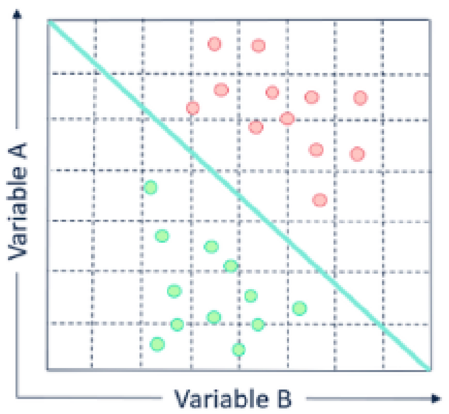
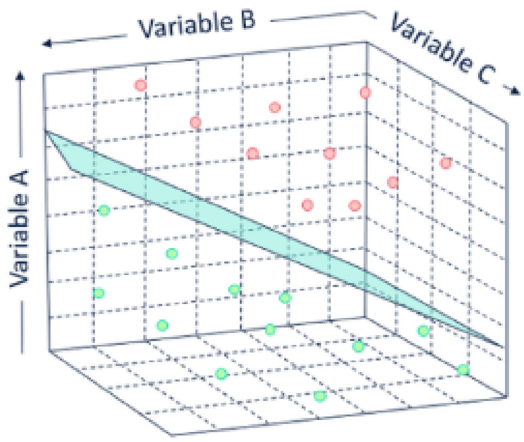
MACHINE LEARNING: SUPPORT VECTOR MACHINE

(SVC) SUPPORT VECTOR CLASSIFIER



2-Dimensional Problem Space



3-Dimensional Problem Space

HEMANT THAPA

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import math
import statistics as st
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
from sklearn.svm import SVR
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import accuracy_score
```

1. DATA ANALYSIS

In [3]:
```
df = pd.read_csv('drug200.csv')
```

In [4]:
```
df[:5]
```

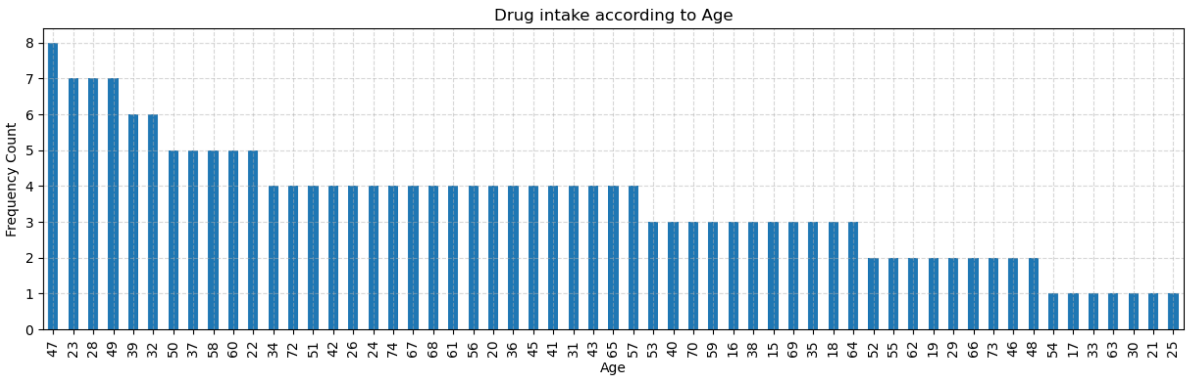
