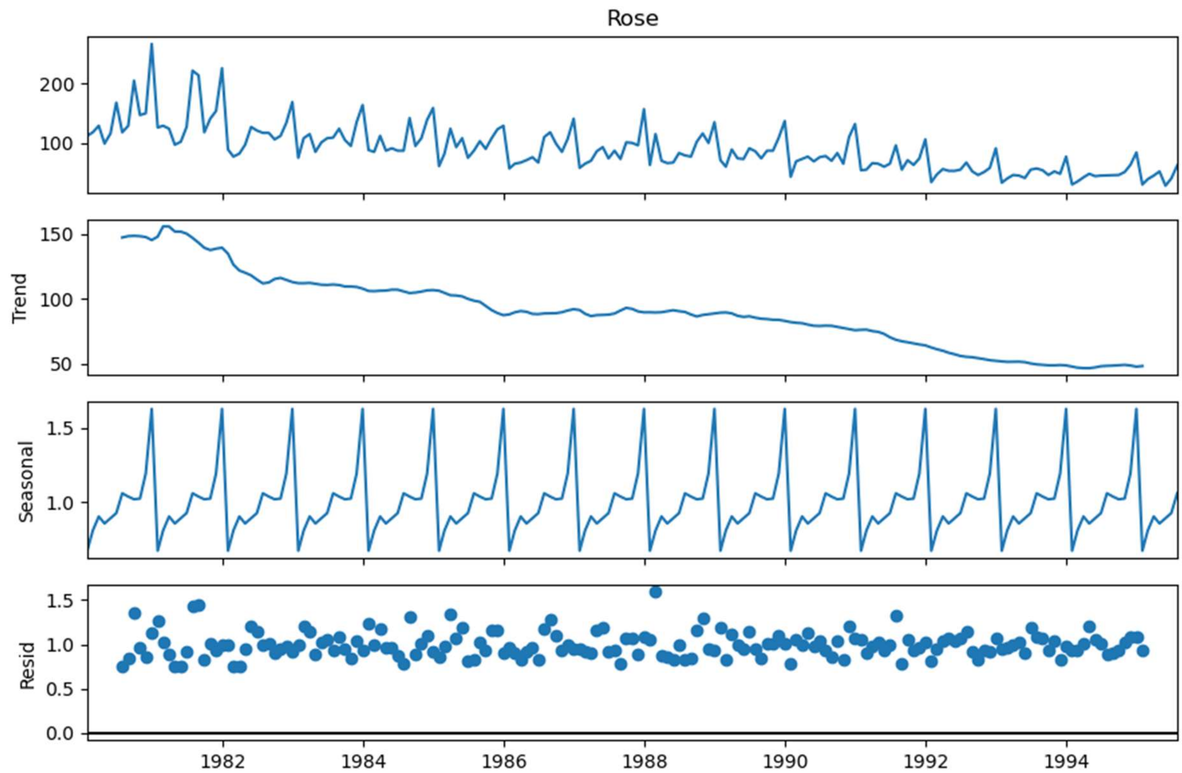
Additive Decomposition:

**Fig.13 Additive Decomposition Plot**




Multiplicative Decomposition:

**Fig.14 Multiplicative Decomposition Plot**



**Insights:**

- The Rose Wine Sales dataset clearly shows a declining trend in the sales from 1980 to 1995.
- The median sales of each year consistently reduce over the period of years.
- Rose Wine Sales dataset shows a clear seasonality pattern.
- The highest median sales are achieved in the month of December which indicates a huge demand during the holiday season.
- March, August, and October also have higher sales when compared to other months.
- Even the dataset clearly shows declining trend, The seasonal pattern remains same in every year.
- January and February months have the lowest sales compared to other months.
- From the multiplicative decomposition plot, we see that a lot of residuals are located around 1. So, the Multiplicative Decomposition is the right way to decompose the time series.

# 3. DATA PRE-PROCESSING

**Missing Value Treatment:**

- There are 2 missing values in this dataset and are treated with interpolate method.

**Train-Test Split:**

- The time series dataset was split, using data before 1991 for training set and data after 1995 for testing.

**Fig.15 Train-Test Split**

First few rows of Training Data

| | Rose |
|---|---|
| 1980-01-31 | 112.0 |
| 1980-02-29 | 118.0 |
| 1980-03-31 | 129.0 |
| 1980-04-30 | 99.0 |
| 1980-05-31 | 116.0 |

First few rows of Test Data

| | Rose |
|---|---|
| 1991-01-31 | 54.0 |
| 1991-02-28 | 55.0 |
| 1991-03-31 | 66.0 |
| 1991-04-30 | 65.0 |
| 1991-05-31 | 60.0 |

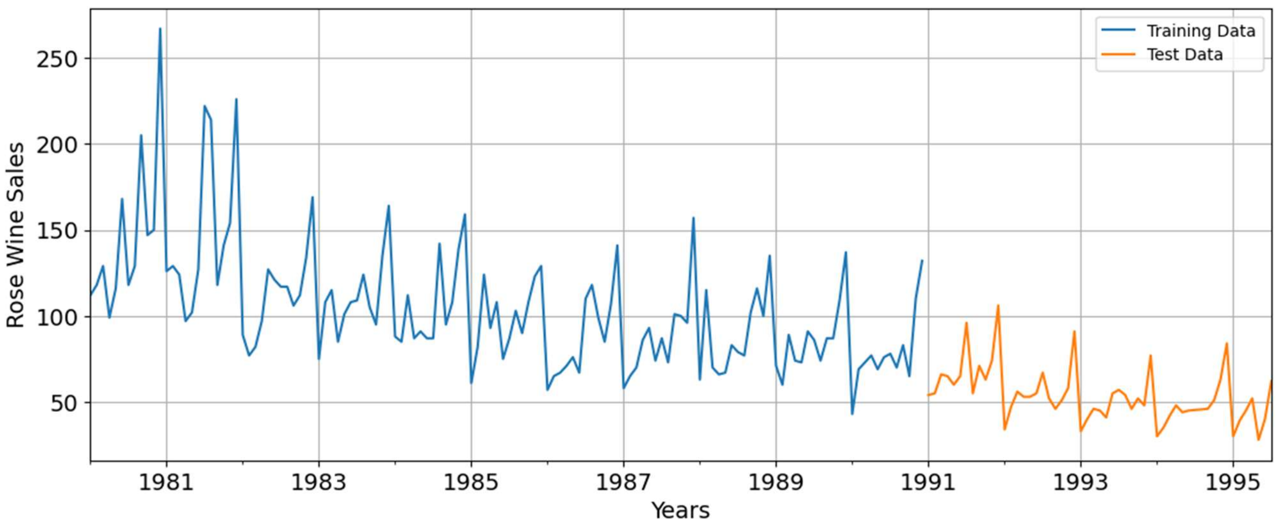
Last few rows of Training Data

| | Rose |
|---|---|
| 1990-08-31 | 70.0 |
| 1990-09-30 | 83.0 |
| 1990-10-31 | 65.0 |
| 1990-11-30 | 110.0 |
| 1990-12-31 | 132.0 |

Last few rows of Test Data

| | Rose |
|---|---|
| 1995-03-31 | 45.0 |
| 1995-04-30 | 52.0 |
| 1995-05-31 | 28.0 |
| 1995-06-30 | 40.0 |
| 1995-07-31 | 62.0 |

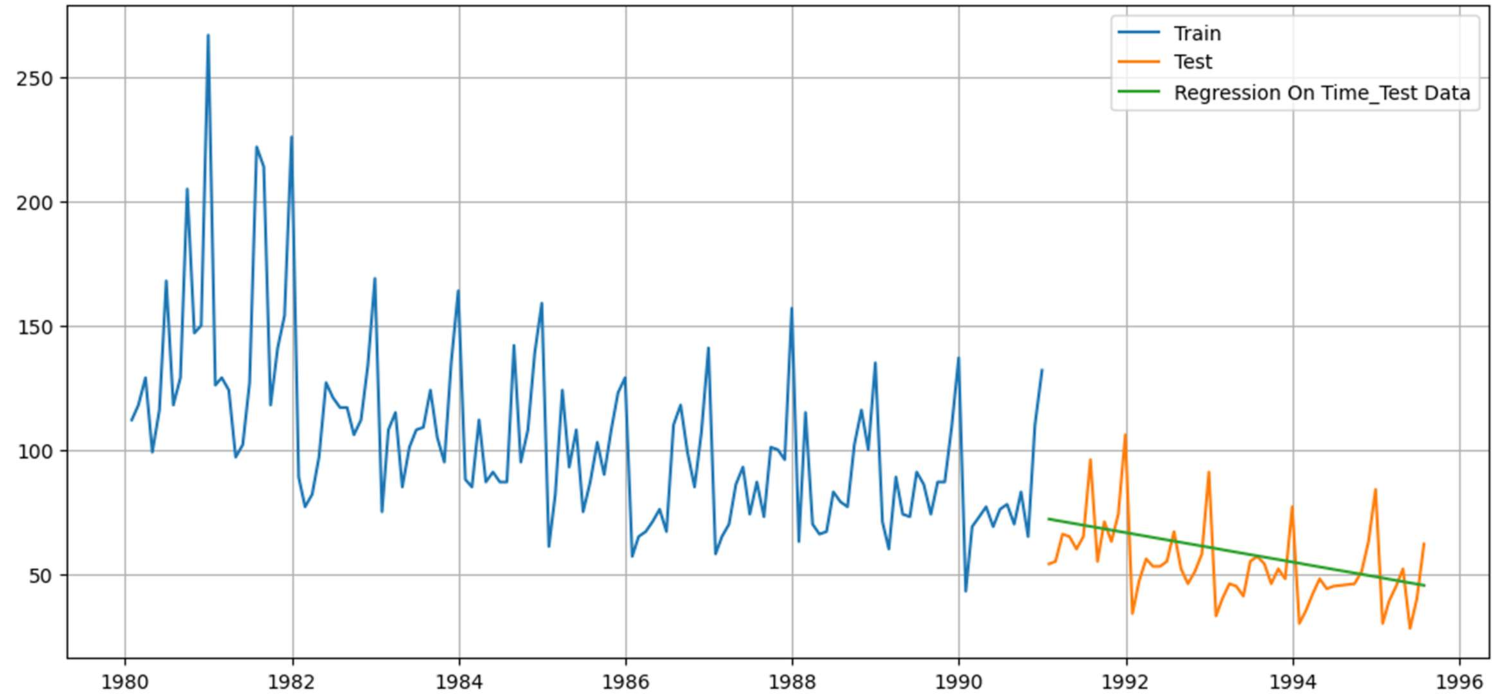
**Fig.16 Visualisation of train-test split**



# 4. MODEL BUILDING – ORIGINAL DATA

## 4.1 LINEAR REGRESSION:

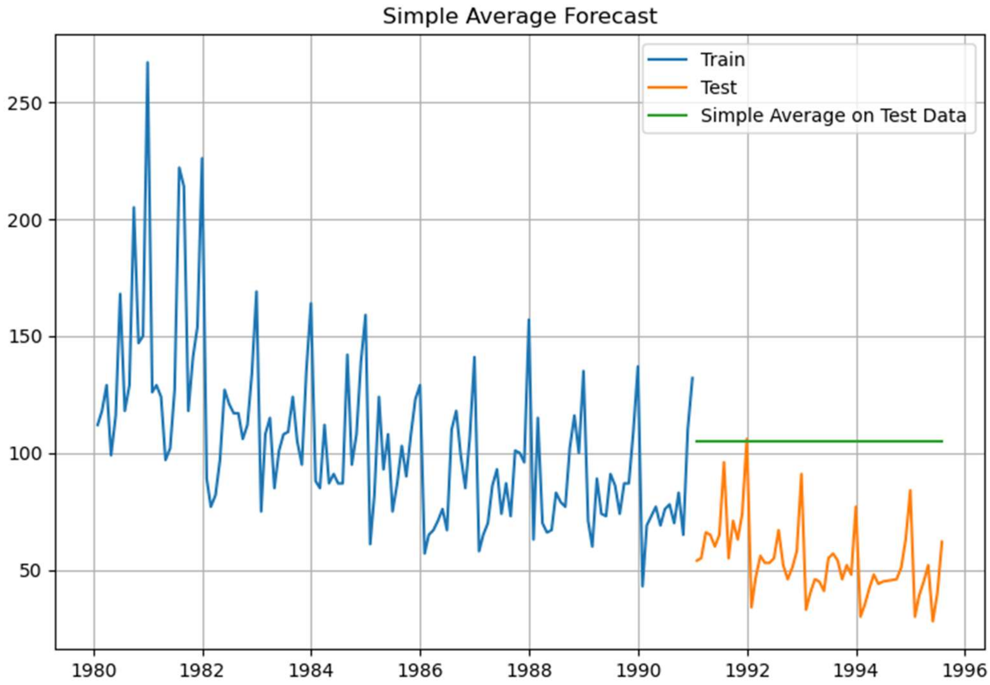
**Fig.17 Regression Model Performance**




- The **Linear Regression** model shows a slight downward trend in the predictions.
- This model has an RMSE score of **15.26**
- Regression Model doesn't capture the seasonality in the Rose wine sales dataset.

