# Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split,GridSearchCV, cross_v
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegres
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_er
import tensorflow as tf
import math
```

```
WARNING:tensorflow:From C:\Users\Teoh\anaconda3\Lib\site-packages\keras\src\l
osses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated.
Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

In [2]:
```
df1 = pd.read_csv('laptops.csv')
```

# Data Cleaning

## Before Data Cleaning

In [3]:

```
df1.head()
```

Out[3]:

| | CompanyName | TypeOfLaptop | Inches | ScreenResolution | Cpu | Ram | Memory | Gpu |
|---|---|---|---|---|---|---|---|---|
| **0** | MSI | Business Laptop | 17.040680 | IPS Panel Retina Display 2560x1600 | Intel Core i7 | 12GB | 512GB SSD | Intel Iris Xe Graphics |
| **1** | Chuwi | 2 in 1 Convertible | 16.542395 | Full HD | Intel Core i5 | 12GB | 128GB PCIe SSD | Intel Iris Xe Graphics |
| **2** | hp | WorkStation | 17.295294 | Full HD | Intel Xeon E3-1505M | 8GB | 1TB HDD | Intel Iris Xe Graphics |
| **3** | MSI | 2 in 1 Convertible | 11.526203 | 2K | Intel Core i7 | 16GB | 512GB NVMe SSD | Intel Iris Xe Graphics |
| **4** | Microsoft | Gaming | 12.649634 | Full HD | Intel Core i5 | 8GB | 512GB SSD | AMD Radeon RX 5600M |

## After Data Cleaning

In [4]:
```
size_mapping = {
    '512GB SSD': '512GB',
    '128GB PCIe SSD': '128GB',
    '1TB HDD': '1TB',
    '512GB NVMe SSD': '512GB',
    '1TB NVMe SSD': '1TB',
    '256GB PCIe SSD': '256GB',
    '128GB SSD': '128GB',
    '1TB Fusion Drive': '1TB',
    '4TB HDD': '4TB',
    '2TB NVMe SSD': '2TB',
    '256GB Flash Storage': '256GB',
    '6TB HDD': '6TB',
    '512GB eMMC': '512GB',
    '256GB eMMC': '256GB',
    '2TB SATA SSD': '2TB',
    '1TB SSHD': '1TB',
    '256GB SSD': '256GB',
    '2TB HDD': '2TB'
}

# Replace values in the 'Memory' column using the size mapping
df1['Memory'] = df1['Memory'].replace(size_mapping)
```

In [5]:
```
df1['ScreenResolution'] = df1['ScreenResolution'].replace('IPS Panel Retin

condition = df1['ScreenResolution'] == '4K'

# Use df.where and dropna to filter rows
filtered_df = df1.where(condition).dropna()
```

In [6]:
```
df1['R_inches'] = df1['Inches'].round().astype(int)
```

In [7]:
```
df1['R_weight'] = df1['Weight'].round(2)
```

In [8]:
```
df1['ScreenResolution'] = df1['ScreenResolution'].replace(['HD 1920x1080 '

condition = df1['ScreenResolution'] == 'Full HD'

# Use df.where and dropna to filter rows
filtered_df = df1.where(condition).dropna()
```

In [9]:
```
inr_to_myr = 0.057

df1['MYR_price'] = df1['Price'] * inr_to_myr
df1['MYR_price'] = df1['MYR_price'].round(2)

filtered_df = df1.drop(['Price', 'Inches', 'Weight'], axis=1)
```

In [10]:
```
df = filtered_df
df.head()
```

Out[10]:

| | CompanyName | TypeOfLaptop | ScreenResolution | Cpu | Ram | Memory | Gpu | OpSys | I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | MSI | Business Laptop | 4K | Intel Core i7 | 12GB | 512GB | Intel Iris Xe Graphics | Linux | |
| **1** | Chuwi | 2 in 1 Convertible | Full HD | Intel Core i5 | 12GB | 128GB | Intel Iris Xe Graphics | No OS | |
| **2** | hp | WorkStation | Full HD | Intel Xeon E3-1505M | 8GB | 1TB | Intel Iris Xe Graphics | Linux | |
| **3** | MSI | 2 in 1 Convertible | 2K | Intel Core i7 | 16GB | 512GB | Intel Iris Xe Graphics | Windows 10 | |
| **4** | Microsoft | Gaming | Full HD | Intel Core i5 | 8GB | 512GB | AMD Radeon RX 5600M | Windows 10 | |

In [11]:
```
df = pd.DataFrame(df)
```

In [12]:
```
df.to_csv('new_laptop.csv', index = False)
```

In [13]:
```
df = pd.read_csv('new_laptop.csv')
df.head()
```

Out[13]:

| | CompanyName | TypeOfLaptop | ScreenResolution | Cpu | Ram | Memory | Gpu | OpSys | I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | MSI | Business Laptop | 4K | Intel Core i7 | 12GB | 512GB | Intel Iris Xe Graphics | Linux | |
| **1** | Chuwi | 2 in 1 Convertible | Full HD | Intel Core i5 | 12GB | 128GB | Intel Iris Xe Graphics | No OS | |
| **2** | hp | WorkStation | Full HD | Intel Xeon E3-1505M | 8GB | 1TB | Intel Iris Xe Graphics | Linux | |
| **3** | MSI | 2 in 1 Convertible | 2K | Intel Core i7 | 16GB | 512GB | Intel Iris Xe Graphics | Windows 10 | |
| **4** | Microsoft | Gaming | Full HD | Intel Core i5 | 8GB | 512GB | AMD Radeon RX 5600M | Windows 10 | |