Out[4]:

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	DrugY
1	47	M	LOW	HIGH	13.093	drugC
2	47	M	LOW	HIGH	10.114	drugC
3	28	F	NORMAL	HIGH	7.798	drugX
4	61	F	LOW	HIGH	18.043	DrugY

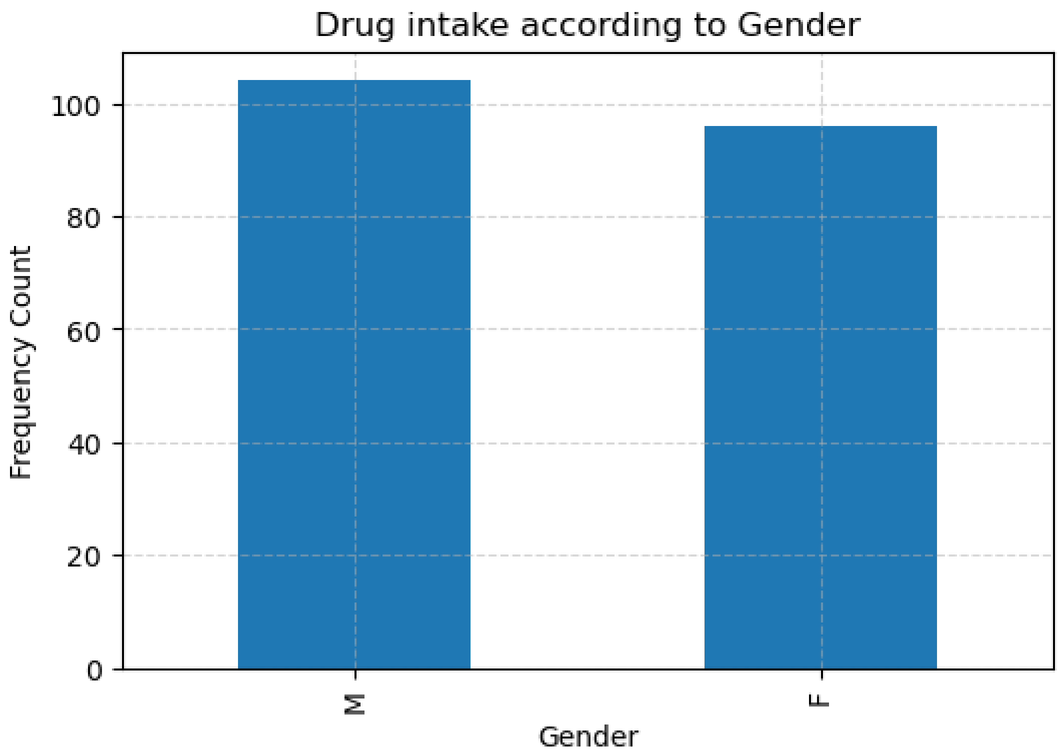
In [5]:
```
df.isnull().sum()
```

Out[5]:
```
Age            0
Sex            0
BP             0
Cholesterol    0
Na_to_K        0
Drug           0
dtype: int64
```

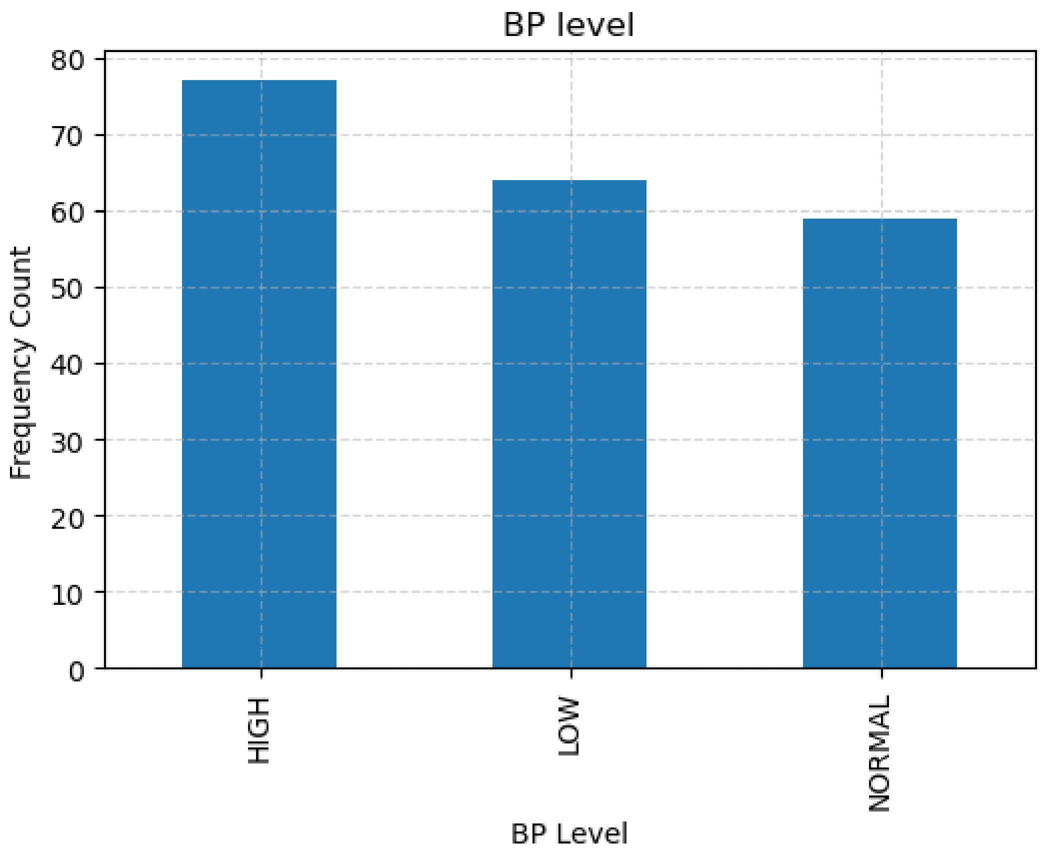
In [6]:
```
plt.figure(figsize=(15,4))
df.Age.value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Age")
plt.ylabel("Frequency Count")