## 4.2 SIMPLE AVERAGE:

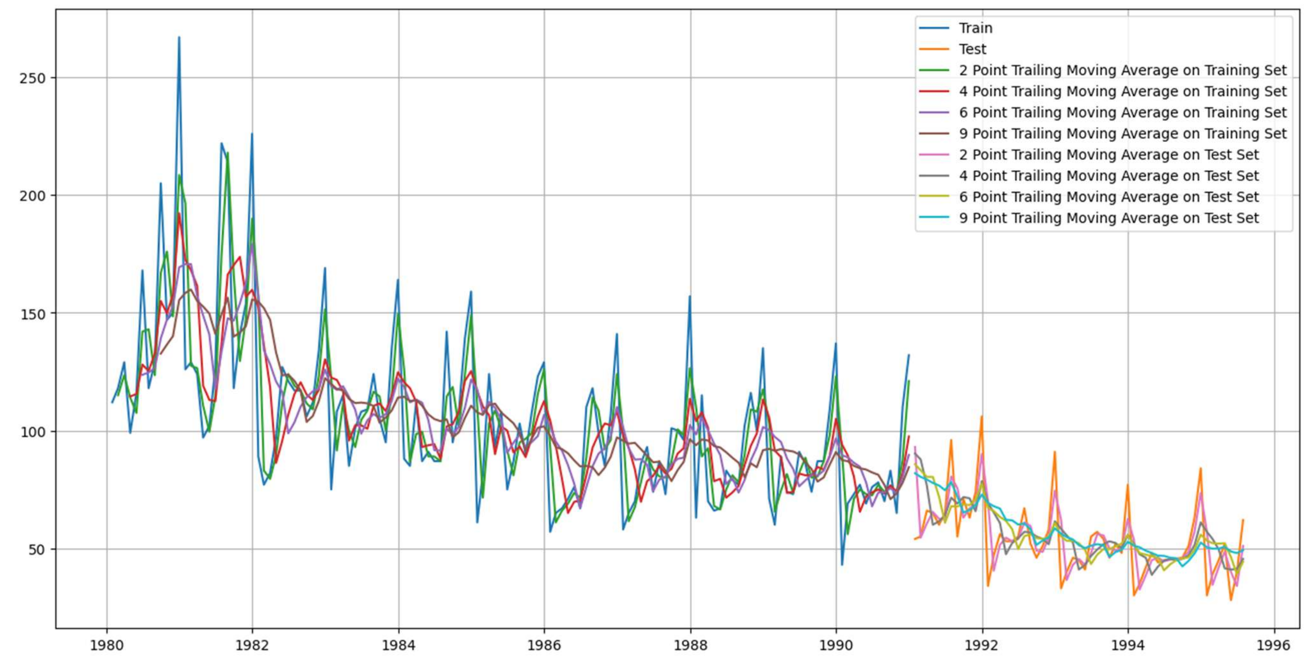
**Fig.18 Simple Average Model Performance**




- The **Simple Average** forecast remains constant over the test dataset and doesn't capture any trend or seasonality.
- This model has an RMSE score of **53.46**

## 4.3 MOVING AVERAGE:

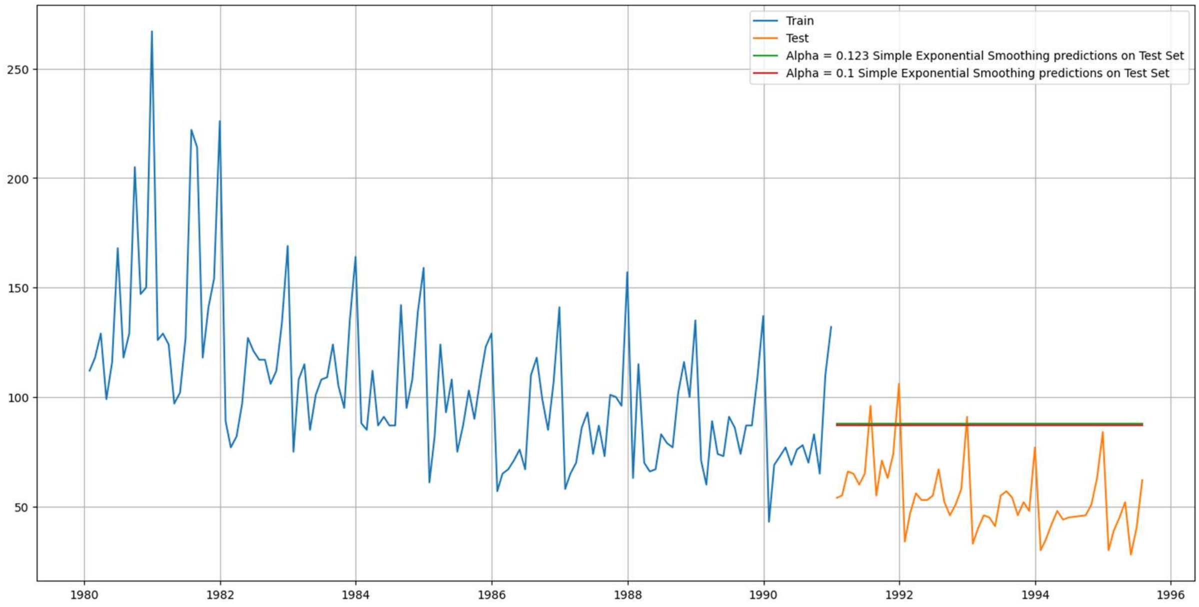
**Fig.19 Moving Average Models Performance**



- The **Moving Average** models captures trend and seasonality.
- The **2-point trailing** moving average model have the lowest RMSE score of **11.52** comparing to other moving average models
- The **9-point trailing** moving average model have the highest RMSE score of **14.72**
- Increasing in window size, results in a smoother curve with low accuracy.

### 4.4 SIMPLE EXPONENTIAL SMOOTHING MODEL:

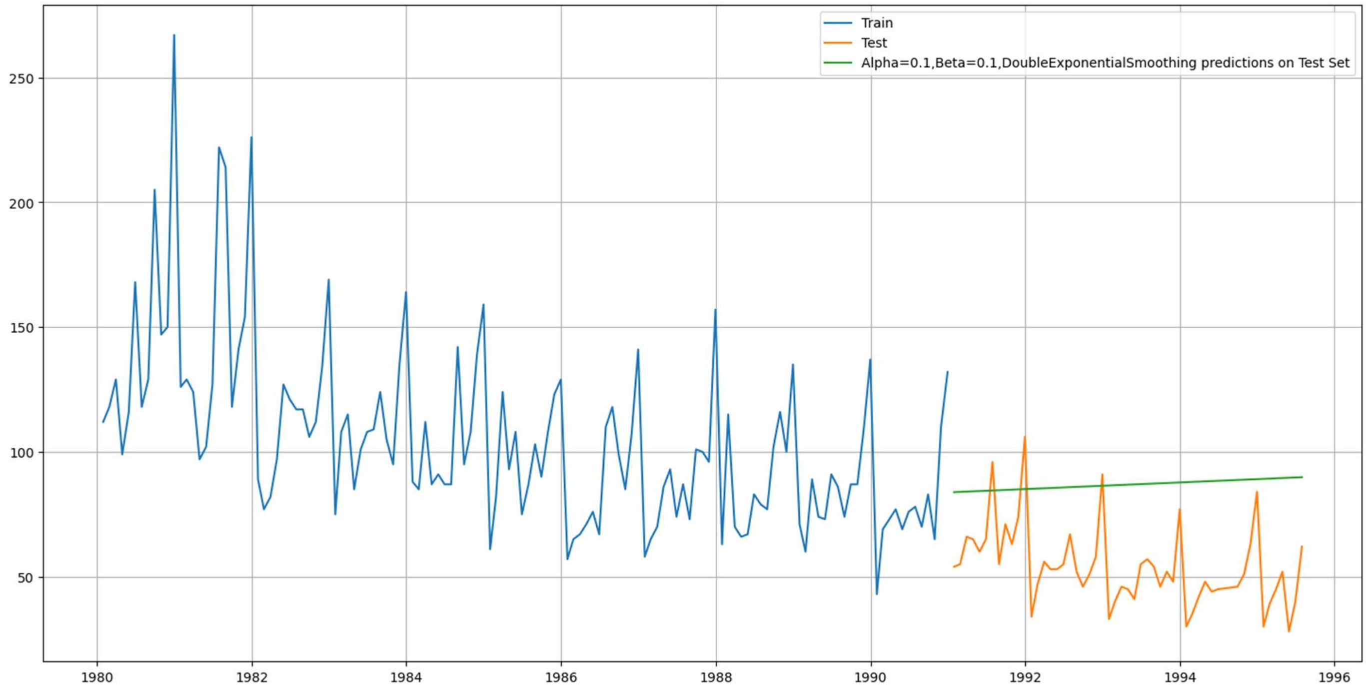
**Fig.20 SES model Performance**




- The **Simple Exponential Smoothing** Model performs better than simple average, but it still doesn't capture the seasonality and almost remains constant.
- RMSE score of SES (α = 0.1) : **36.82**
- RMSE score of SES (α = 0.123) : **37.59**