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   CompanyName       1000 non-null   object 
 1   TypeOfLaptop      1000 non-null   object 
 2   ScreenResolution  1000 non-null   object 
 3   Cpu               1000 non-null   object 
 4   Ram               1000 non-null   object 
 5   Memory            1000 non-null   object 
 6   Gpu               1000 non-null   object 
 7   OpSys             1000 non-null   object 
 8   R_inches          1000 non-null   int64  
 9   R_weight          1000 non-null   float64
 10  MYR_price         1000 non-null   float64
dtypes: float64(2), int64(1), object(8)
memory usage: 86.1+ KB
```

In [15]:
```
df.isna().sum()
```

Out[15]:
```
CompanyName         0
TypeOfLaptop        0
ScreenResolution    0
Cpu                 0
Ram                 0
Memory              0
Gpu                 0
OpSys               0
R_inches            0
R_weight            0
MYR_price           0
dtype: int64
```

# Exploratory Data Analysis (EDA)

In [16]:
```
df.describe()
```

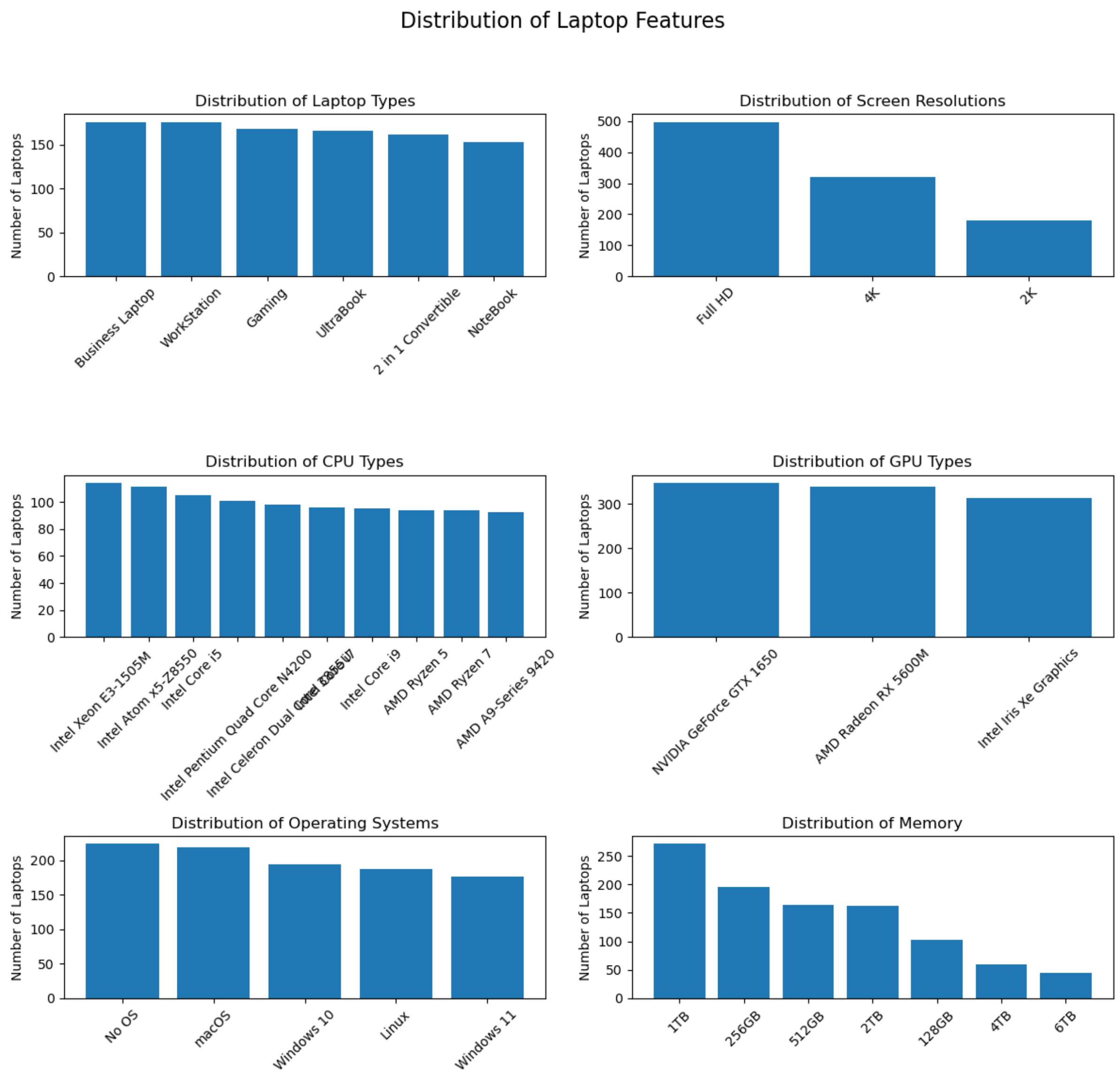
Out[16]:

| | R_inches | R_weight | MYR_price |
|---|---|---|---|
| **count** | 1000.000000 | 1000.000000 | 1000.000000 |
| **mean** | 14.499000 | 3.469810 | 2941.328620 |
| **std** | 2.113401 | 0.857131 | 786.761588 |
| **min** | 11.000000 | 2.000000 | 1713.440000 |
| **25%** | 13.000000 | 2.720000 | 2301.467500 |
| **50%** | 15.000000 | 3.480000 | 2888.990000 |
| **75%** | 16.000000 | 4.190000 | 3528.147500 |
| **max** | 18.000000 | 4.990000 | 6562.830000 |

In [17]:

```
# Type of Laptop
count_type = df['TypeOfLaptop'].value_counts().reset_index()
count_type.columns = ['TypeOfLaptop', 'Count']

# Screen Resolution
resolution = df['ScreenResolution'].value_counts().reset_index()
resolution.columns = ['ScreenResolution', 'Count']

# CPU
cpu = df['Cpu'].value_counts().reset_index()
cpu.columns = ['Cpu', 'Count']

# GPU
gpu = df['Gpu'].value_counts().reset_index()
gpu.columns = ['Gpu', 'Count']

# Operating System
os = df['OpSys'].value_counts().reset_index()
os.columns = ['OpSys', 'Count']

# Memory
ssd = df['Memory'].value_counts().reset_index()
ssd.columns = ['Memory', 'Count']

fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(12, 12))
fig.suptitle('Distribution of Laptop Features', fontsize=16)