plt.title("Drug intake according to Age")
plt.show()
```



In [7]:
```
plt.figure(figsize=(6,4))
df.Sex.value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Gender")
plt.ylabel("Frequency Count")
plt.title("Drug intake according to Gender")
plt.show()
```

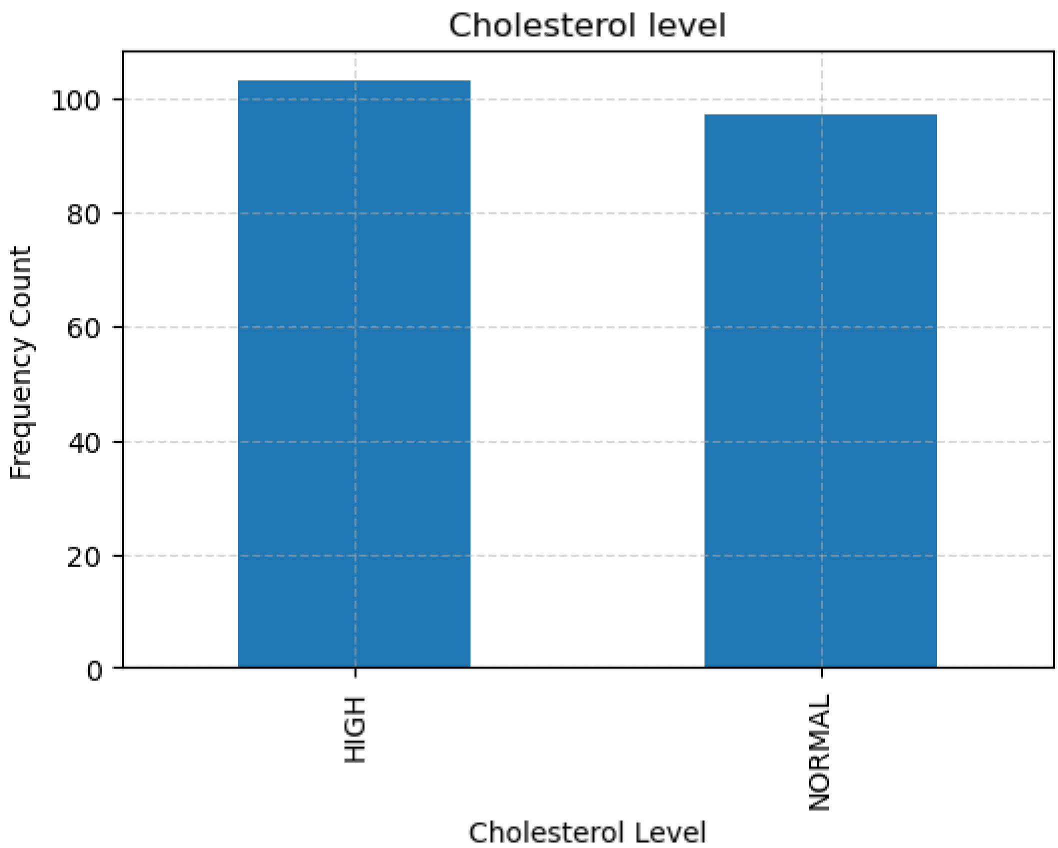


In [8]:
```
plt.figure(figsize=(6,4))
df.BP.value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("BP Level")
plt.ylabel("Frequency Count")
plt.title("BP level")
plt.show()
```



In [9]:
```
plt.figure(figsize=(6,4))
df.Cholesterol.value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