## 4.5 DOUBLE EXPONENTIAL SMOOTHING MODEL:

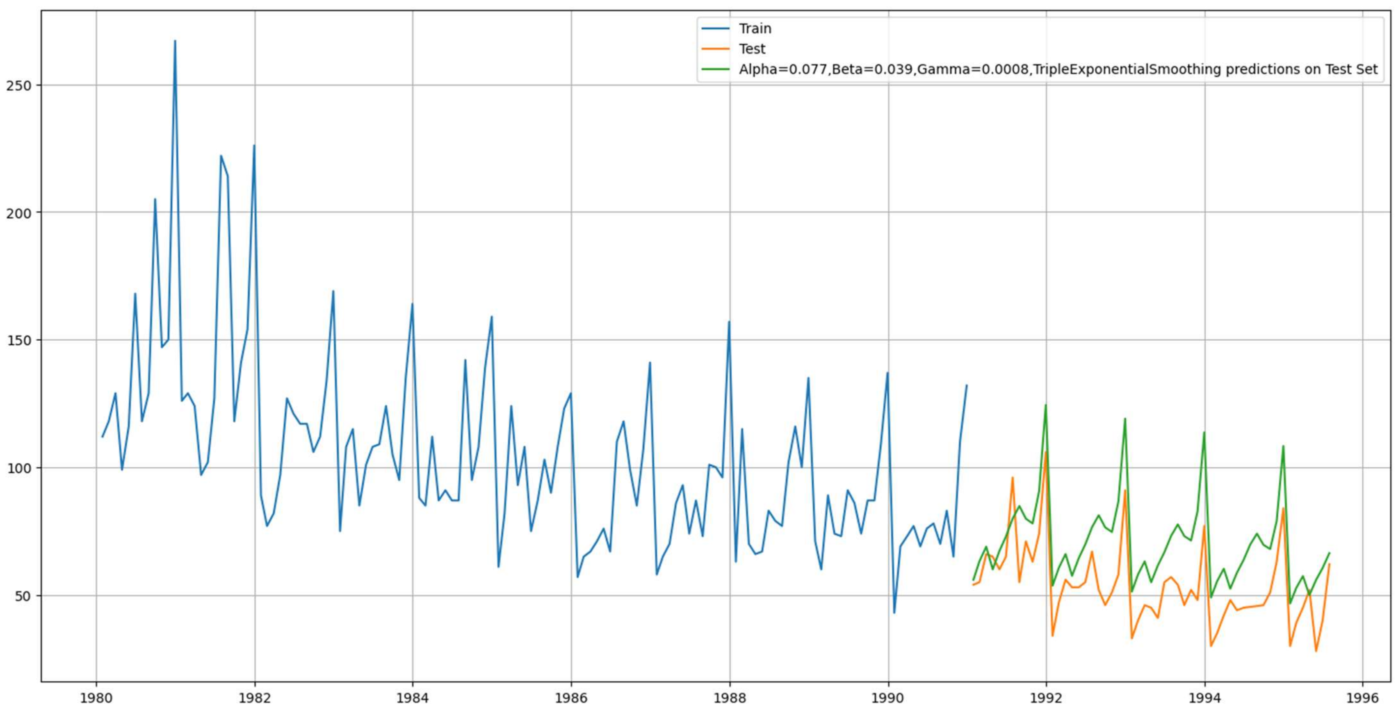
**Fig.21 DES model Performance**



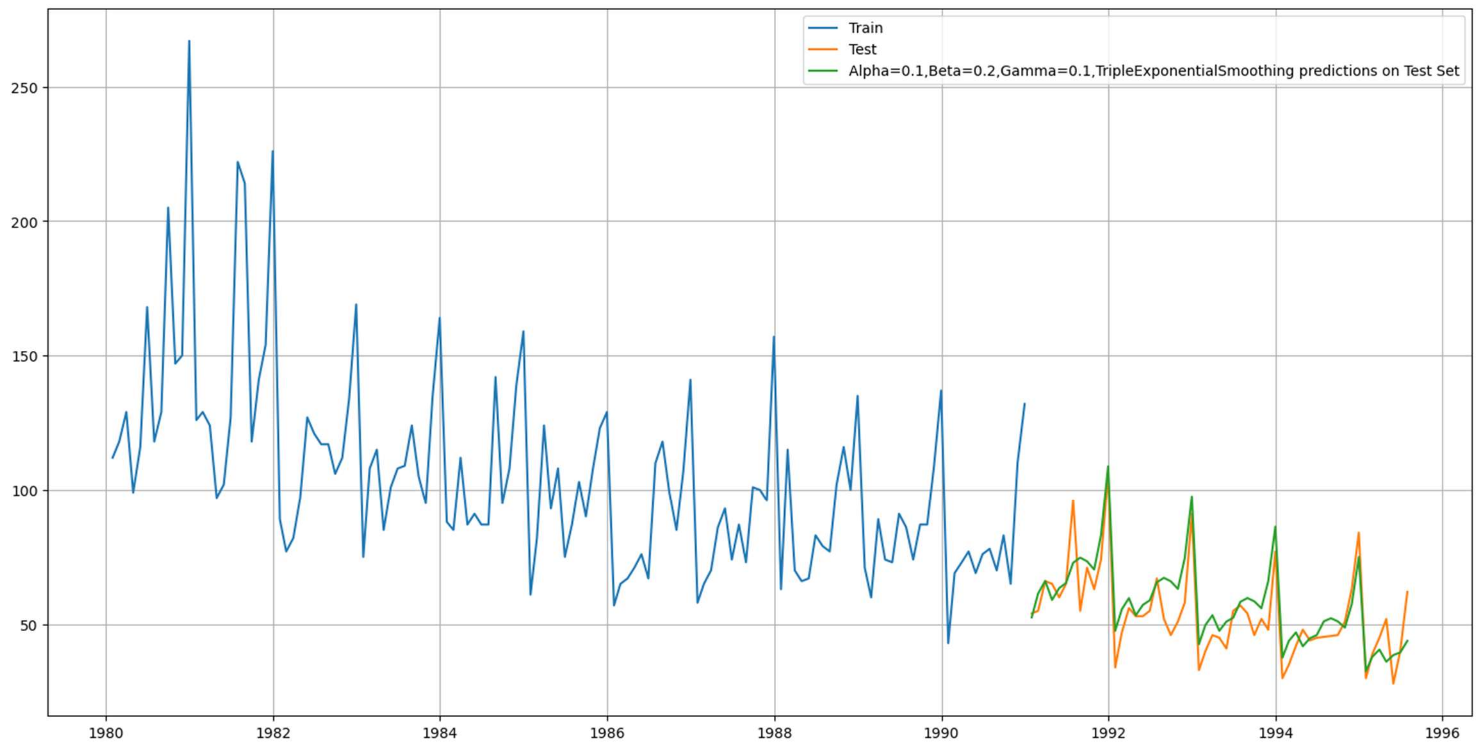

- The **Double Exponential Smoothing model (α=0.1, β=0.1)** shows slight trend and doesn't capture seasonality with RMSE of **36.92**

## 4.6 TRIPLE EXPONENTIAL SMOOTHING MODEL:

**Fig.22 TES model 1 Performance**



## Fig.23 TES model 2 Performance




- The **Triple Exponential Smoothing** model performs better than other models and have the least RMSE scores.
- As we can clearly observe that, the second TES model performs better than the autofit TES model.
- RMSE score of TES (α = 0.077, β = 0.039, γ = 0.0008): **19.11**
- RMSE score of TES (α = 0.1, β = 0.2, γ = 0.1): **9.22**

## 4.7 MODEL PERFORMANCE EVALUATION:

**Fig.24 Model Comparison plot (Regression, Simple average, Moving average)**

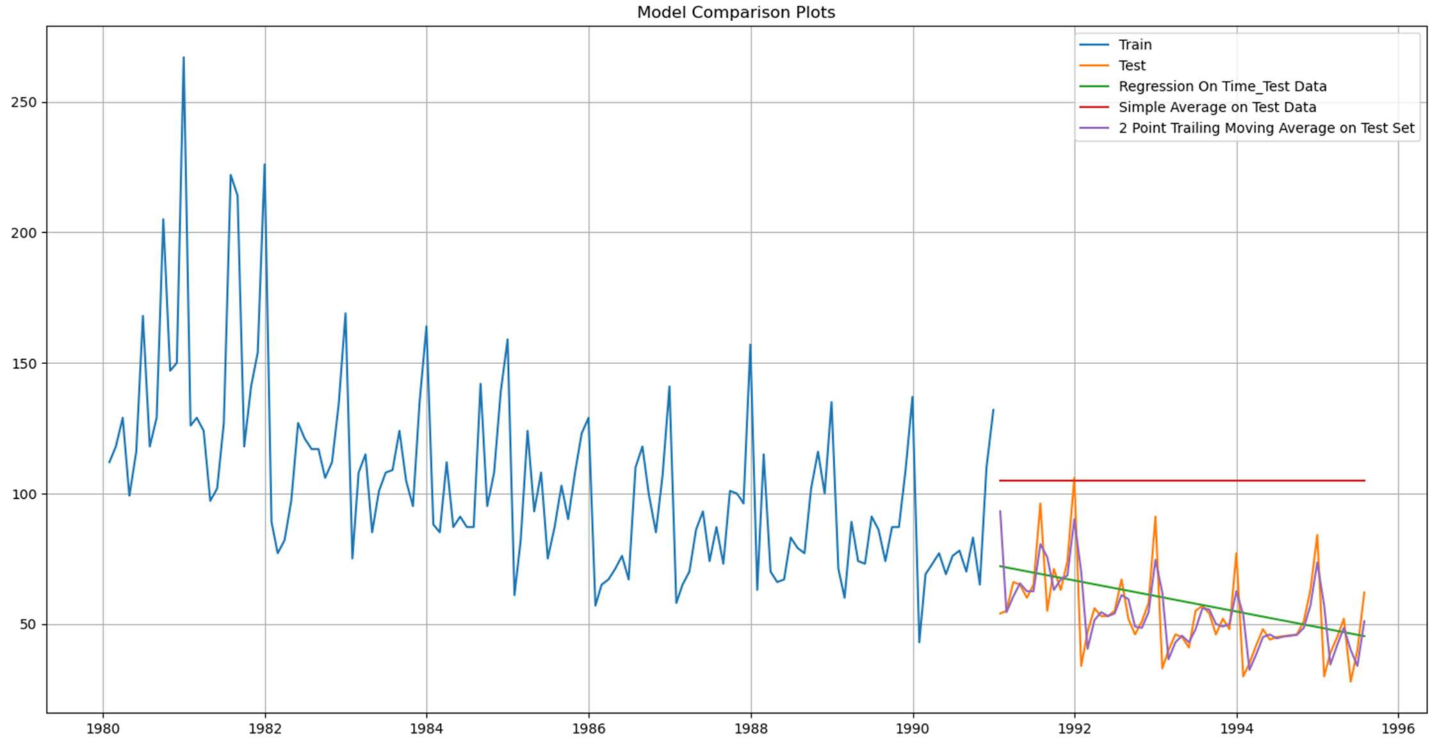
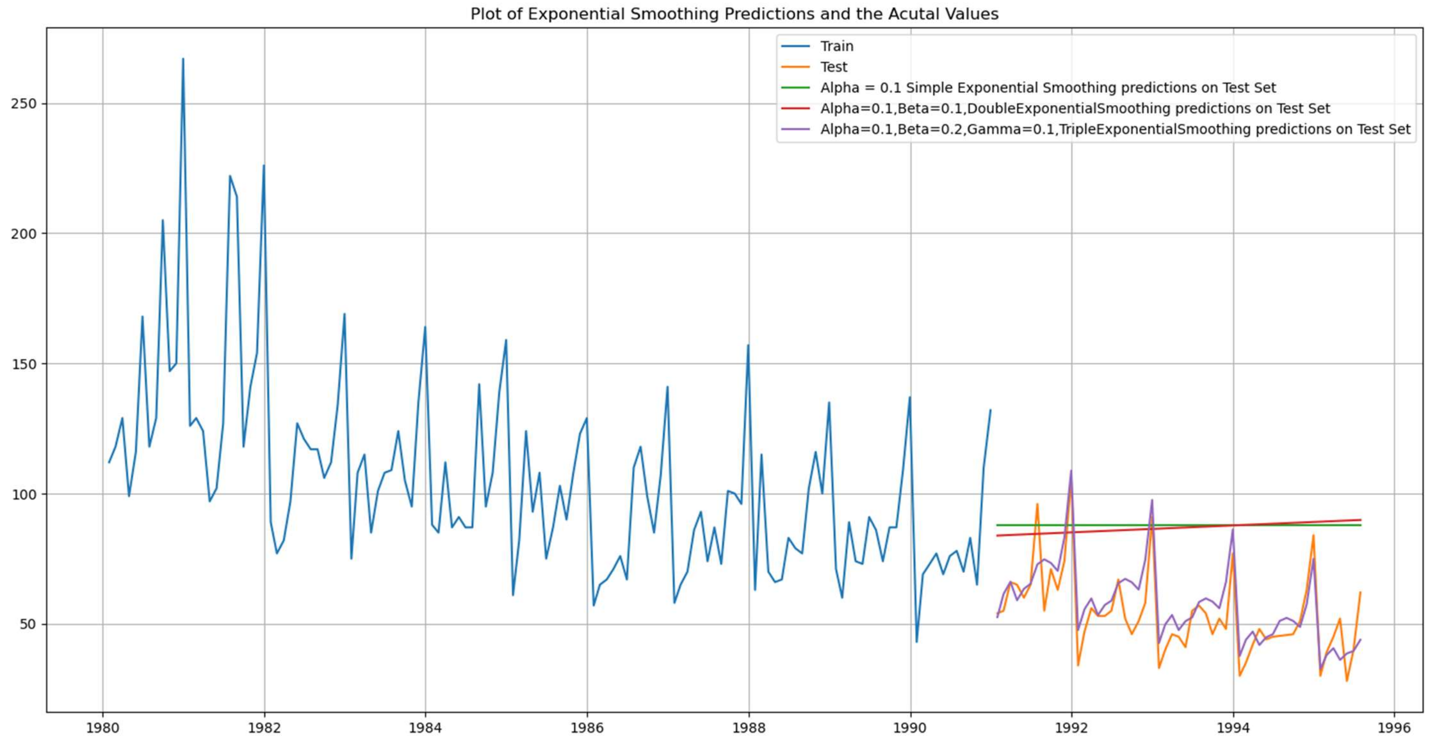



**Fig.25 Model Comparison plot (Exponential Smoothing Models)**



### Fig.26 RMSE Scores of all models

| | Test RMSE |
|---|---|
| Alpha=0.1,Beta=0.2,Gamma=0.1,TripleExponentialSmoothing | 9.223504 |
| 2-point Trailing MovingAverage | 11.529278 |
| 4-point Trailing MovingAverage | 14.451403 |
| 6-point Trailing MovingAverage | 14.566327 |
| 9-point Trailing MovingAverage | 14.727630 |
| Linear Regression Model | 15.268955 |
| Alpha=0.077,Beta=0.039,Gamma=0.0008,TripleExponentialSmoothing | 19.113110 |
| Alpha=0.1,SimpleExponentialSmoothing | 36.828033 |
| Alpha=0.1,Beta=0.1,DoubleExponentialSmoothing | 36.923416 |
| Alpha=0.123,SimpleExponentialSmoothing | 37.592212 |
| SimpleAverageModel | 53.460570 |

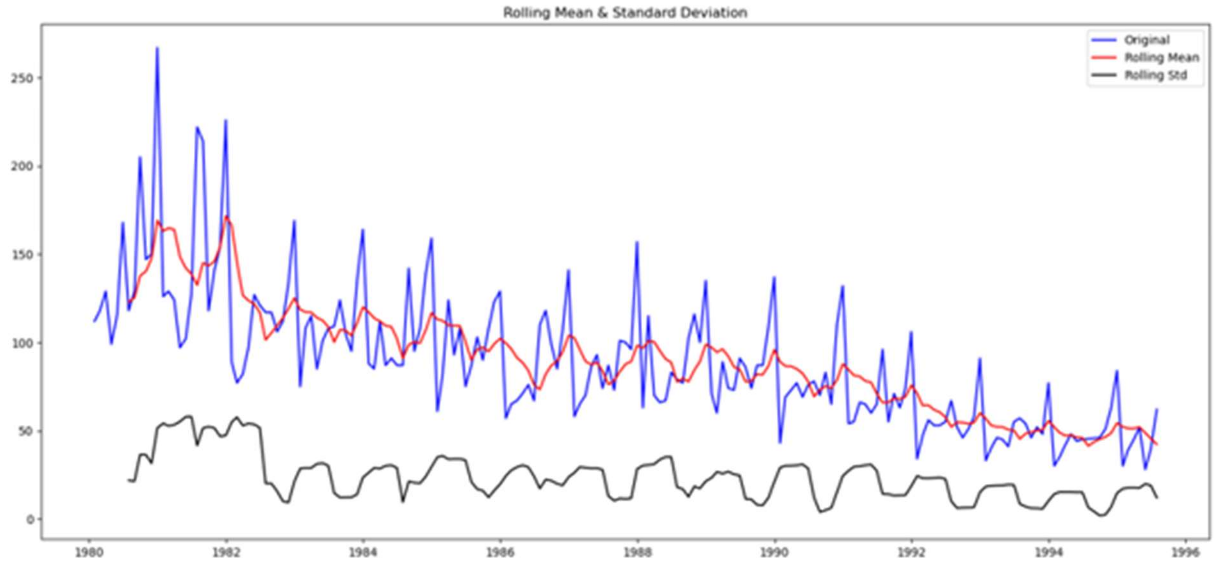
**INSIGHTS:**

- The **Triple Exponential Smoothing model ($\alpha = 0.1$, $\beta = 0.2$, $\gamma = 0.1$)** has the lowest RMSE of 9.22 and performs better than other models.
- The Simple Average model has the highest RMSE score of 53.46
- In Moving Average models, the 2-point Trailing moving average model has the lowest RMSE of 11.52
- The Linear Regression model performs better than SES and DES models with RMSE of 15.26
- The Simple average model, DES model and SES models doesn’t capture seasonality which leads to poor performance.