# Plot 1
axes[0, 0].bar(count_type['TypeOfLaptop'], count_type['Count'])
axes[0, 0].set_title('Distribution of Laptop Types')
axes[0, 0].set_ylabel('Number of Laptops')
axes[0, 0].tick_params(axis='x', rotation=45)

# Plot 2
axes[0, 1].bar(resolution['ScreenResolution'], resolution['Count'])
axes[0, 1].set_title('Distribution of Screen Resolutions')
axes[0, 1].set_ylabel('Number of Laptops')
axes[0, 1].tick_params(axis='x', rotation=45)

# Plot 3
axes[1, 0].bar(cpu['Cpu'], cpu['Count'])
axes[1, 0].set_title('Distribution of CPU Types')
axes[1, 0].set_ylabel('Number of Laptops')
axes[1, 0].tick_params(axis='x', rotation=45)

# Plot 4
axes[1, 1].bar(gpu['Gpu'], gpu['Count'])
axes[1, 1].set_title('Distribution of GPU Types')
axes[1, 1].set_ylabel('Number of Laptops')
axes[1, 1].tick_params(axis='x', rotation=45)

# Plot 5
axes[2, 0].bar(os['OpSys'], os['Count'])
axes[2, 0].set_title('Distribution of Operating Systems')
axes[2, 0].set_ylabel('Number of Laptops')
axes[2, 0].tick_params(axis='x', rotation=45)

```

```python
axes[2, 1].bar(ssd['Memory'], ssd['Count'])
axes[2, 1].set_title('Distribution of Memory')
axes[2, 1].set_ylabel('Number of Laptops')
axes[2, 1].tick_params(axis='x', rotation=45)



plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

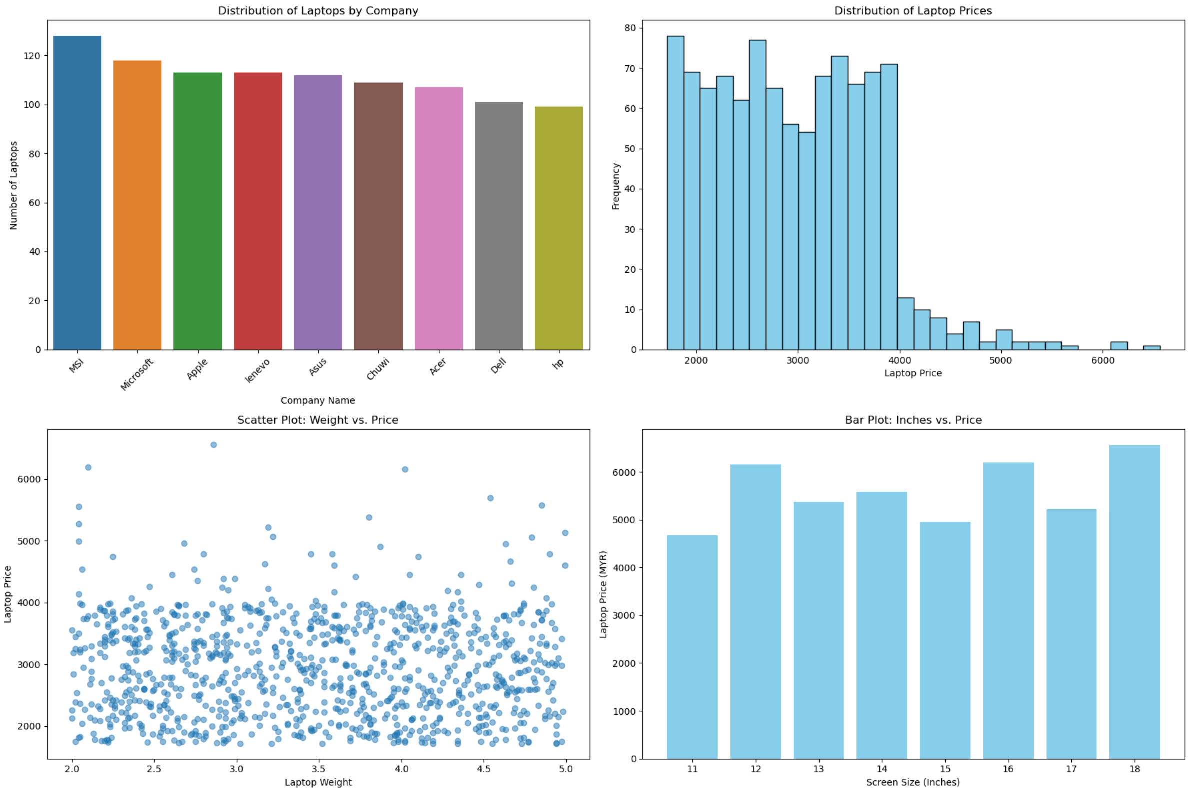


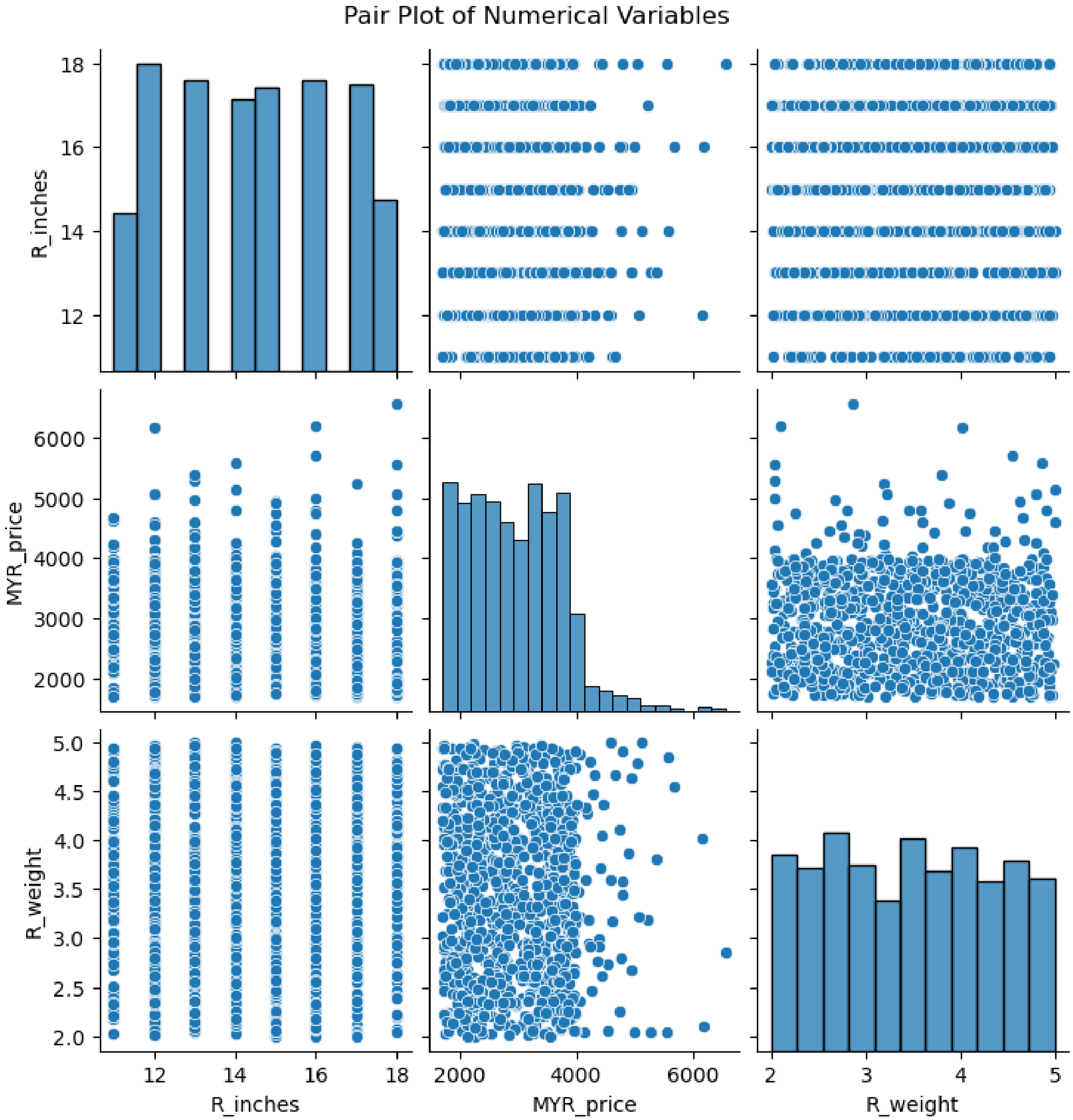
# Data Visualization

In [18]:

```
# Company Distribution
company_distribution = df['CompanyName'].value_counts().reset_index()
company_distribution.columns = ['CompanyName', 'Count']

plt.figure(figsize=(18, 12))

# Subplot 1: Company Distribution
plt.subplot(2, 2, 1)
sns.barplot(x='CompanyName', y='Count', data=company_distribution)
plt.title('Distribution of Laptops by Company')
plt.xlabel('Company Name')
plt.ylabel('Number of Laptops')
plt.xticks(rotation=45)

# Subplot 2: Price Distribution
plt.subplot(2, 2, 2)
plt.hist(df['MYR_price'], bins=30, color='skyblue', edgecolor='black')
plt.title('Distribution of Laptop Prices')
plt.xlabel('Laptop Price')
plt.ylabel('Frequency')

# Subplot 3: Scatter Plot - Price vs. Weight
plt.subplot(2, 2, 3)
plt.scatter(df['R_weight'], df['MYR_price'], alpha=0.5)
plt.title('Scatter Plot: Weight vs. Price')
plt.xlabel('Laptop Weight')
plt.ylabel('Laptop Price')

# Subplot 4: Bar Plot - Inches vs. Price
plt.subplot(2, 2, 4)
plt.bar(df['R_inches'], df['MYR_price'], color='skyblue')
plt.title('Bar Plot: Inches vs. Price')
plt.xlabel('Screen Size (Inches)')
plt.ylabel('Laptop Price (MYR)')

# Adjust layout
plt.tight_layout()

# Show the pair plot
pairplot_vars = ['R_inches', 'MYR_price', 'R_weight']
sns.pairplot(df[pairplot_vars])
plt.suptitle('Pair Plot of Numerical Variables', y=1.02)

plt.show()
```

```
C:\Users\Teoh\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarnin
g: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

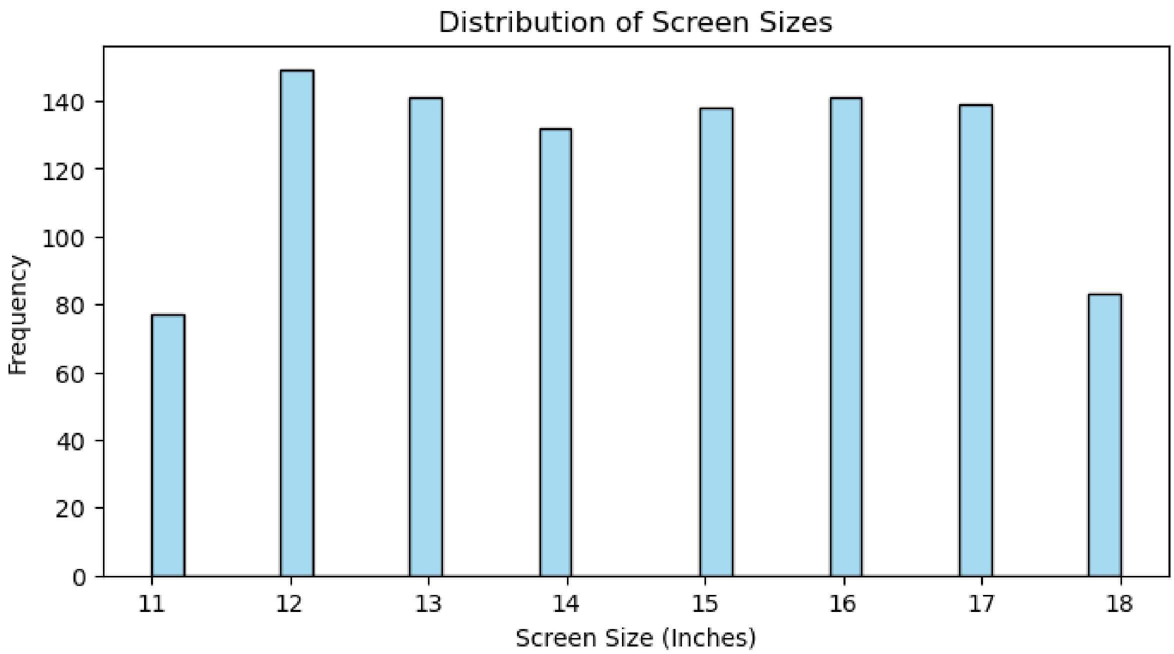

Distribution of Laptops by Company
Number of Laptops
MSI
Microsoft
Apple
lenevo
Asus
Chuwi
Acer
Dell
hp
Company Name
Distribution of Laptop Prices
Frequency
Laptop Price
Scatter Plot: Weight vs. Price
Laptop Price
Laptop Weight
Bar Plot: Inches vs. Price
Laptop Price (MYR)
Screen Size (Inches)




In [19]:
```
df.columns
```

Out[19]:
```
Index(['CompanyName', 'TypeOfLaptop', 'ScreenResolution', 'Cpu', 'Ram',
       'Memory', 'Gpu', 'OpSys', 'R_inches', 'R_weight', 'MYR_price'],
      dtype='object')
```

In [53]:
```
plt.figure(figsize=(8, 4))
sns.histplot(df['R_inches'], bins=30, color='skyblue')
plt.title('Distribution of Screen Sizes')
plt.xlabel('Screen Size (Inches)')
plt.ylabel('Frequency')
plt.show()
```




## Preprocessing

In [21]:
```
df_encoded = df.copy()