```

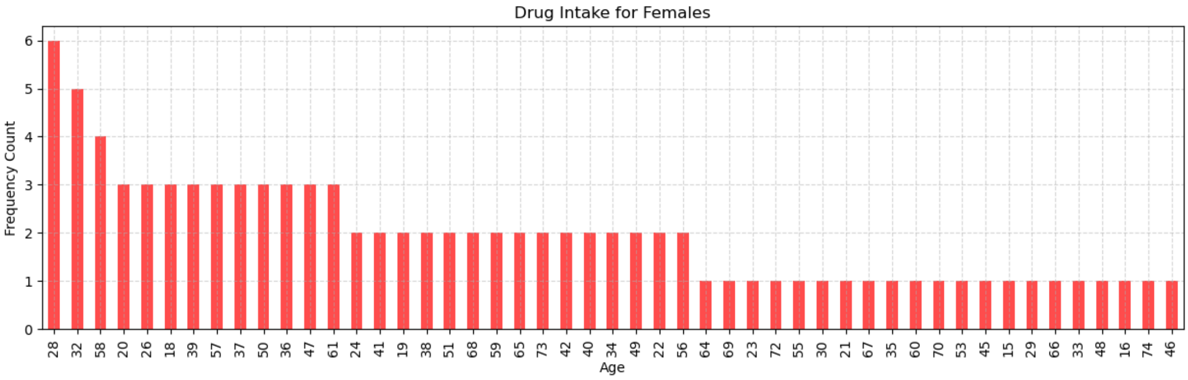
```
plt.xlabel("Cholesterol Level")
plt.ylabel("Frequency Count")
plt.title("Cholesterol level")
plt.show()
```

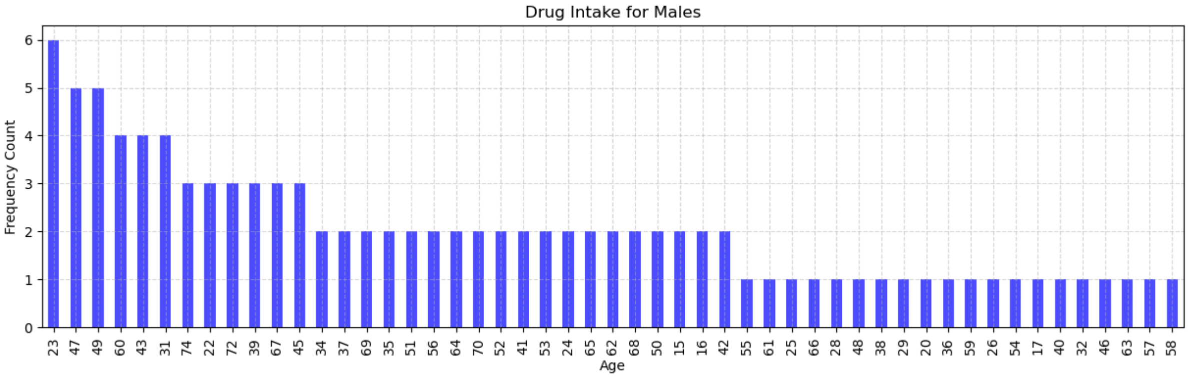


2. INVESTIGATING MALE & FEMALE DATASET

In [10]:
```
df_male = df[df['Sex']=="M"]
df_female = df[df['Sex']=="F"]
```

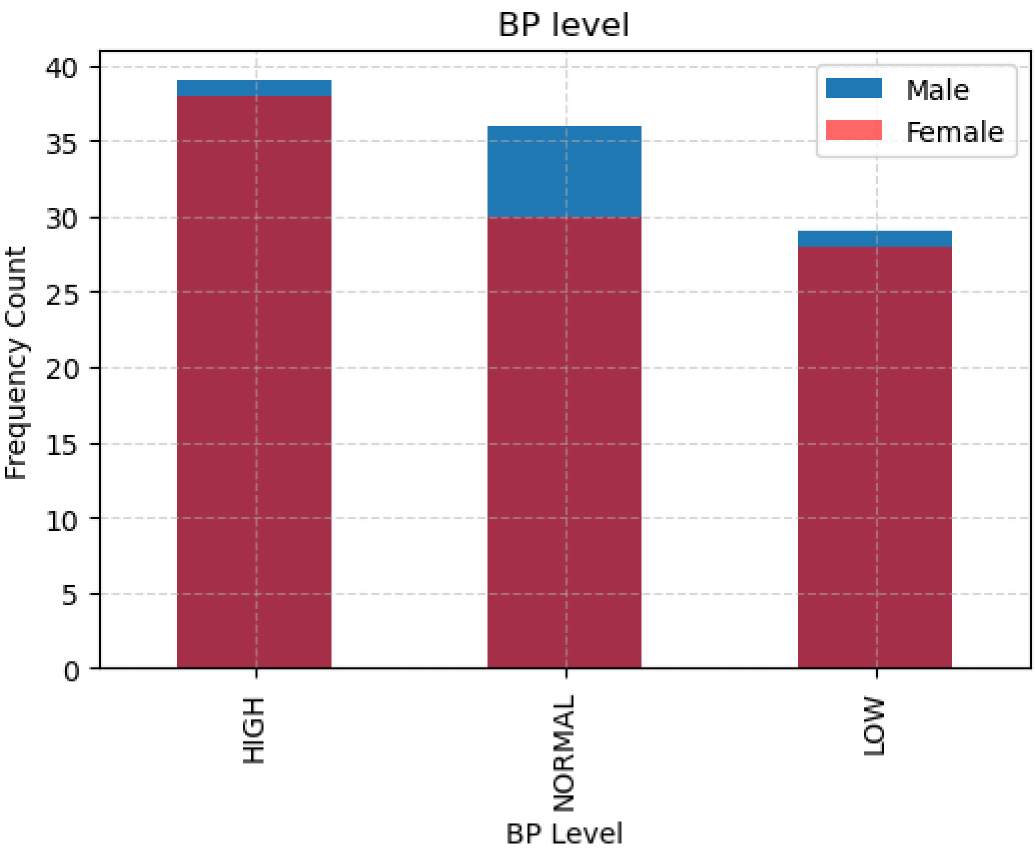
In [11]:
```
plt.figure(figsize=(15, 4))
df_female.Age.value_counts().plot(kind="bar", color="red", alpha=0.7)
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Age")
plt.ylabel("Frequency Count")
plt.title("Drug Intake for Females")