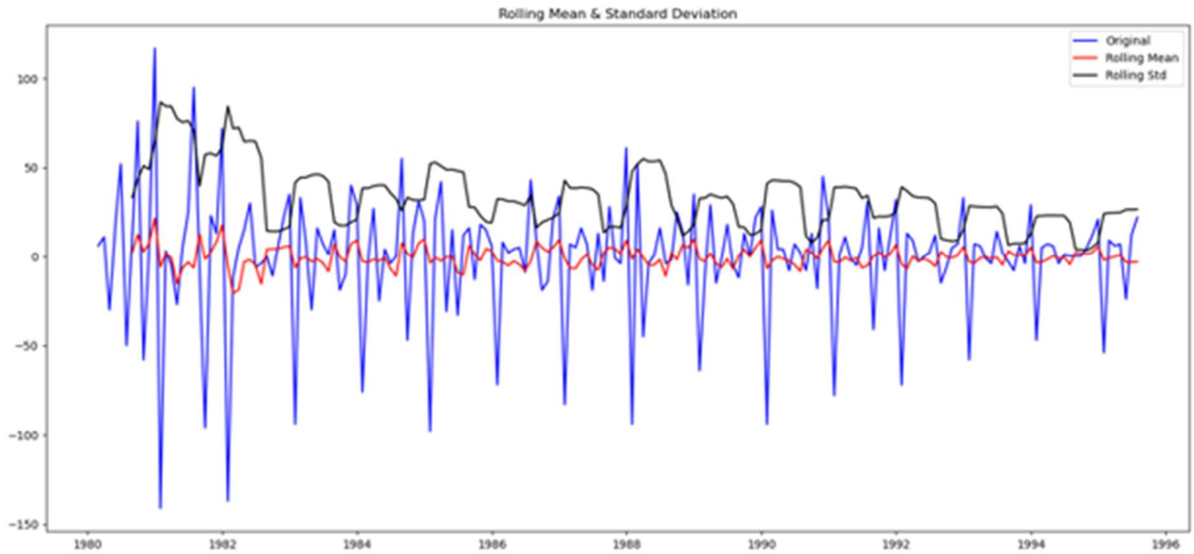
# 5. CHECK FOR STATIONARITY

## Checking for Stationarity on the whole Time series data:

### Fig.27 Stationarity check (whole data)



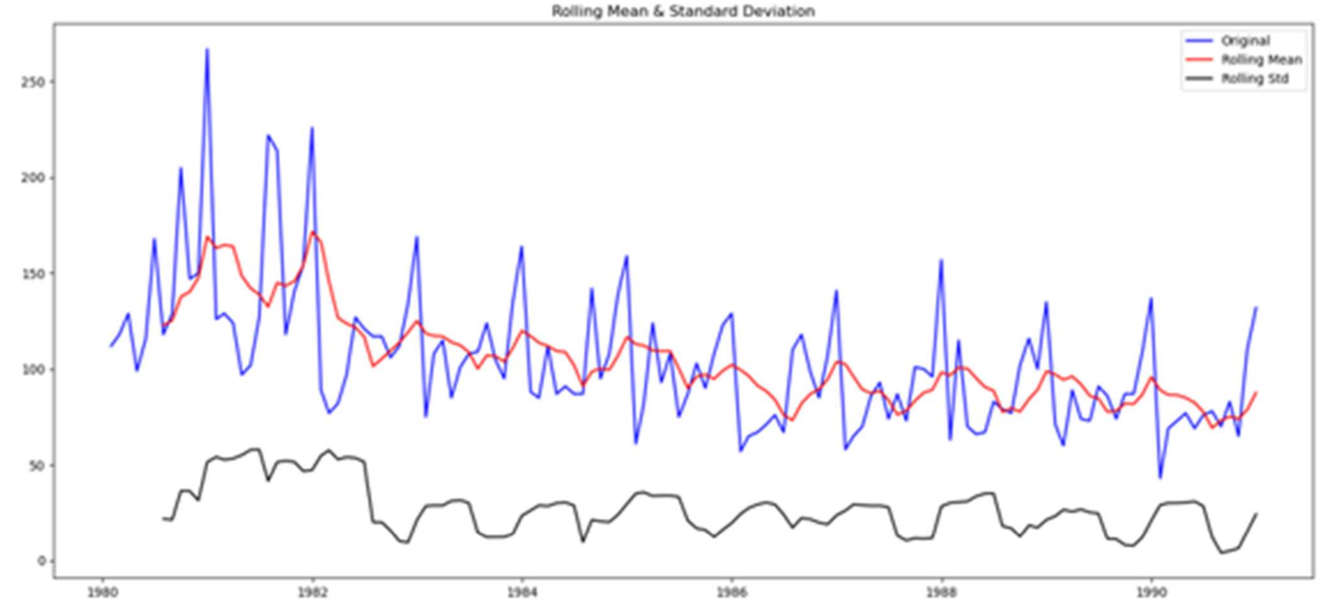

```
Results of Dickey-Fuller Test:
Test Statistic                  -1.876699
p-value                          0.343101
#Lags Used                      13.000000
Number of Observations Used    173.000000
Critical Value (1%)             -3.468726
Critical Value (5%)             -2.878396
Critical Value (10%)            -2.575756
dtype: float64
```



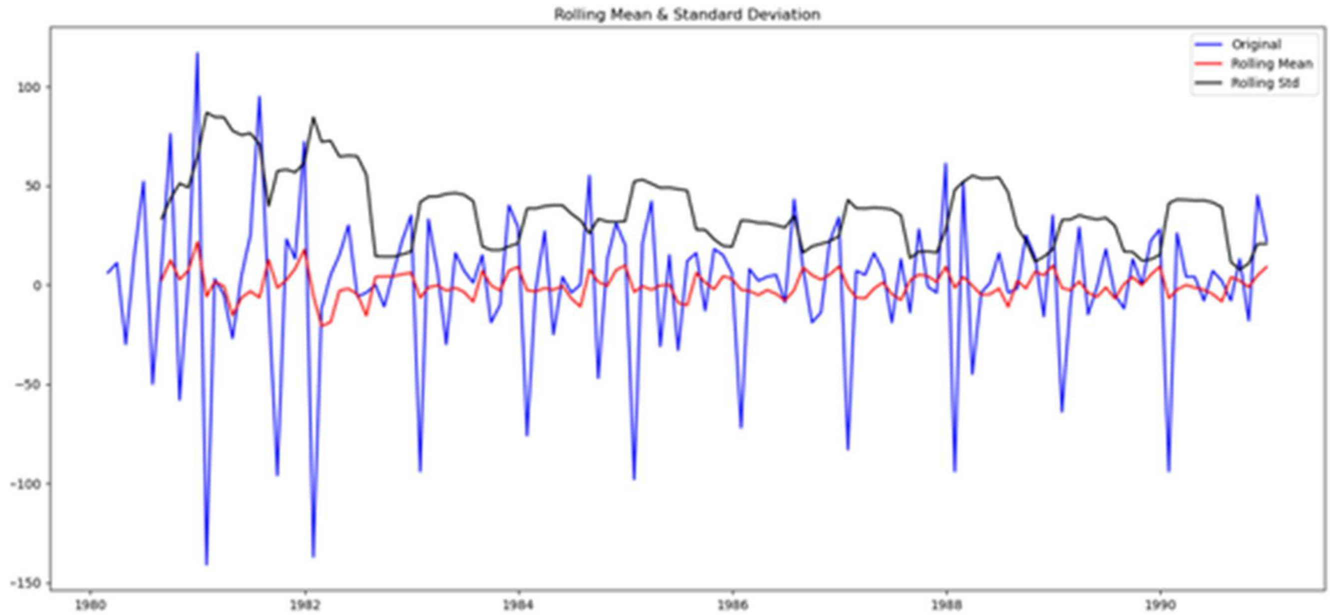

```
Results of Dickey-Fuller Test:
Test Statistic                 -8.044392e+00
p-value                         1.810895e-12
#Lags Used                      1.200000e+01
Number of Observations Used     1.730000e+02
Critical Value (1%)            -3.468726e+00
Critical Value (5%)            -2.878396e+00
Critical Value (10%)           -2.575756e+00
dtype: float64
```

## Checking for Stationarity on the Training data:

**Fig.28 Stationarity check (Training data)**




```
Results of Dickey-Fuller Test:
Test Statistic                  -2.164250
p-value                          0.219476
#Lags Used                      13.000000
Number of Observations Used    118.000000
Critical Value (1%)             -3.487022
Critical Value (5%)             -2.886363
Critical Value (10%)            -2.580009
dtype: float64
```




```
Results of Dickey-Fuller Test:
Test Statistic                 -6.592372e+00
p-value                         7.061944e-09
#Lags Used                      1.200000e+01
Number of Observations Used     1.180000e+02
Critical Value (1%)            -3.487022e+00
Critical Value (5%)            -2.886363e+00
Critical Value (10%)           -2.580009e+00
dtype: float64
```

**Whole Time series Dataset:**

- From the Dickey-Fuller Test in whole time series, we can clearly observe that the p-value is 0.34, which is greater than 0.05 at 5% significance level. The Time series is non-stationary.
- After taking a difference of order 1, we see that at 5% significance level, the Time Series data is stationary.

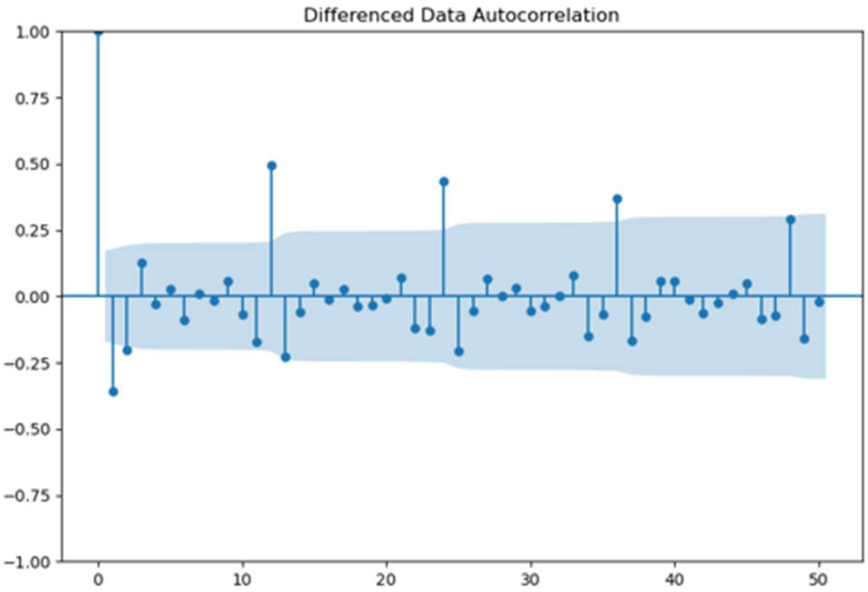
**Training Dataset:**

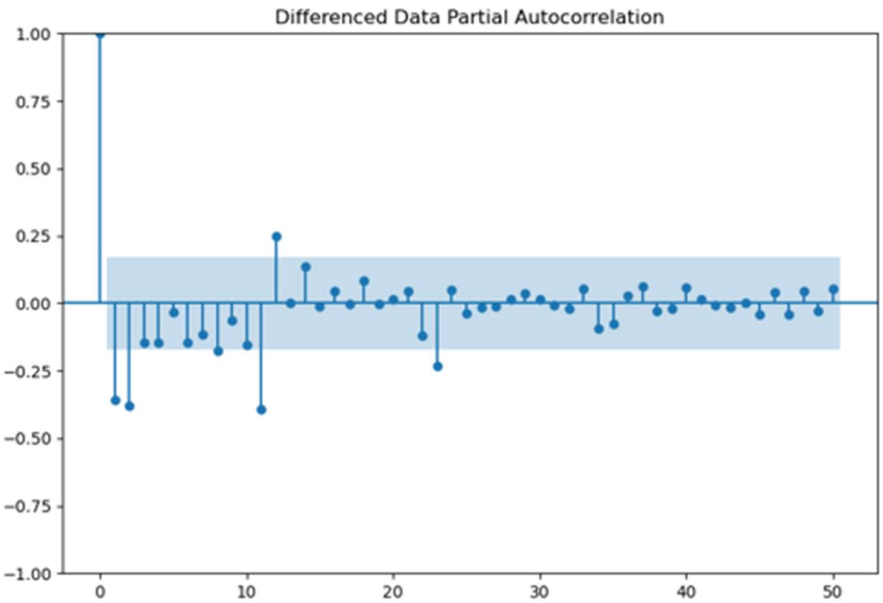
- From the Dickey-Fuller Test in training set, we can clearly observe that the p-value is 0.21, which is greater than 0.05 at 5% significance level. The Time series is non-stationary.
- After taking a difference of order 1, we see that at 5% significance level, the Time Series data is stationary.