# List of categorical columns to encode
categorical_columns = ['TypeOfLaptop', 'Cpu', 'OpSys','CompanyName',
                       'ScreenResolution','Gpu','Ram','Memory']

# Apply LabelEncoder to each categorical column
label_encoder = LabelEncoder()
df_encoded[categorical_columns] = df[categorical_columns].apply(label_enco
```

In [22]:
```
# Assuming 'df_encoded' includes numerical features you want to normalize
numerical_features = ['R_inches', 'Ram', 'R_weight']
```

In [23]:
```
df_encoded.head()
```

Out[23]:

| | CompanyName | TypeOfLaptop | ScreenResolution | Cpu | Ram | Memory | Gpu | OpSys | R_inches |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 5 | 1 | 1 | 6 | 0 | 5 | 1 | 0 | 17 |
| **1** | 3 | 0 | 2 | 5 | 0 | 0 | 1 | 1 | 17 |
| **2** | 7 | 5 | 2 | 9 | 3 | 1 | 1 | 0 | 17 |
| **3** | 5 | 0 | 0 | 6 | 1 | 5 | 1 | 2 | 12 |
| **4** | 6 | 2 | 2 | 5 | 3 | 5 | 0 | 2 | 13 |

In [24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   CompanyName       1000 non-null   object 
 1   TypeOfLaptop      1000 non-null   object 
 2   ScreenResolution  1000 non-null   object 
 3   Cpu               1000 non-null   object 
 4   Ram               1000 non-null   object 
 5   Memory            1000 non-null   object 
 6   Gpu               1000 non-null   object 
 7   OpSys             1000 non-null   object 
 8   R_inches          1000 non-null   int64  
 9   R_weight          1000 non-null   float64
 10  MYR_price         1000 non-null   float64
dtypes: float64(2), int64(1), object(8)
memory usage: 86.1+ KB
```

In [25]:
```
X = df_encoded.drop('MYR_price', axis=1).values
y = df_encoded['MYR_price'].values

type(X)
type(y)
```

Out[25]: numpy.ndarray

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
```

In [27]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [28]:
```
X_train.shape, X_test.shape
```

Out[28]: ((800, 10), (200, 10))

In [29]:
```
X_train
```

Out[29]:
```
array([[-0.79361996,  1.46625911, -0.45407325, ..., -0.68948962,
        -0.71346687, -1.00784391],
       [-0.01076427, -1.46479358, -0.45407325, ..., -0.68948962,
         1.66277583, -0.98439273],
       [-0.40219211,  0.88004857,  0.87654433, ...,  1.40781721,
         0.71227875, -0.59744821],
       ...,
       [-0.40219211, -1.46479358, -0.45407325, ..., -0.68948962,
         0.23703021, -0.99611832],
       [-1.18504781, -1.46479358, -0.45407325, ...,  0.70871494,
         0.71227875,  1.2082929 ],
       [-0.79361996,  0.29383803,  0.87654433, ...,  1.40781721,
         1.66277583,  0.03573374]])
```

In [30]:
```
y_train.shape, y_test.shape
```

Out[30]:
```
((800,), (200,))
```

In [31]:
```
model = RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

# Get feature importances
feature_importances = model.feature_importances_

# Create a DataFrame to display feature importances
feature_importance_df = pd.DataFrame({
    'Feature': df_encoded.drop('MYR_price', axis=1).columns,
    'Importance': feature_importances
})

# Sort the DataFrame by importance in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance',

top5_features = feature_importance_df.head(5)
```

In [60]:
```
# # Select only numeric columns
# numeric_columns = df_encoded.select_dtypes(include=['number'])

