Task 1 : Analyze sales data over time and forecast future sales

In [46]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error
from statsmodels.tsa.arima.model import ARIMA

# Disable scientific notation for large numbers
pd.options.display.float_format = '{:.0f}'.format

# Setting display options for Pandas to show three decimal places for floati
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

Data Loading

In [47]:
```
# import data
sales_df = pd.read_csv('/content/drive/MyDrive/sales.csv', parse_dates=['Tim
```

Data Exploration

In [48]:
```
sales_df.info() # Display information about the DataFrame, including data ty
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374 entries, 0 to 373
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Timestamp           374 non-null    datetime64[ns]
 1   Sales Amount (USD)  374 non-null    int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 6.0 KB
```

In [49]:
```
sales_df.head() # Display top 5 records
```

Out[49]:

	Timestamp	Sales Amount (USD)
0	2000-01-01	1000
1	2000-02-01	1100
2	2000-03-01	1050
3	2000-04-01	1200
4	2000-05-01	1150

Data Cleaning

In [50]:
```
sales_df.isna().sum() # Print the sum of missing values
```

Out[50]:

	0
Timestamp	0
Sales Amount (USD)	0

dtype: int64

Since, the sum of missing values, so there is no need to replace the missing values.

In [51]:
```
print(sales_df.duplicated().sum())  # Print the sum of duplicated values
```

```
0
```

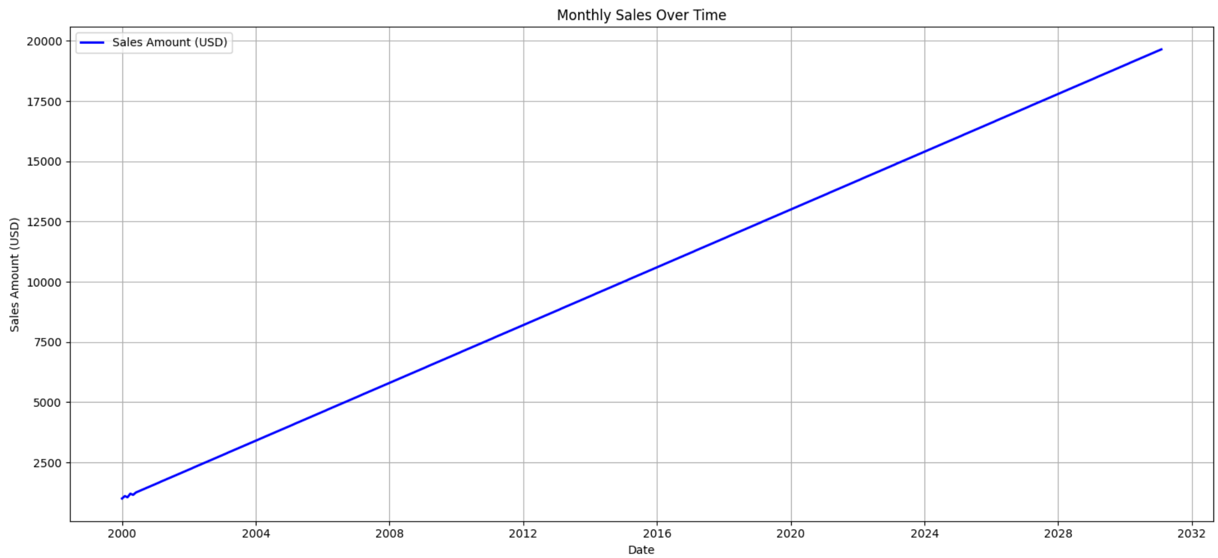
Since, the sum of duplicated values, so there is no need to drop duplicates.