# 6. MODEL BUILDING – STATIONARY DATA

## 6.1 ACF AND PACF PLOTS:

**Fig.29 ACF, PACF plots (Training data)**




- By observing the PACF plot, the Auto-regressive (AR) parameter p value is taken as 2.
- By observing the ACF plot, the Moving-Average (MA) parameter q value is taken as 2.
- By using these values, we can set a range and iterate with different values for manual ARIMA and SARIMA models.

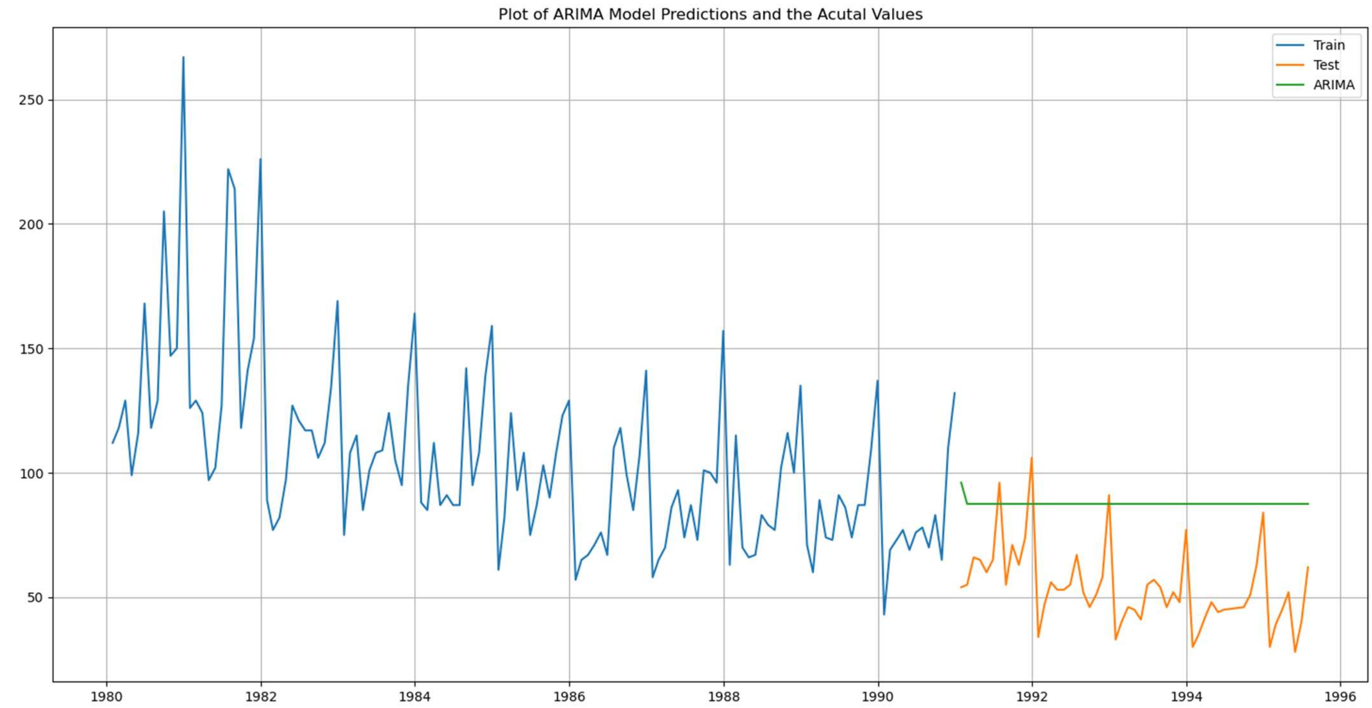
## 6.2 AUTO ARIMA:

- An Auto ARIMA model was built on the training data in which the parameters are selecting using the lowest Akaike Information Criteria (AIC) values by iterating different p ,q values.
- This ARIMA model was built on parameters (0,1,2)
- Test RMSE: 37.306

**Fig.30 Auto ARIMA Results**

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                   Rose   No. Observations:                  132
Model:                 ARIMA(0, 1, 2)   Log Likelihood                -636.836
Date:                Sun, 09 Mar 2025   AIC                           1279.672
Time:                        19:41:58   BIC                           1288.297
Sample:                    01-31-1980   HQIC                          1283.176
                         - 12-31-1990
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.6970      0.072     -9.689      0.000      -0.838      -0.556
ma.L2         -0.2042      0.073     -2.794      0.005      -0.347      -0.061
sigma2       965.8407     88.305     10.938      0.000     792.766    1138.915
===================================================================================
Ljung-Box (L1) (Q):                   0.14   Jarque-Bera (JB):                39.24
Prob(Q):                              0.71   Prob(JB):                         0.00
Heteroskedasticity (H):               0.36   Skew:                             0.82
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.13
===================================================================================
```

**Fig.31 Auto ARIMA model plot**



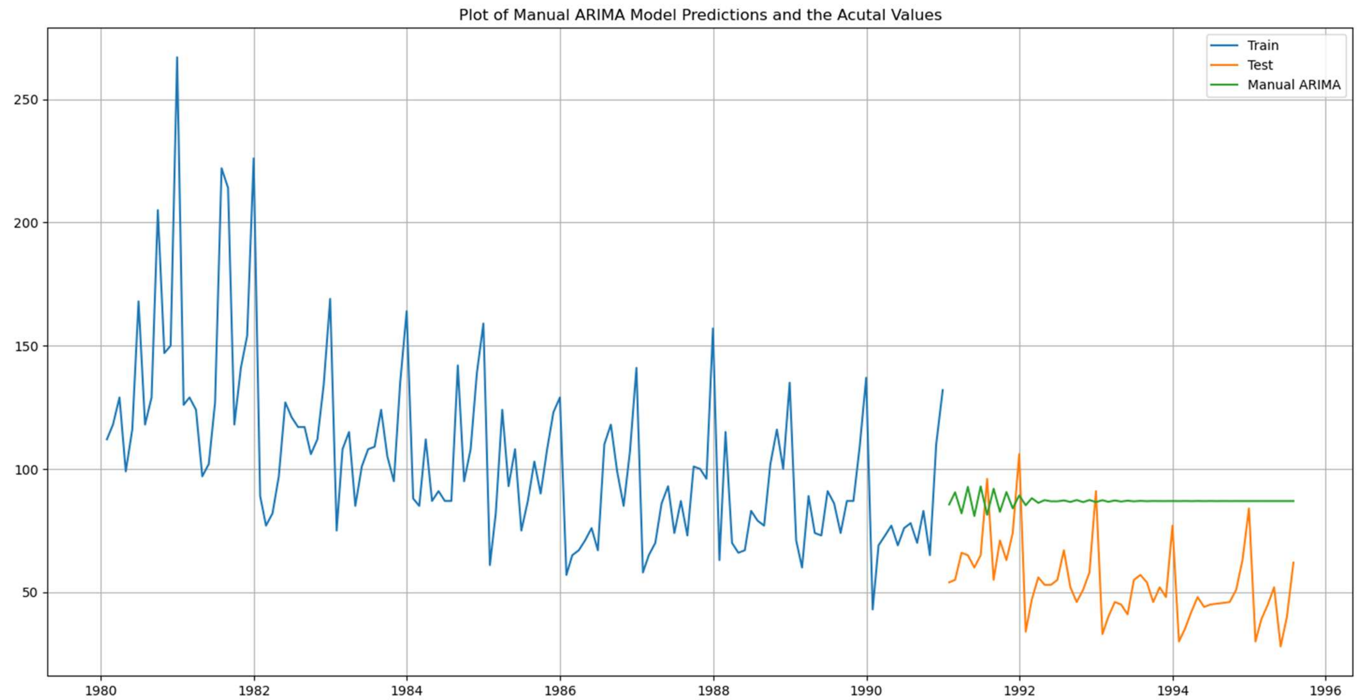
## 6.3 MANUAL ARIMA MODEL:

- From observing the PACF and ACF plots, p and q values are selected from a range of (0-4)
- Data is made stationary after differencing of order 1 (So, d=1)
- After iterating all the values, the same set of parameters (2,1,3) yield the lowest AIC score, with test RMSE of 36.81

**Fig.32 Manual ARIMA Results**

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                   Rose   No. Observations:                  132
Model:                 ARIMA(2, 1, 3)   Log Likelihood                -631.348
Date:                Sun, 09 Mar 2025   AIC                           1274.695
Time:                        19:42:26   BIC                           1291.947
Sample:                    01-31-1980   HQIC                          1281.705
                         - 12-31-1990
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -1.6781      0.084    -19.987      0.000      -1.843      -1.514
ar.L2         -0.7289      0.084     -8.682      0.000      -0.893      -0.564
ma.L1          1.0446      0.627      1.665      0.096      -0.185       2.274
ma.L2         -0.7720      0.133     -5.827      0.000      -1.032      -0.512
ma.L3         -0.9046      0.569     -1.591      0.112      -2.019       0.210
sigma2       860.8147    528.609      1.628      0.103    -175.239    1896.868
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                24.48
Prob(Q):                              0.88   Prob(JB):                         0.00
Heteroskedasticity (H):               0.40   Skew:                             0.71
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.57
===================================================================================
```

**Fig.33 Manual ARIMA plot**



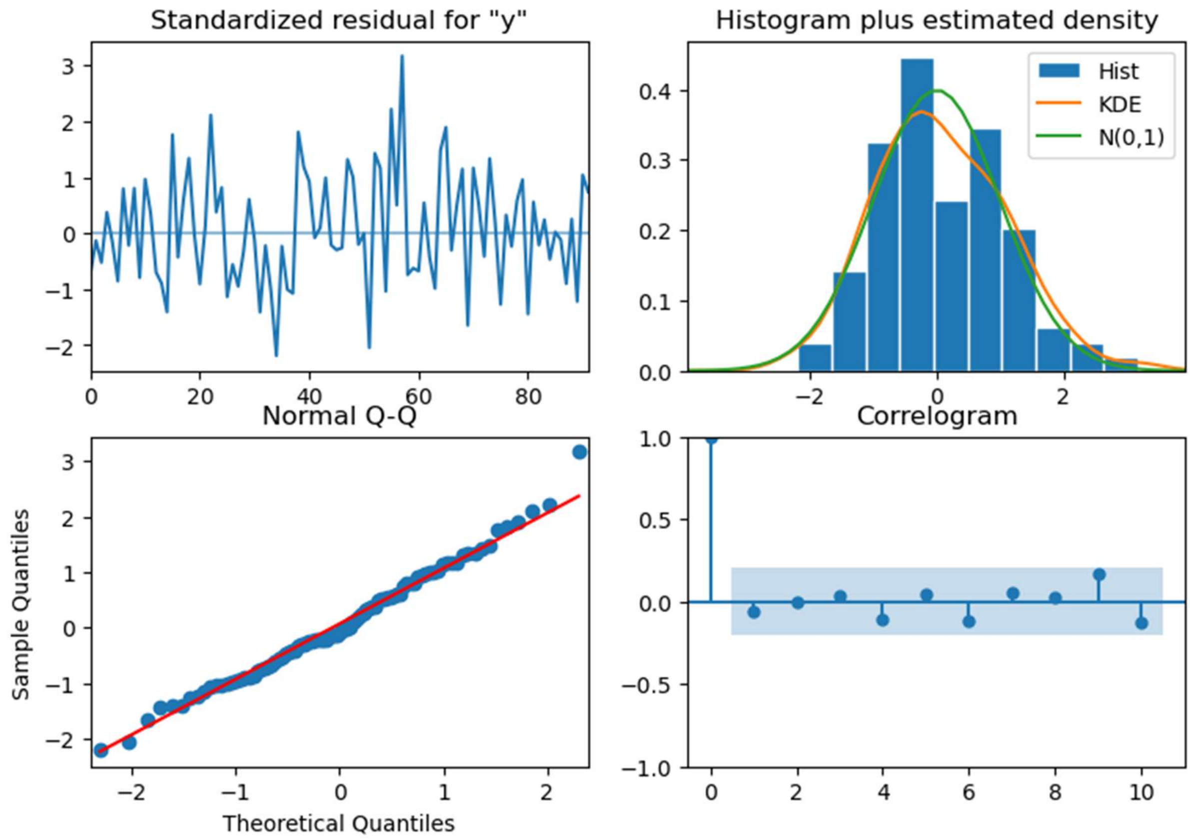
## 6.4 AUTO SARIMA MODEL:

- From observing the ACF plots, we can clearly observe that seasonality s = 12
- An Auto SARIMA model was built on the training data in which the parameters are selecting using the lowest Akaike Information Criteria (AIC) values by iterating different parameters.
- This SARIMA model was built on parameters (3,1,1) (3,0 ,2,12)
- Test RMSE: 18.88

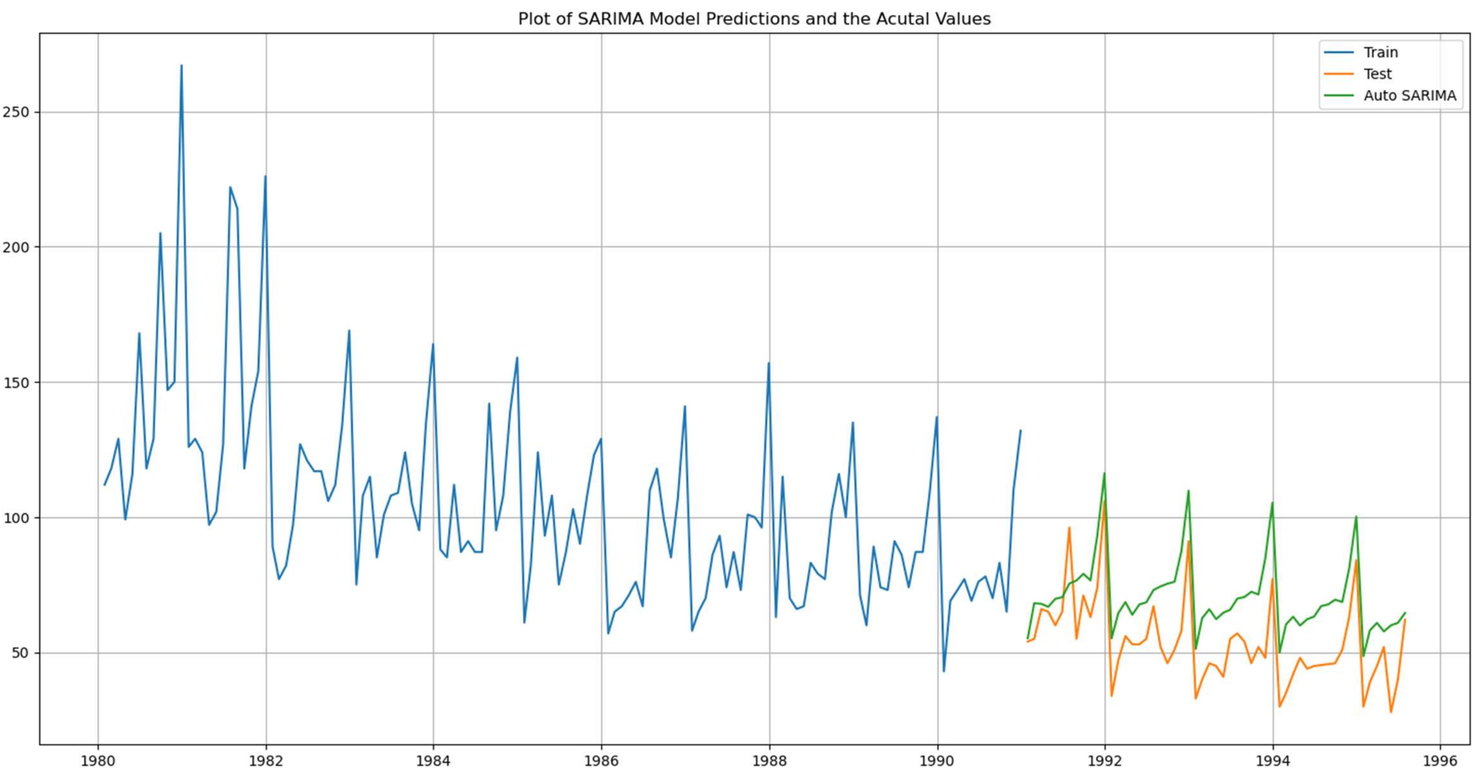
**Fig.34 Auto SARIMA results**

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                  132
Model:             SARIMAX(3, 1, 1)x(3, 0, [1, 2], 12)   Log Likelihood            -377.200
Date:                            Sun, 09 Mar 2025   AIC                            774.400
Time:                                    19:46:15   BIC                            799.618
Sample:                                         0   HQIC                           784.578
                                            - 132
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0464      0.126      0.367      0.714      -0.202       0.294
ar.L2         -0.0060      0.120     -0.050      0.960      -0.241       0.229
ar.L3         -0.1808      0.098     -1.837      0.066      -0.374       0.012
ma.L1         -0.9370      0.067    -13.904      0.000      -1.069      -0.805
ar.S.L12       0.7639      0.165      4.639      0.000       0.441       1.087
ar.S.L24       0.0840      0.159      0.527      0.598      -0.229       0.397
ar.S.L36       0.0727      0.095      0.764      0.445      -0.114       0.259
ma.S.L12      -0.4968      0.250     -1.988      0.047      -0.987      -0.007
ma.S.L24      -0.2191      0.210     -1.044      0.296      -0.630       0.192
sigma2       192.1615     39.630      4.849      0.000     114.487     269.836
===================================================================================
Ljung-Box (L1) (Q):                   0.30   Jarque-Bera (JB):                 1.64
Prob(Q):                              0.58   Prob(JB):                         0.44
Heteroskedasticity (H):               1.11   Skew:                             0.33
Prob(H) (two-sided):                  0.77   Kurtosis:                         3.03
===================================================================================
```

## Fig.35Auto SARIMA diagnostics




## Fig.36 Auto SARIMA plot



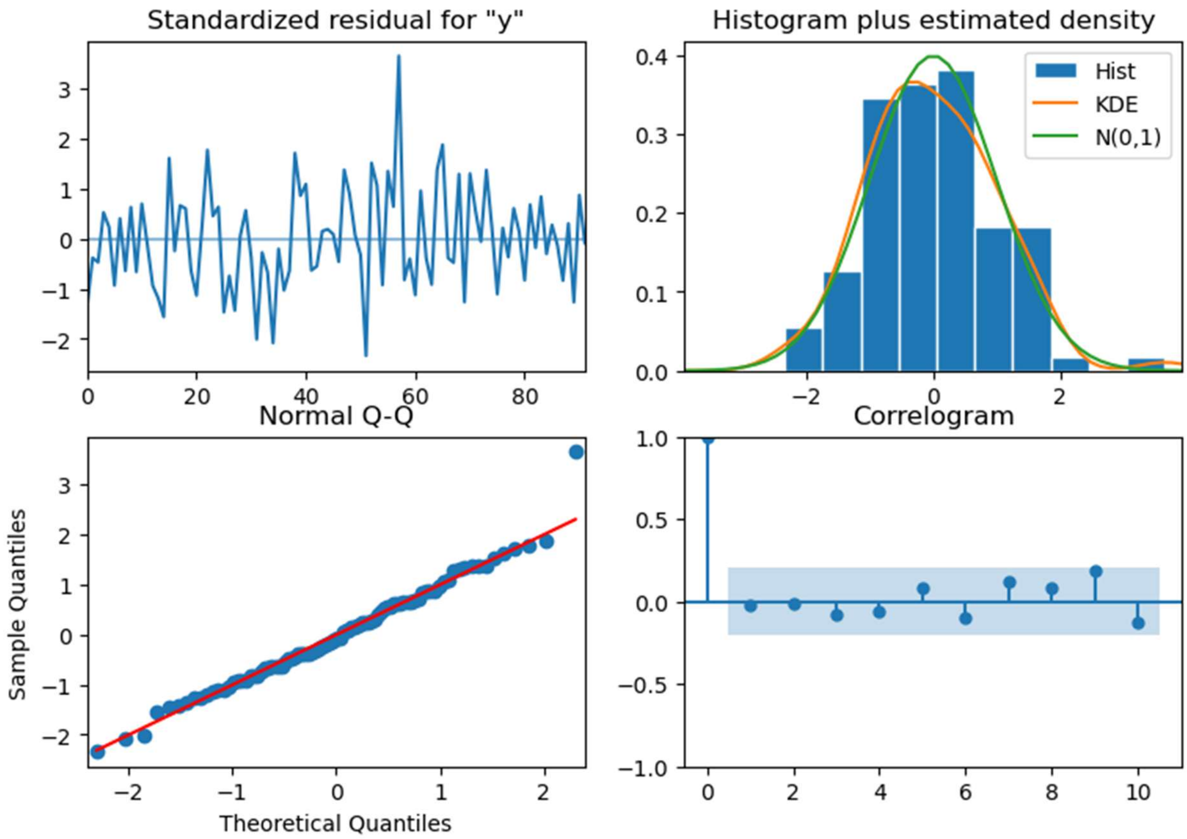
## 6.5 MANUAL SARIMA MODEL:

- From observing the PACF and ACF plots, p and q values are selected from a range of (0-2)
- Data is made stationary after differencing of order 1 (So, **d=1**)
- Since there are strong seasonal patterns in ACF, **seasonal differencing** can be done. (So, **D=1**)
- After iterating different values, the SARIMA model was built with parameters (0,1,2) (2,1,2,12) which yield the lowest AIC score, with test RMSE of 16.5

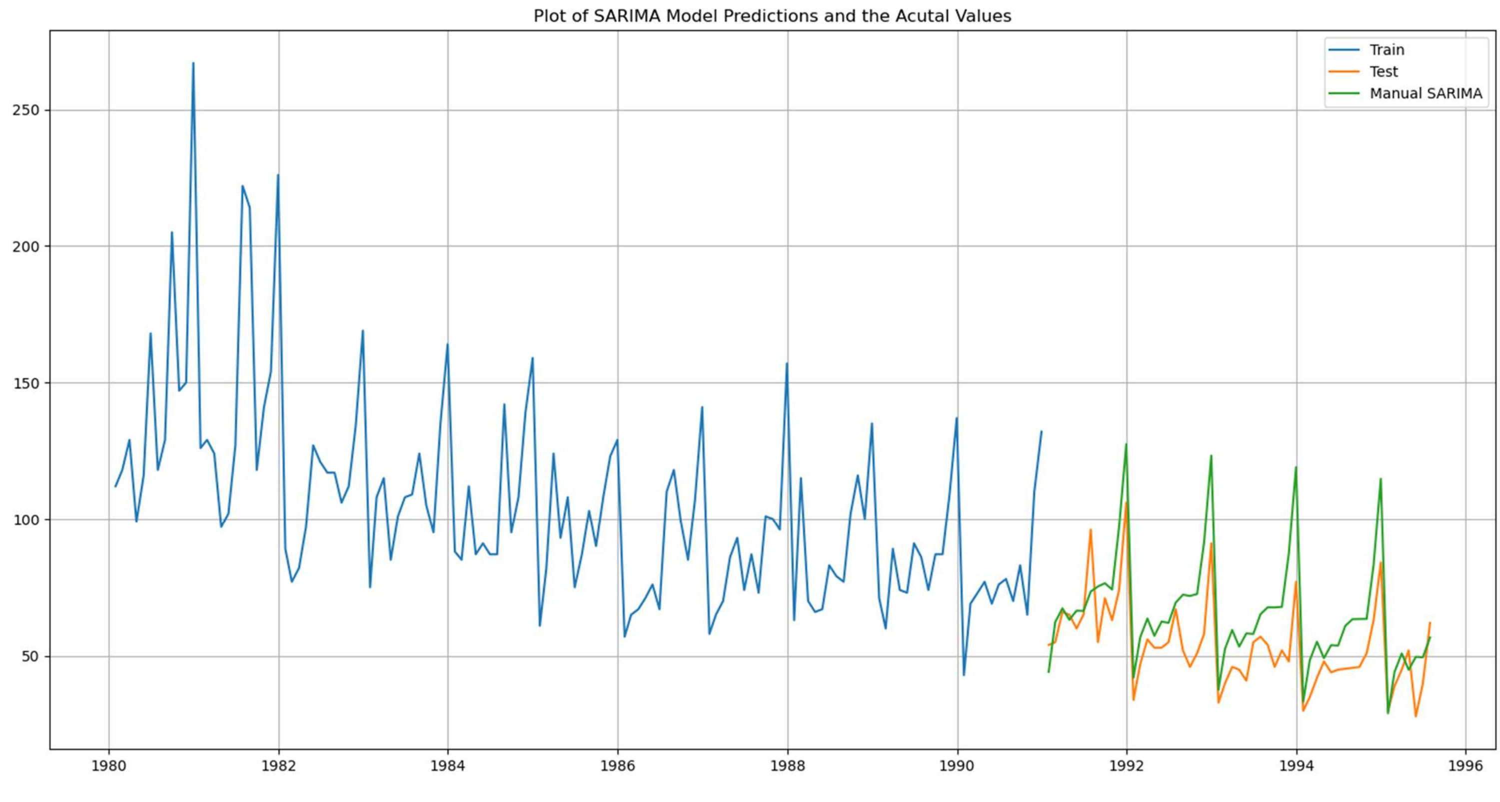
**Fig.37 Manual SARIMA Results**

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                 y   No. Observations:                  132
Model:             SARIMAX(0, 1, 2)x(2, 1, 2, 12)   Log Likelihood                -380.485
Date:                           Sun, 09 Mar 2025   AIC                            774.969
Time:                                   19:47:07   BIC                            792.622
Sample:                                        0   HQIC                           782.094
                                           - 132
Covariance Type:                             opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.9524      0.184     -5.166      0.000      -1.314      -0.591
ma.L2         -0.0764      0.126     -0.605      0.545      -0.324       0.171
ar.S.L12       0.0480      0.177      0.271      0.786      -0.299       0.395
ar.S.L24      -0.0419      0.028     -1.513      0.130      -0.096       0.012
ma.S.L12      -0.7526      0.301     -2.503      0.012      -1.342      -0.163
ma.S.L24      -0.0722      0.204     -0.354      0.723      -0.472       0.327
sigma2       187.8623     45.281      4.149      0.000      99.114     276.611
===================================================================================
Ljung-Box (L1) (Q):                   0.06   Jarque-Bera (JB):                 4.86
Prob(Q):                              0.81   Prob(JB):                         0.09
Heteroskedasticity (H):               0.91   Skew:                             0.41
Prob(H) (two-sided):                  0.79   Kurtosis:                         3.77
===================================================================================
```