# # Calculate the correlation matrix
# correlation_matrix = numeric_columns.corr()

# # Create a heatmap
# plt.figure(figsize=(10, 8))
# sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",
# plt.title('Correlation Matrix Heatmap')
# plt.show()
```

In [33]:
```
top5_features
```

Out[33]:

| | Feature | Importance |
|---|---|---|
| 9 | R_weight | 0.207590 |
| 0 | CompanyName | 0.157484 |
| 4 | Ram | 0.137156 |
| 3 | Cpu | 0.096947 |
| 8 | R_inches | 0.087866 |

In [34]:
```
new_df = df_encoded
new_df.head()
```

Out[34]:

| | CompanyName | TypeOfLaptop | ScreenResolution | Cpu | Ram | Memory | Gpu | OpSys | R_inches |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 5 | 1 | 1 | 6 | 0 | 5 | 1 | 0 | 17 |
| 1 | 3 | 0 | 2 | 5 | 0 | 0 | 1 | 1 | 17 |
| 2 | 7 | 5 | 2 | 9 | 3 | 1 | 1 | 0 | 17 |
| 3 | 5 | 0 | 0 | 6 | 1 | 5 | 1 | 2 | 12 |
| 4 | 6 | 2 | 2 | 5 | 3 | 5 | 0 | 2 | 13 |

In [35]:
```
X1 = new_df.drop('MYR_price', axis=1).values
y1 = new_df['MYR_price'].values

X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=0.2,
```

In [36]:
```
sc = StandardScaler()
X_train_a = sc.fit_transform(X_train)
X_test_a = sc.fit_transform(X_test)
```

In [37]:
```
# Train Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train_a, y_train)

# Make predictions using the trained Linear Regression model
linear_predictions = linear_model.predict(X_test_a)

print(y_train[0], linear_predictions[0])
# Evaluate Linear Regression model
linear_mse = mean_squared_error(y_test, linear_predictions)
print(f'Linear Regression Root Mean Squared Error: {math.sqrt(linear_mse)}

linear_r2_score = r2_score(y_test, linear_predictions)
print(f'Linear Regression R2 score: {linear_r2_score}')
```

```
2790.43 2985.9468470188212
Linear Regression Root Mean Squared Error: 816.8307479311965
Linear Regression R2 score: -0.0074273876498964775
```

In [38]:

```
param_grid = {
    'copy_X': [True,False],
    'fit_intercept':[True, False],
    'n_jobs': [None,1,2],
    'positive': [True,False]
}

# base_model = RandomForestRegressor(random_state=42)

grid_search = GridSearchCV(linear_model, param_grid, cv=5,
                           scoring='f1_micro',n_jobs=-1)

grid_search.fit(X_train_a, y_train)

best_params = grid_search.best_params_
best_estimator = grid_search.best_estimator_

print(best_params)
print(best_estimator)
```

```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'positive': True}
LinearRegression(positive=True)
```

```
C:\Users\Teoh\anaconda3\Lib\site-packages\sklearn\model_selection\_search.py:
976: UserWarning: One or more of the test scores are non-finite: [nan nan nan
nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan]
  warnings.warn(
```

In [39]:

```
# Train Linear Regression model
linear_model = LinearRegression(copy_X= True, fit_intercept= True, n_jobs=
linear_model.fit(X_train_a, y_train)

# Make predictions using the trained Linear Regression model
linear_predictions = linear_model.predict(X_test_a)

print(y_train[0], linear_predictions[0])
# Evaluate Linear Regression model
linear_mse = mean_squared_error(y_test, linear_predictions)
print(f'Linear Regression Root Mean Squared Error: {math.sqrt(linear_mse)}

linear_r2_score = r2_score(y_test, linear_predictions)
print(f'Linear Regression R2 score: {linear_r2_score}')
```

```
2790.43 2879.1638493193004
Linear Regression Root Mean Squared Error: 810.855366055161
Linear Regression R2 score: 0.007258017149069151
```

# Machine Learning

In [40]:
```
# Build and train the ANN model
ann_model = tf.keras.models.Sequential()
ann_model.add(tf.keras.layers.Dense(5, activation='relu'))
ann_model.add(tf.keras.layers.Dense(5, activation='relu'))
ann_model.add(tf.keras.layers.Dense(1, activation='linear'))  # Output lay