Data Visualization

Plot sales data

In [52]:
```
# Set the Timestamp as the DataFrame index for time series plotting
sales_df.set_index('Timestamp', inplace=True)

# Create a line plot
plt.figure(figsize=(15, 7))
plt.plot(sales_df.index, sales_df['Sales Amount (USD)'], color='blue', linew
plt.title('Monthly Sales Over Time')
plt.xlabel('Date')
plt.ylabel('Sales Amount (USD)')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



Line plot of moving averages

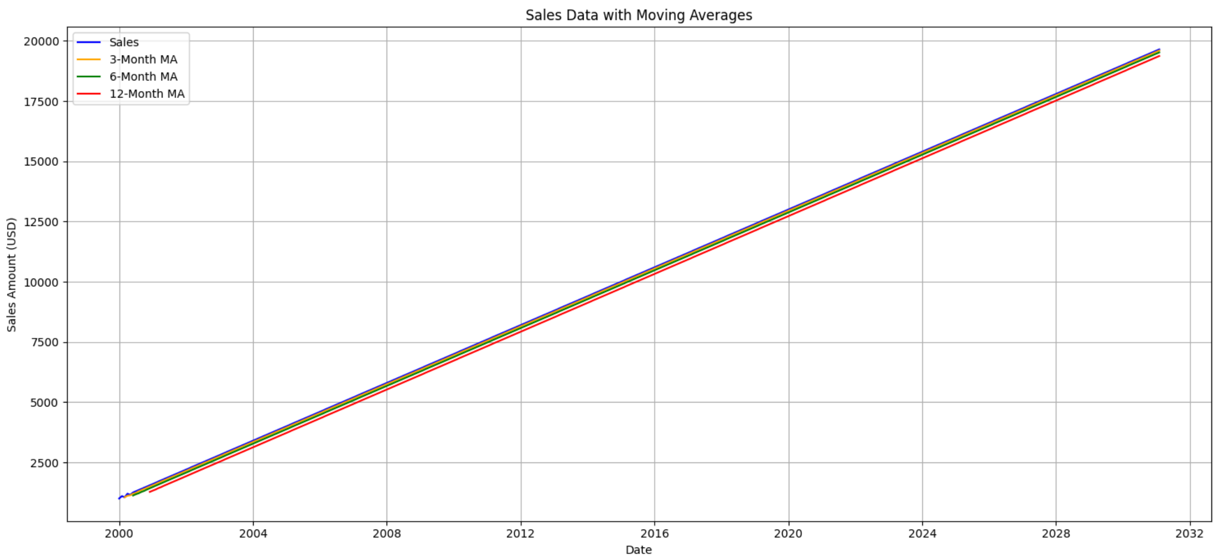
In [53]:
```
# Calculate moving averages
sales_df['MA_3'] = sales_df['Sales Amount (USD)'].rolling(window=3).mean()
sales_df['MA_6'] = sales_df['Sales Amount (USD)'].rolling(window=6).mean()
sales_df['MA_12'] = sales_df['Sales Amount (USD)'].rolling(window=12).mean()

plt.figure(figsize=(15, 7))

# Plot original sales line
plt.plot(sales_df.index, sales_df['Sales Amount (USD)'], label='Sales', colo

# Plot moving averages
plt.plot(sales_df.index, sales_df['MA_3'], label='3-Month MA', color='orange
plt.plot(sales_df.index, sales_df['MA_6'], label='6-Month MA', color='green'
plt.plot(sales_df.index, sales_df['MA_12'], label='12-Month MA', color='red'

plt.title('Sales Data with Moving Averages')
plt.xlabel('Date')
plt.ylabel('Sales Amount (USD)')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



Sales Forecasting

In [54]:
```
# Fit ARIMA model
model = ARIMA(sales_df['Sales Amount (USD)'], order=(5,1,0))
model_fit = model.fit()
print(model_fit.summary())
```

```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
```

```
                               SARIMAX Results
==============================================================================
==
Dep. Variable:     Sales Amount (USD)   No. Observations:                    3
74
Model:                 ARIMA(5, 1, 0)   Log Likelihood               -1031.9
70
Date:                Mon, 28 Jul 2025   AIC                           2075.9
40
Time:                        16:27:53   BIC                           2099.4
70
Sample:                    01-01-2000   HQIC                          2085.2
83
                         - 02-01-2031
Covariance Type:                  opg
==============================================================================
==
                 coef    std err          z      P>|z|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
ar.L1         -1.2032      0.015    -78.047      0.000      -1.233      -1.1
73
ar.L2          0.1456      0.021      6.898      0.000       0.104       0.1
87
ar.L3          1.0994      0.017     65.573      0.000       1.067       1.1
32
ar.L4          0.6856      0.020     34.445      0.000       0.647       0.7
25
ar.L5          0.2721      0.017     15.684      0.000       0.238       0.3
06
sigma2        14.3464      0.184     77.761      0.000      13.985      14.7
08
==============================================================================
=======
Ljung-Box (L1) (Q):                   0.04   Jarque-Bera (JB):             54
6916.67
Prob(Q):                              0.85   Prob(JB):
0.00
Heteroskedasticity (H):               0.00   Skew:
11.47
Prob(H) (two-sided):                  0.00   Kurtosis:
189.18
==============================================================================
=======

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (compl
ex-step).
```