plt.show()

plt.figure(figsize=(15, 4))
df_male.Age.value_counts().plot(kind="bar", color="blue", alpha=0.7)
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Age")
plt.ylabel("Frequency Count")
plt.title("Drug Intake for Males")
plt.show()
```



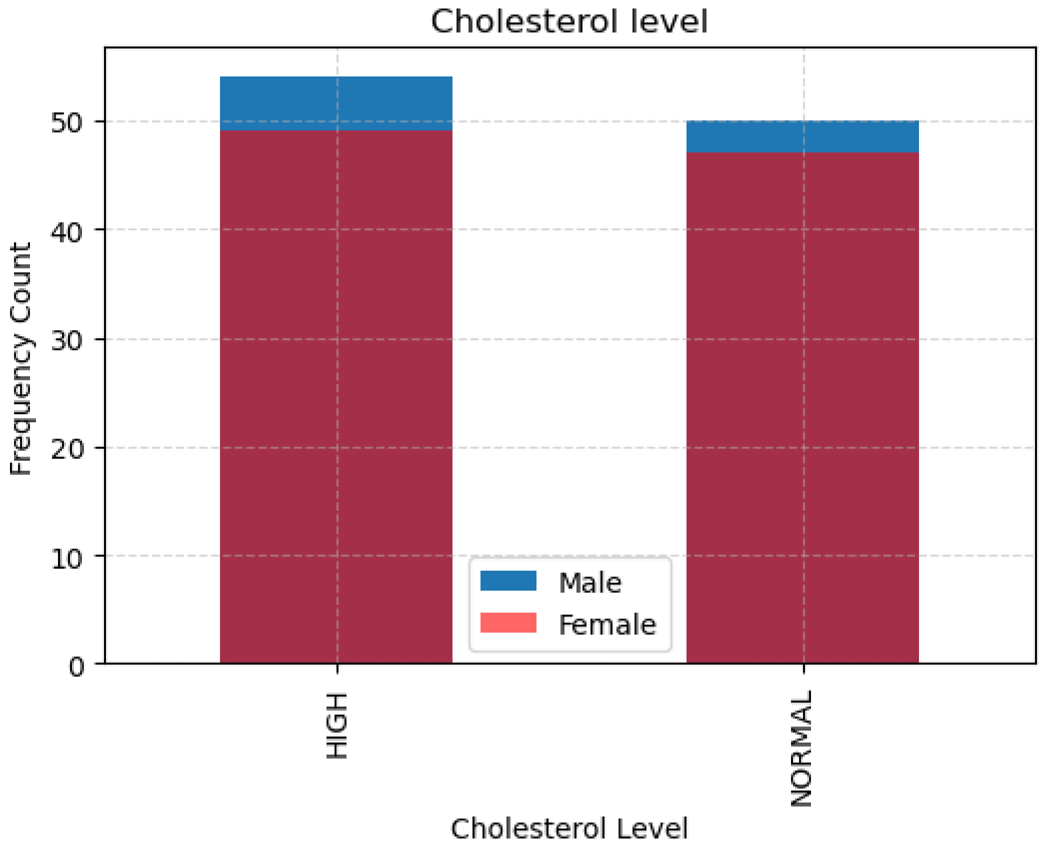


In [12]:

```
plt.figure(figsize=(6,4))
df_male.BP.value_counts().plot(kind="bar", label="Male")
df_female.BP.value_counts().plot(kind="bar", color="red", alpha=0.6, label="
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("BP Level")
plt.ylabel("Frequency Count")
plt.title("BP level")