ann_model.compile(optimizer='adam', loss='mean_squared_error', metrics=[tf
```

```
WARNING:tensorflow:From C:\Users\Teoh\anaconda3\Lib\site-packages\keras\src\b
ackend.py:873: The name tf.get_default_graph is deprecated. Please use tf.com
pat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\Teoh\anaconda3\Lib\site-packages\keras\src\o
ptimizers\__init__.py:309: The name tf.train.Optimizer is deprecated. Please
use tf.compat.v1.train.Optimizer instead.
```

In [41]:
```
# training model with train dataset
history = ann_model.fit(X_train_a, y_train, batch_size=32, epochs=100, val
history
```

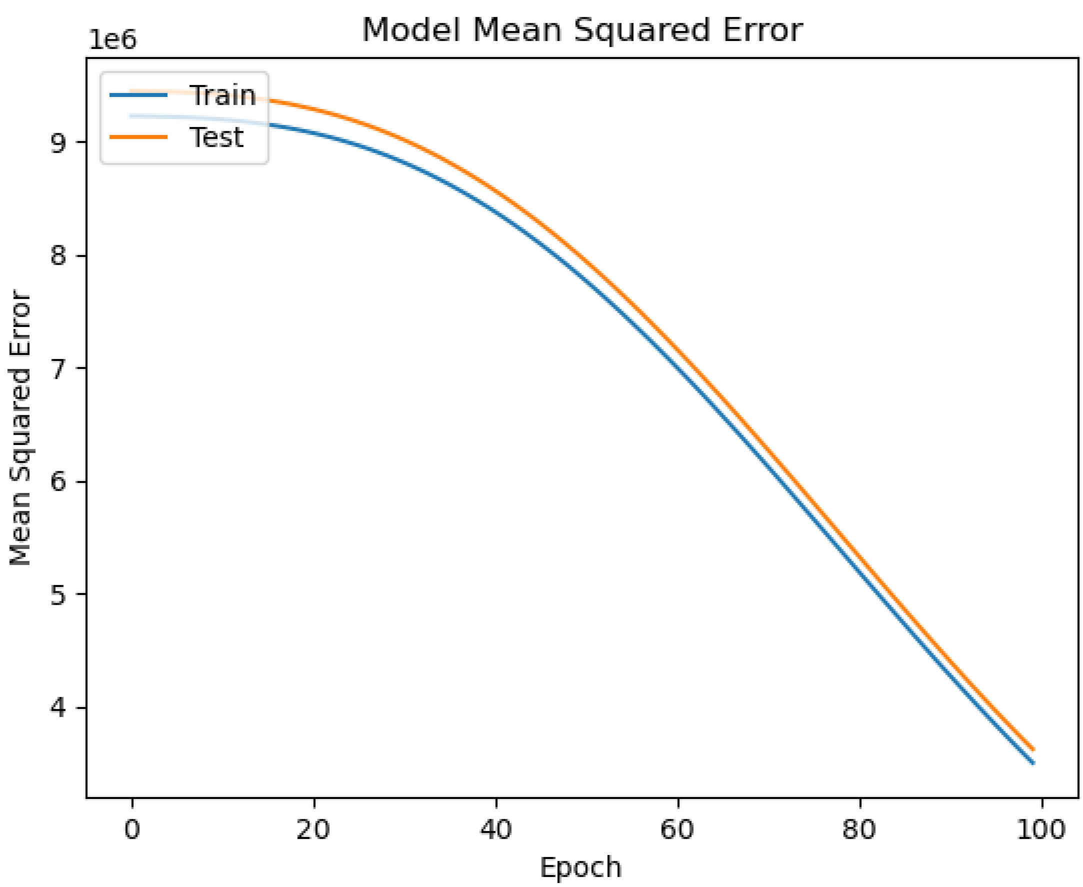
```
25/25 [==============================] - 0s 6ms/step - loss: 9223396.0000 -
mean_squared_error: 9223396.0000 - val_loss: 9445743.0000 - val_mean_square
d_error: 9445743.0000
Epoch 3/100
25/25 [==============================] - 0s 5ms/step - loss: 9221922.0000 -
mean_squared_error: 9221922.0000 - val_loss: 9444090.0000 - val_mean_square
d_error: 9444090.0000
Epoch 4/100
25/25 [==============================] - 0s 4ms/step - loss: 9220125.0000 -
mean_squared_error: 9220125.0000 - val_loss: 9442154.0000 - val_mean_square
d_error: 9442154.0000
Epoch 5/100
25/25 [==============================] - 0s 4ms/step - loss: 9218015.0000 -
mean_squared_error: 9218015.0000 - val_loss: 9439834.0000 - val_mean_square
d_error: 9439834.0000
Epoch 6/100
25/25 [==============================] - 0s 4ms/step - loss: 9215512.0000 -
mean_squared_error: 9215512.0000 - val_loss: 9437096.0000 - val_mean_square
d_error: 9437096.0000
Epoch 7/100
```

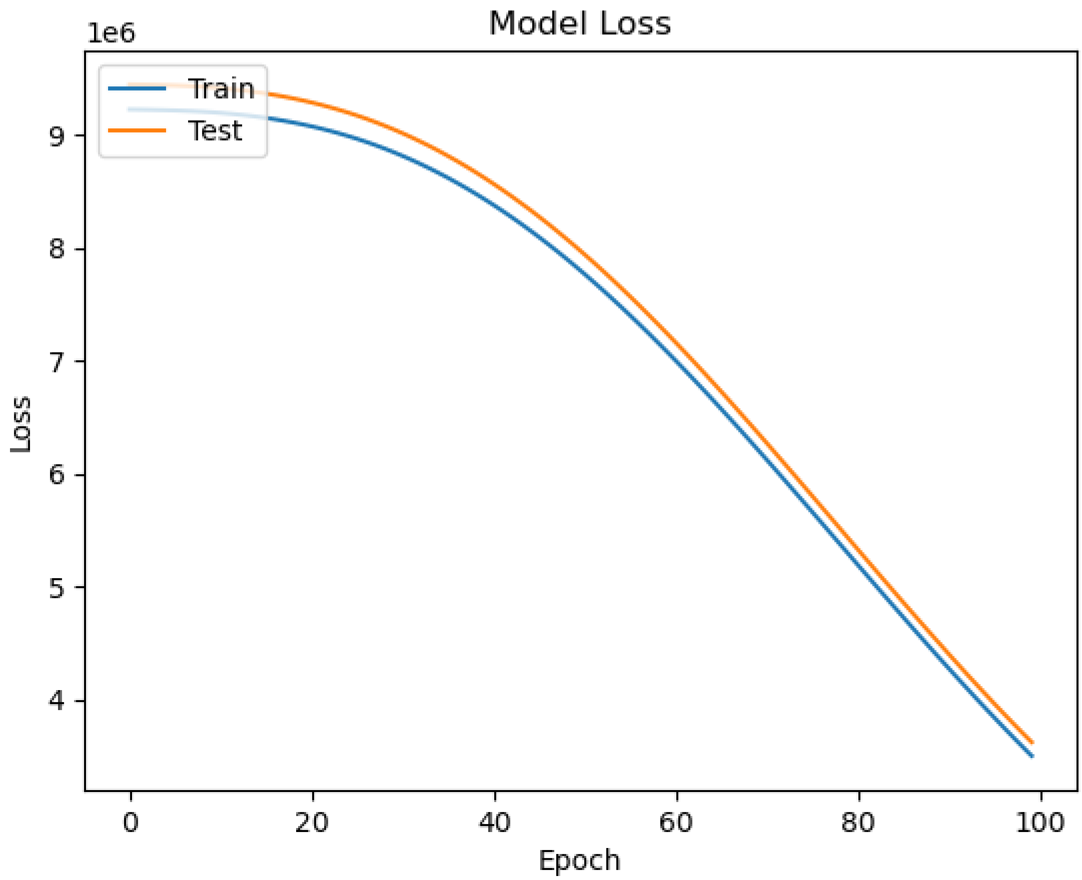
In [42]:
```
ann_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 5)                 55        
                                                                 