Forecast Sales of next 12 months

In [55]:

```
# Forecast next 12 months
forecast_steps = 12
forecast = model_fit.forecast(steps=forecast_steps)
```

```
# Create datestamp for future periods
last_date = sales_df.index[-1]
forecast_index = pd.date_range(start=last_date, periods=forecast_steps+1, fr
forecast_df = pd.DataFrame({'Forecast': forecast.values}, index=forecast_inc
print(forecast_df)
```

```
            Forecast
2031-03-01  19699.97
2031-04-01  19749.98
2031-05-01  19799.94
2031-06-01  19849.93
2031-07-01  19899.90
2031-08-01  19949.87
2031-09-01  19999.85
2031-10-01  20049.80
2031-11-01  20099.77
2031-12-01  20149.71
2032-01-01  20199.67
2032-02-01  20249.62
```

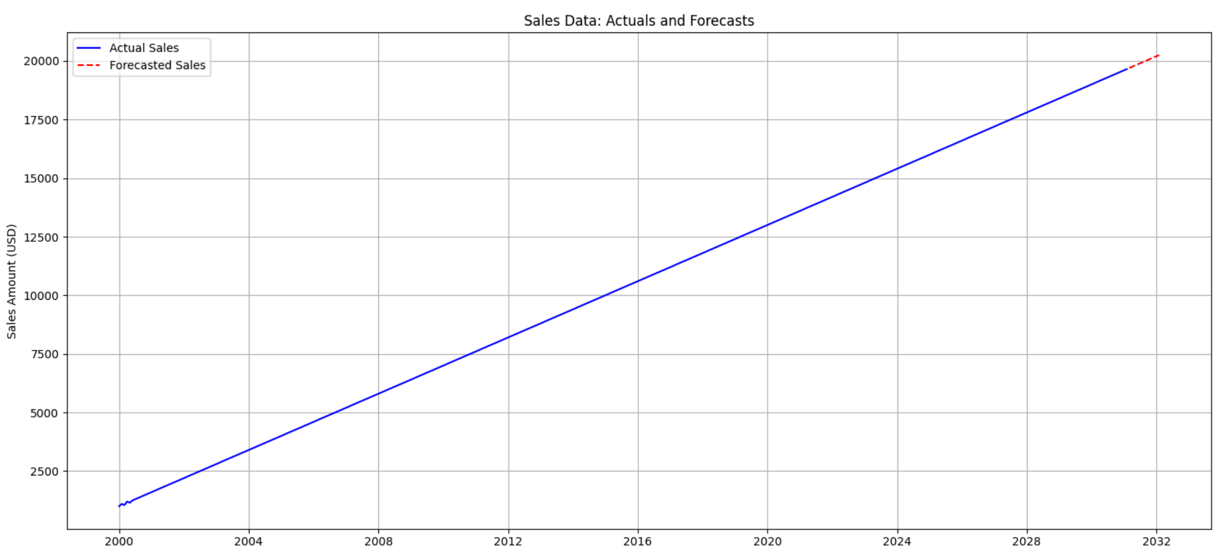
Line plot for Actual and Forecast sales

In [56]:
```
plt.figure(figsize=(15, 7))

# Plot the actual sales data
plt.plot(sales_df.index, sales_df['Sales Amount (USD)'], label='Actual Sales

# Plot the future sales forecast
plt.plot(forecast_df.index, forecast_df['Forecast'], label='Forecasted Sales

plt.title('Sales Data: Actuals and Forecasts')
plt.xlabel('Date')
plt.ylabel('Sales Amount (USD)')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



Model Training

In [57]:
```
# Split 80% for training, 20% for testing
train_size = int(len(sales_df) * 0.8)
train, test = sales_df.iloc[:train_size], sales_df.iloc[train_size:]
```

In [58]:
```
# Fit the ARIMA model on the training data
order = (5, 1, 0)
model = ARIMA(train['Sales Amount (USD)'], order=order)
model_fit = model.fit()

# Forecast for the number of points in the test set
forecast = model_fit.forecast(steps=len(test))
```

```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:47
3: ValueWarning: No frequency information was provided, so inferred frequenc
y MS will be used.
  self._init_dates(dates, freq)
```

Model evaluation

In [59]:
```
# Calculate the metrics
mse = mean_squared_error(test['Sales Amount (USD)'], forecast)
rmse = np.sqrt(mse)
mae = mean_absolute_error(test['Sales Amount (USD)'], forecast)