## Fig.38 Manual SARIMA diagnostics




## Fig.39 Manual SARIMA plot

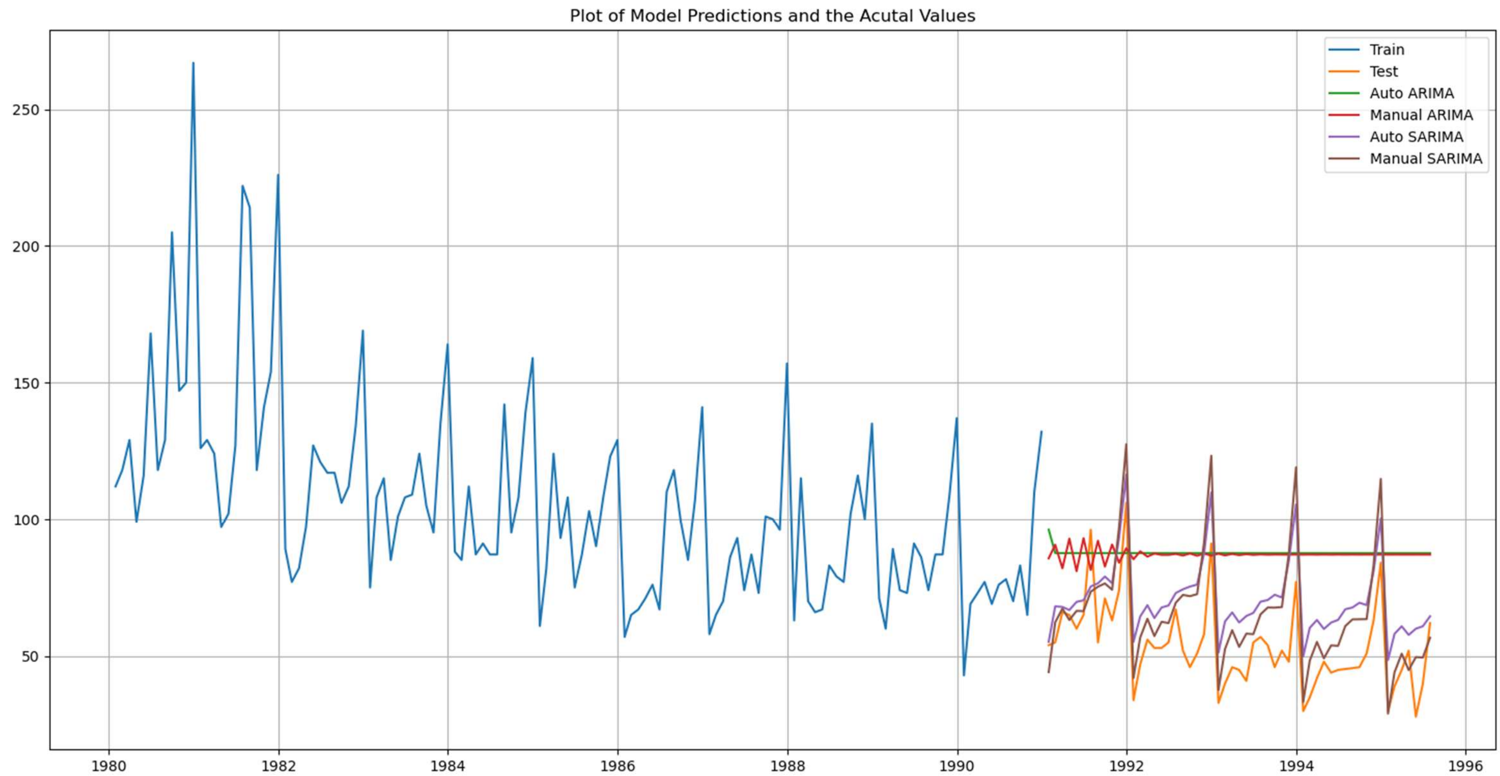


## 6.6 MODEL PERFORMANCE EVALUATION:

### Fig.40 ARIMA & SARIMA model performances

| | |
|---|---|
| ARIMA(0,1,2) | 37.306480 |
| Manual ARIMA(2,1,3) | 36.813039 |
| SARIMA(3,1,1)(3,0,2,12) | 18.881936 |
| Manual SARIMA(0,1,2)(2,1,2,12) | 16.500280 |

### Fig.41 ARIMA & SARIMA model predictions



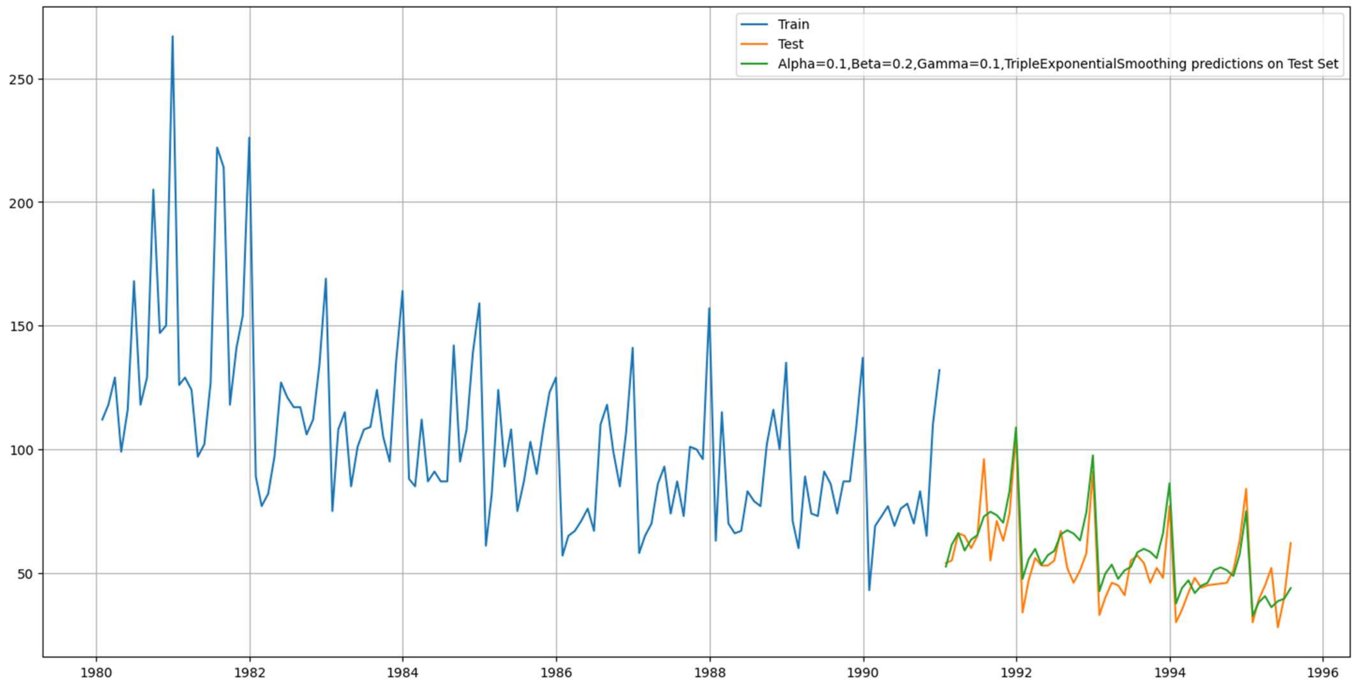

- Both Auto ARIMA and Manual ARIMA models perform similar with approx. RMSE score of 37
- These ARIMA models underperforms when compared to other models.
- Auto SARIMA model performs slightly better than the ARIMA models with the Test RMSE of 18.88
- Manual SARIMA with parameters as (0,1,2) (2,1,2,12) has the lowest RMSE score of 16.5 when compared to other ARIMA/SARIMA models

# 7. MODEL PERFORMANCE COMPARISON AND FINAL MODEL SELECTION FOR FORECAST

**Fig.42 All model performances**

| | Test RMSE |
|---|---|
| Alpha=0.1,Beta=0.2,Gamma=0.1,TripleExponentialSmoothing | 9.223504 |
| 2-point Trailing MovingAverage | 11.529278 |
| 4-point Trailing MovingAverage | 14.451403 |
| 6-point Trailing MovingAverage | 14.566327 |
| 9-point Trailing MovingAverage | 14.727630 |
| Linear Regression Model | 15.268955 |
| Manual SARIMA(0,1,2)(2,1,2,12) | 16.500280 |
| SARIMA(3,1,1)(3,0,2,12) | 18.881936 |
| Alpha=0.077,Beta=0.039,Gamma=0.0008,TripleExponentialSmoothing | 19.113110 |
| Manual ARIMA(2,1,3) | 36.813039 |
| Alpha=0.1,SimpleExponentialSmoothing | 36.828033 |
| Alpha=0.1,Beta=0.1,DoubleExponentialSmoothing | 36.923416 |
| ARIMA(0,1,2) | 37.306480 |
| Alpha=0.123,SimpleExponentialSmoothing | 37.592212 |
| SimpleAverageModel | 53.460570 |

**Fig.43 Triple Exponential Smoothing** (α = 0.1, β = 0.2 and γ = 0.1)



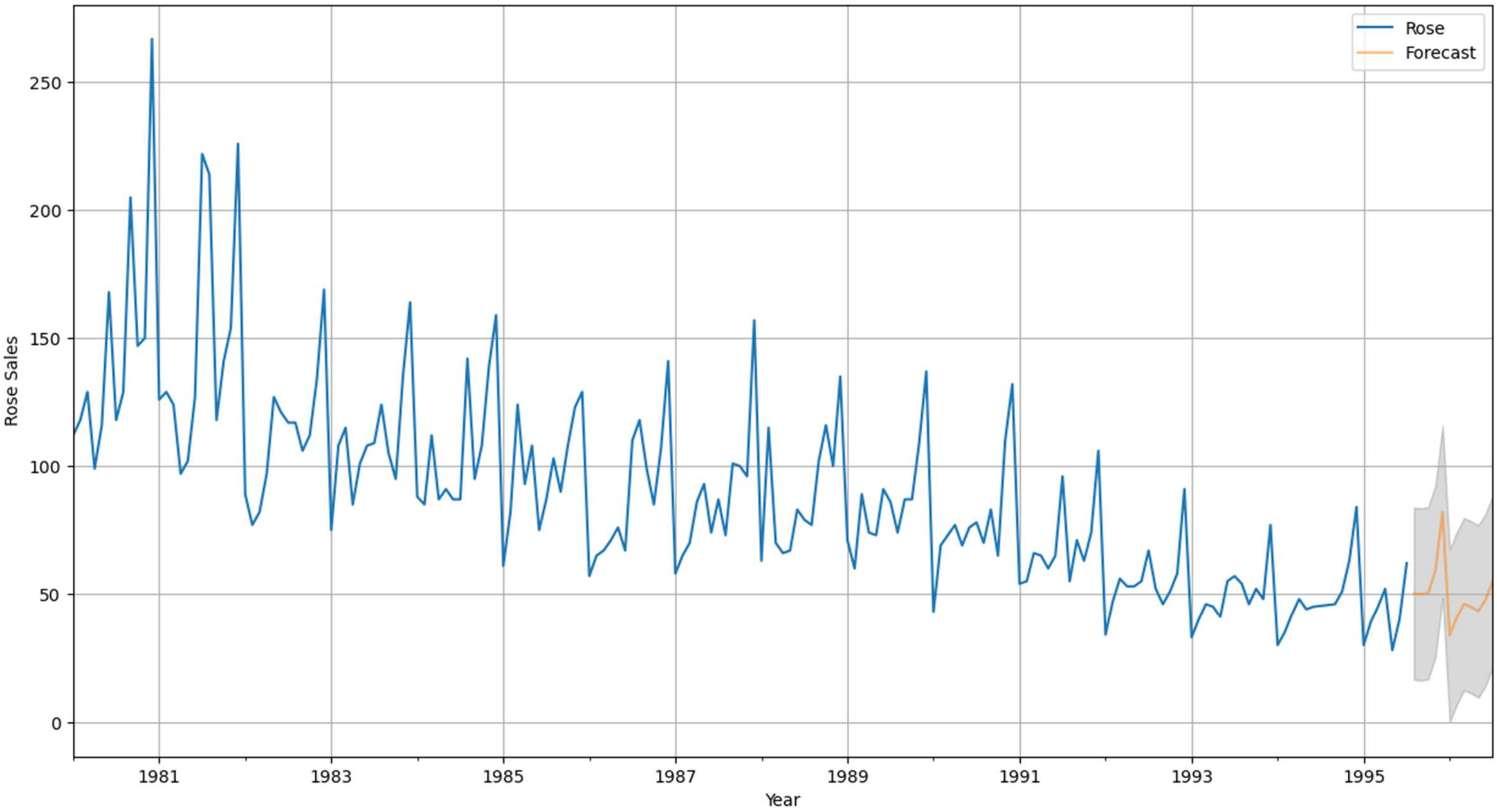
- The **Triple Exponential Smoothing** with the parameters $\alpha = 0.1$, $\beta = 0.2$ and $\gamma = 0.1$ has the lowest Test RMSE score of **9.22** and is considered as the **best forecasting model** for this Rose wine dataset.
- 2-Point Trailing Moving Average model has the RMSE score of 11.52 and performs better compared to other Moving Average models.
- The Simple Averaging Model has the highest Test RMSE score of 53.46 and is considered as the worst performing model.