 dense_1 (Dense)             (None, 5)                 30        
                                                                 
 dense_2 (Dense)             (None, 1)                 6         
                                                                 
=================================================================
Total params: 91 (364.00 Byte)
Trainable params: 91 (364.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [43]:

```
# plot model accuracy
plt.plot(history.history['mean_squared_error'])
plt.plot(history.history['val_mean_squared_error'])
plt.title('Model Mean Squared Error')
plt.ylabel('Mean Squared Error')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```






In [44]:
```
ann_model.save('ann_model.keras')
```

In [45]:
```
from tensorflow.keras.models import load_model
```

In [47]:
```
model = load_model('ann_model.keras')
```

In [51]:
```
X_test
```

Out[51]:
```
array([[ 5.  ,  2.  ,  0.  , ...,  0.  , 14.  ,  3.89],
       [ 3.  ,  0.  ,  2.  , ...,  3.  , 17.  ,  4.95],
       [ 8.  ,  1.  ,  1.  , ...,  1.  , 14.  ,  2.42],
       ...,
       [ 4.  ,  1.  ,  2.  , ...,  0.  , 14.  ,  2.89],
       [ 4.  ,  4.  ,  0.  , ...,  2.  , 18.  ,  4.63],
       [ 8.  ,  1.  ,  2.  , ...,  3.  , 14.  ,  3.39]])
```

In [54]:

```
predictions = model.predict(X_test)
print(predictions)
results_df = pd.DataFrame(
    {'Predicted':y_pred.flatten(),
    'Actual':y_test.flatten()
    }
)
results_df
```

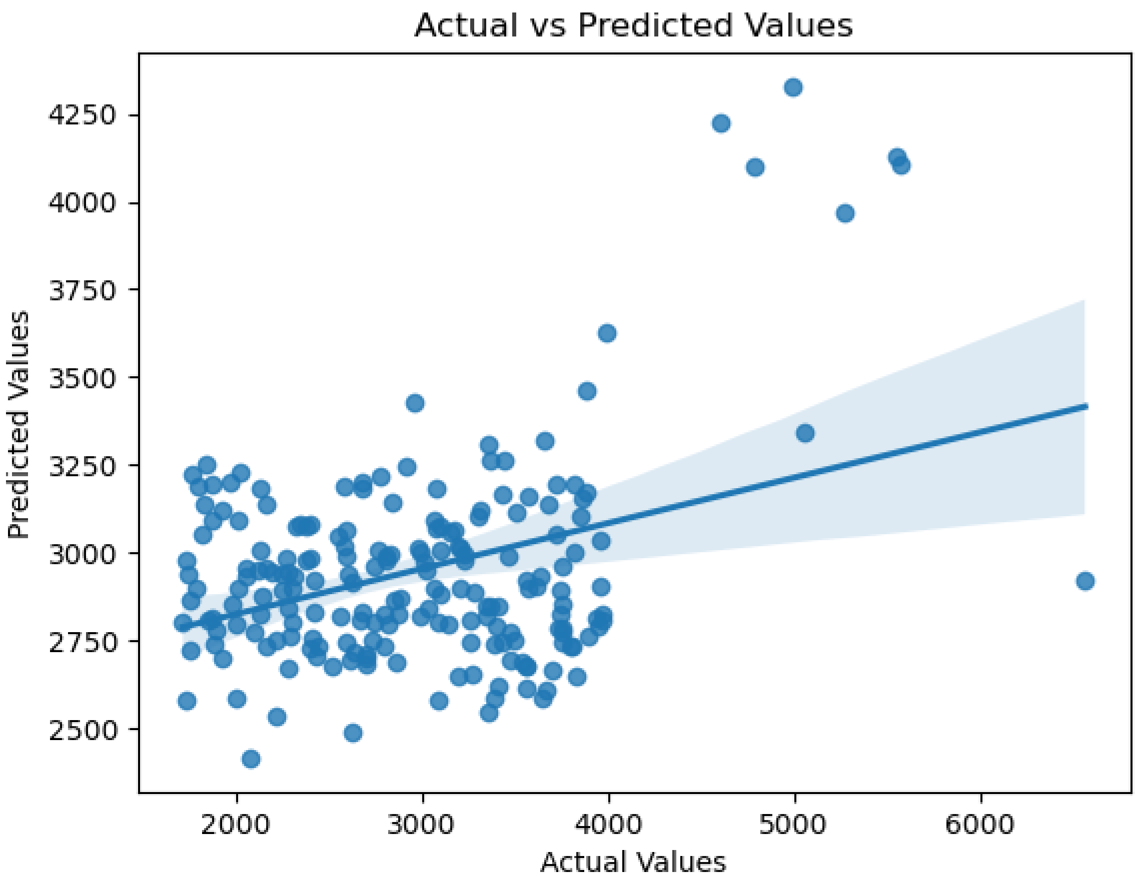
```
7/7 [==============================] - 0s 2ms/step
[[ 7871.286 ]
 [11458.876 ]
 [ 9733.594 ]
 [10643.661 ]
 [10401.983 ]
 [ 9595.286 ]
 [13460.831 ]
 [11984.081 ]
 [11305.202 ]
 [10077.124 ]
 [ 8760.771 ]
 [12096.459 ]
 [ 9855.362 ]
 [10317.438 ]
 [12599.042 ]
 [11758.437 ]
 [10297.414 ]
 [11304.86  ]
```

In [50]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 5)                 55

 dense_1 (Dense)             (None, 5)                 30

 dense_2 (Dense)             (None, 1)                 6

=================================================================
Total params: 91 (364.00 Byte)
Trainable params: 91 (364.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [49]:
```
sns.regplot(x='Actual', y='Predicted', data=results_df)
plt.title('Actual vs Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```




In [ ]:
```
```