# Print metrics
print(f'MSE: {mse:.2f}')
print(f'RMSE: {rmse:.2f}')
print(f'MAE: {mae:.2f}')
```

```
MSE: 45.58
RMSE: 6.75
MAE: 5.12
```

Task 2 : Predicting Heart Disease

Data Loading

In [60]:
```
# import data
heart_disease_df = pd.read_csv('/content/drive/MyDrive/heart_disease.csv')
```

Data Exploration

In [61]:
```
heart_disease_df.info() # Display information about the DataFrame, including
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   patientid          1000 non-null   int64  
 1   age                1000 non-null   int64  
 2   gender             1000 non-null   int64  
 3   chestpain          1000 non-null   int64  
 4   restingBP          1000 non-null   int64  
 5   serumcholestrol    1000 non-null   int64  
 6   fastingbloodsugar  1000 non-null   int64  
 7   restingrelectro    1000 non-null   int64  
 8   maxheartrate       1000 non-null   int64  
 9   exerciseangia      1000 non-null   int64  
 10  oldpeak            1000 non-null   float64
 11  slope              1000 non-null   int64  
 12  noofmajorvessels   1000 non-null   int64  
 13  target             1000 non-null   int64  
dtypes: float64(1), int64(13)
memory usage: 109.5 KB
```

In [62]:
```
heart_disease_df.head() # Display top 5 records
```

Out[62]:

	patientid	age	gender	chestpain	restingBP	serumcholestrol	fastingbloo
0	103368	53	1	2	171	0	
1	119250	40	1	0	94	229	
2	119372	49	1	2	133	142	
3	132514	43	1	0	138	295	
4	146211	31	1	1	199	0	

Data Cleaning

In [63]:
```
print(heart_disease_df.isna().sum().sum())  # Print the sum of missing value
```

```
0
```

Since, the sum of missing values is zero, so there is no need to replace missing values.

In [64]:
```
print(heart_disease_df.duplicated().sum())  # Print the sum of duplicated va
```

```
0
```

Since, the sum of duplicated values is zero, so there is no need to drop duplicates.

Check for outliers

In [65]:
```
# Specify the columns for outlier removal
cols = ['age', 'serumcholestrol', 'restingBP']

# Remove outliers using IQR
for col in cols:
    Q1 = heart_disease_df[col].quantile(0.25)
    Q3 = heart_disease_df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
    heart_disease_df = heart_disease_df[(heart_disease_df[col] >= lower) & (

    # Boolean mask for outliers
    outliers = (heart_disease_df[col] < lower) | (heart_disease_df[col] > up
    print(f'Number of {col} outliers:', outliers.sum())
    print(heart_disease_df.loc[outliers, col])
```

```
Number of age outliers: 0
Series([], Name: age, dtype: int64)
Number of serumcholestrol outliers: 0
Series([], Name: serumcholestrol, dtype: int64)
Number of restingBP outliers: 0
Series([], Name: restingBP, dtype: int64)
```

In [66]:
```
print(f"Shape after removing outliers: {heart_disease_df.shape}")
```

```
Shape after removing outliers: (1000, 14)
```

Feature Engineering

In [67]:
```
from sklearn.preprocessing import StandardScaler

# Specify the numerical features to scale
numerical_features = ['age', 'serumcholestrol', 'restingBP']

# Initialize the scaler
scaler = StandardScaler()

# Fit the scaler and transform these features
scaled_features = scaler.fit_transform(heart_disease_df[numerical_features])

# Add the scaled columns to your DataFrame for comparison
for i, col in enumerate(numerical_features):
    heart_disease_df[f'scaled_{col}'] = scaled_features[:, i]
```

In [68]:
```
heart_disease_df.head() # Check for newly added columns
```

Out[68]:

	patientid	age	gender	chestpain	restingBP	serumcholestrol	fastingbloo
0	103368	53	1	2	171	0	
1	119250	40	1	0	94	229	
2	119372	49	1	2	133	142	
3	132514	43	1	0	138	295	
4	146211	31	1	1	199	0	

Model training and evaluation

In [69]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f

features = ['scaled_age', 'scaled_serumcholestrol', 'scaled_restingBP']  # A
X = heart_disease_df[features]
y = heart_disease_df['target']

# Split the dataset into training and testing sets (80% - 20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

# Initialize Logistic Regression model
model = LogisticRegression(max_iter=1000)

# Train the model
model.fit(X_train, y_train)

# Predict on test data
y_pred = model.predict(X_test)

# Evaluate the model
a_s = accuracy_score(y_test, y_pred)
p_s = precision_score(y_test, y_pred)
r_s = recall_score(y_test, y_pred)
f_s = f1_score(y_test, y_pred)

# Print
print(f'Accuracy: {a_s:.2f}')
print(f"Precision: {p_s:.2f}")
print(f"Recall: {r_s:.2f}")
print(f"F1 Score: {f_s:.2f}")

# Print confusion matrix and report
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.84
Precision: 0.89
Recall: 0.84
F1 Score: 0.86

Confusion Matrix:
 [[71 12]
 [19 98]]

Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.86      0.82        83
           1       0.89      0.84      0.86       117

    accuracy                           0.84       200
   macro avg       0.84      0.85      0.84       200
weighted avg       0.85      0.84      0.85       200
```