**Forecasted Results of the best model (For next 12 months):**

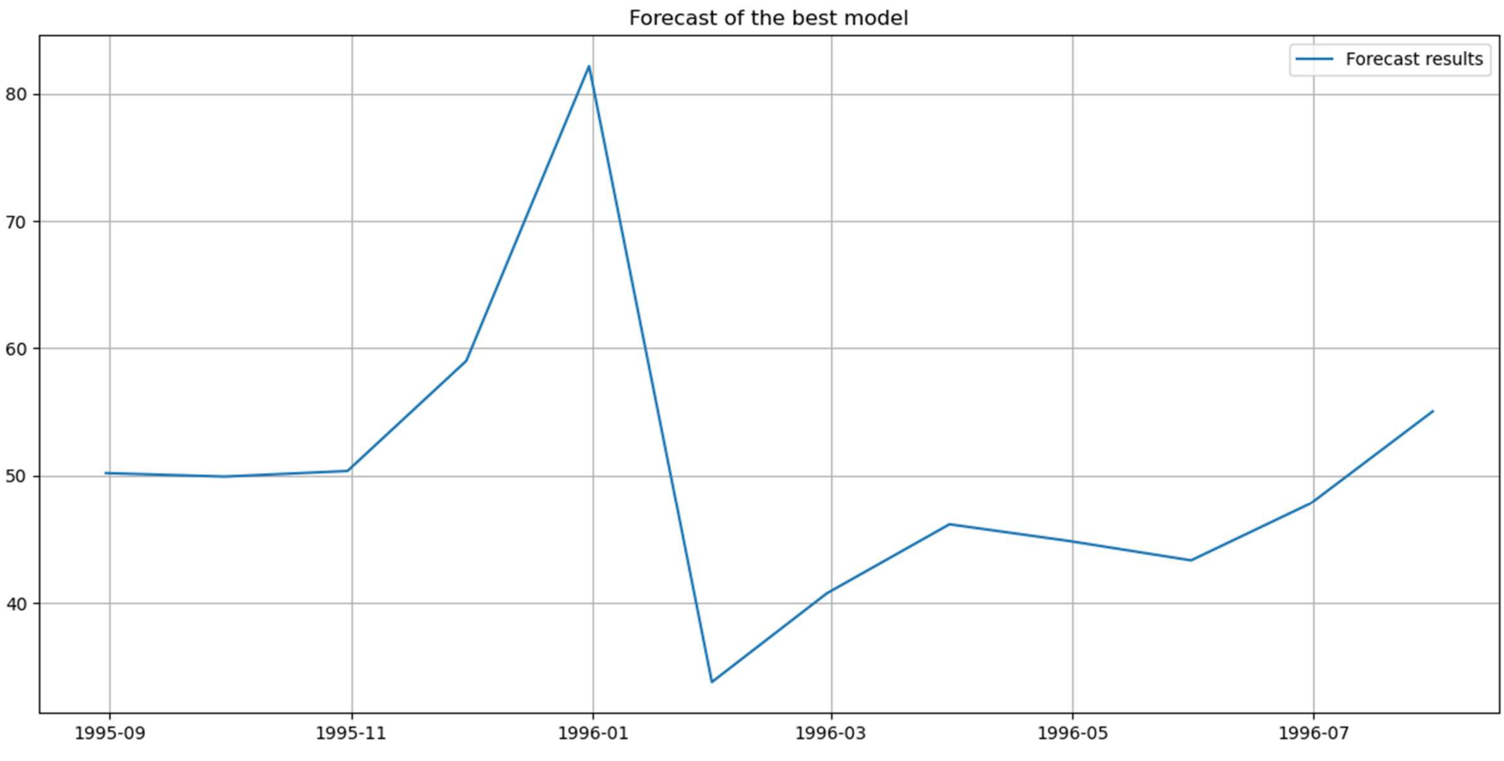
**Fig.44 Forecasted Results**

```
1995-08-31    50.188630
1995-09-30    49.914641
1995-10-31    50.355447
1995-11-30    59.009122
1995-12-31    82.169663
1996-01-31    33.801242
1996-02-29    40.732280
1996-03-31    46.135859
1996-04-30    44.838420
1996-05-31    43.313514
1996-06-30    47.750927
1996-07-31    55.037547
Freq: M, dtype: float64
```

## Fig.45 Forecast of the best model




## Fig.46 Plotting only Forecast results



# 8. ACTIONABLE INSIGHTS & RECOMMENDATIONS

- The Rose Wine Sales dataset clearly shows a declining trend in the sales from 1980 to 1995.

**Fig.47 Time Series Trend**

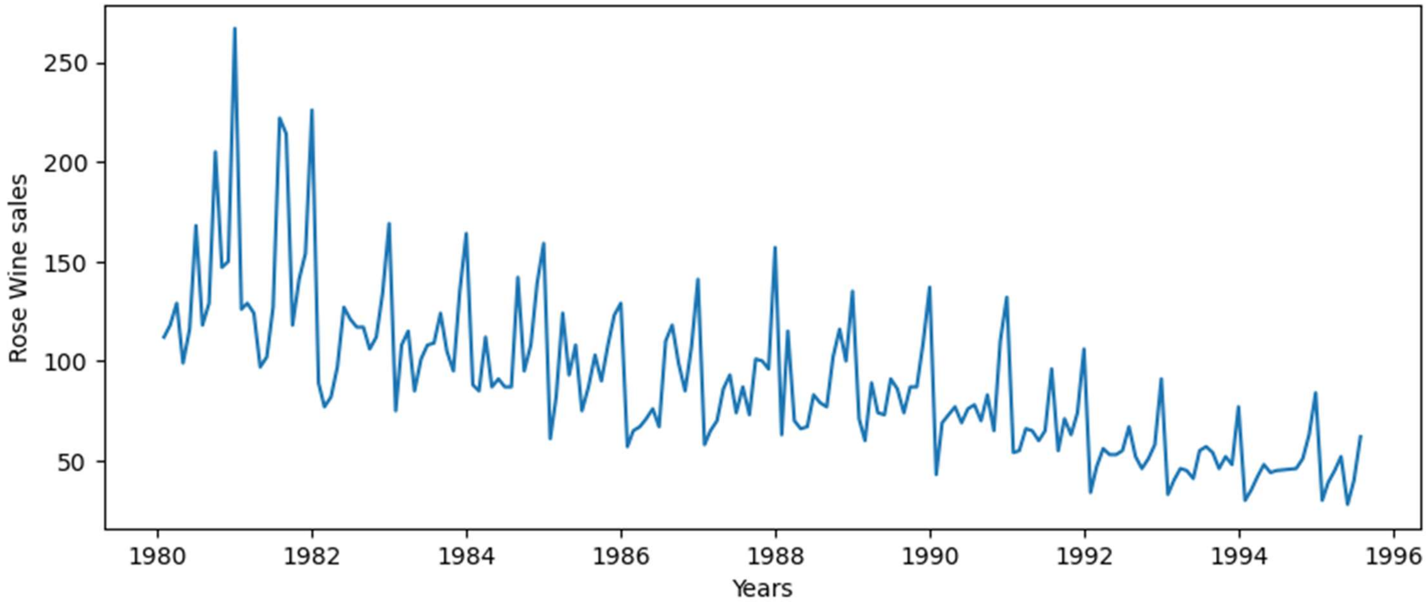
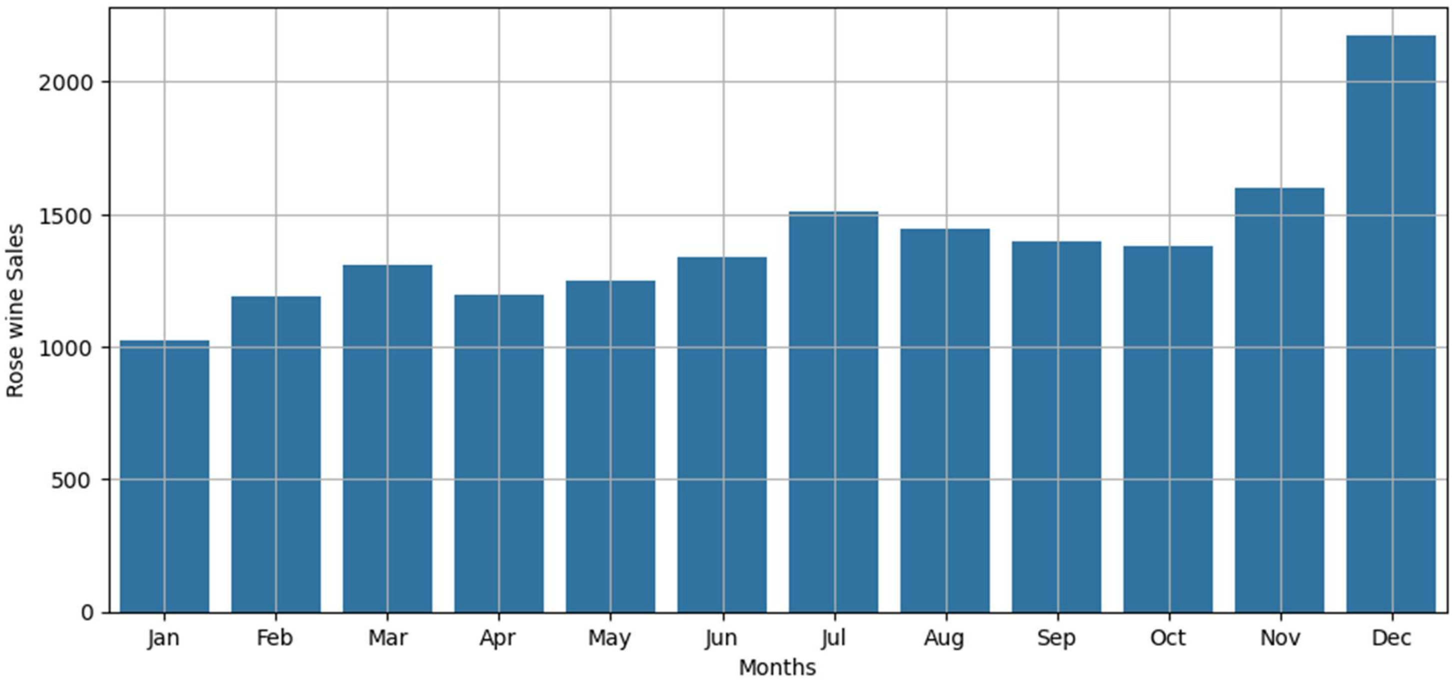



**Fig.48 Monthly Sales**



- **December** month have the highest sales compared to other months due to holiday and festival season demands.
- Peak sales can be improved by restocking and optimizing supply chain department.
- **January** and **February** months have the lowest sales and can be boosted by giving limited time discounts after holiday season.
- By using data driven analysis and forecasting methods, the **declining trend of the Rose wine sales** can be studied for improving the sales.
- The Factors behind the **declining trend** can be studied by obtaining frequent customer feedbacks at regular intervals and addressing their requests.
- Promoting new ad campaigns for rose wine or rebranding with unique and trendy posters can increase the product's reach and sales.
- Rebranding with introductory offers will helps to increase the sales.
- To increase customer engagement, public wine tasting sessions and events can be arranged for getting feedback.
- By partnering with local restaurants and bars, product’s reach can be increased.
- Product packages with eco-friendly measures can introduce new set of customers.