plt.legend()
plt.show()
```

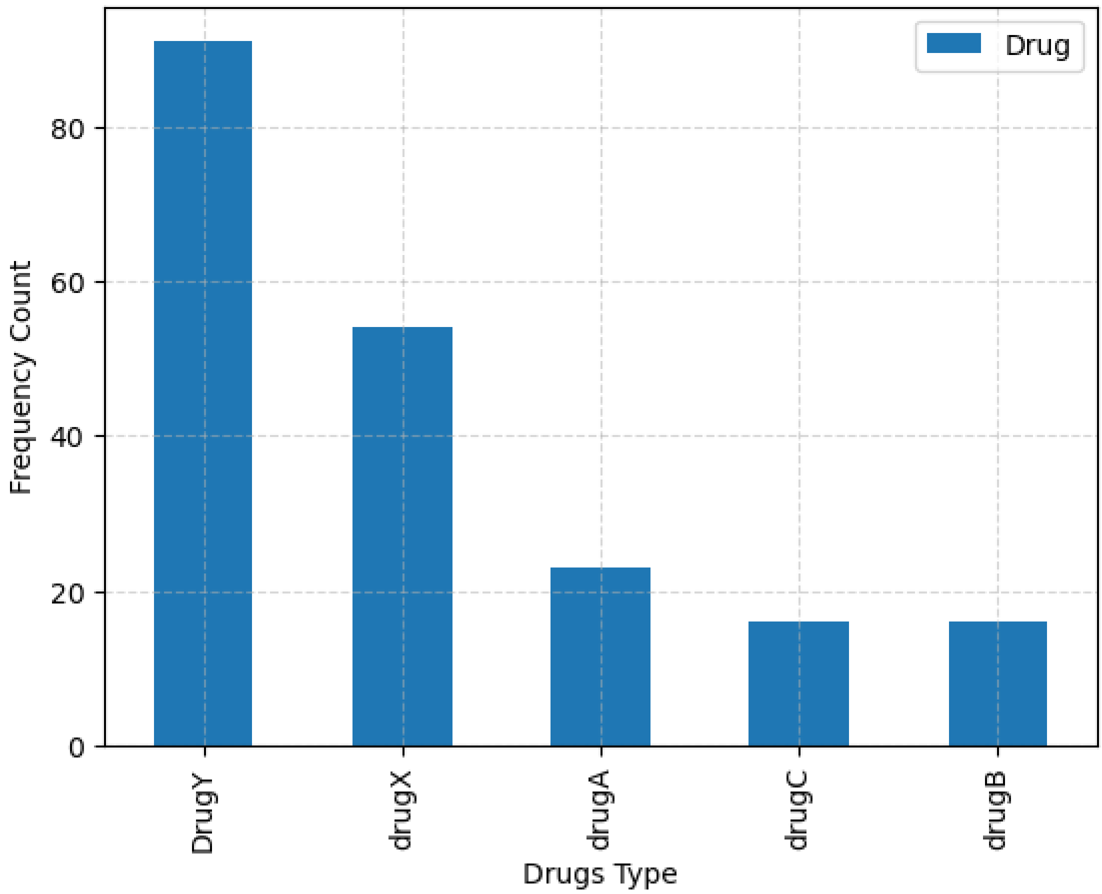


In [13]:
```
plt.figure(figsize=(6,4))
df_male.Cholesterol.value_counts().plot(kind="bar", label="Male")
df_female.Cholesterol.value_counts().plot(kind="bar", color="red", alpha=0.6
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Cholesterol Level")
plt.ylabel("Frequency Count")
plt.title("Cholesterol level")
plt.legend()
plt.show()
```



3. SUPPORT VECTOR CLASSIFIER PART 1

In [14]:
```
df['Drug'].value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Drugs Type")
plt.ylabel("Frequency Count")
plt.legend()
plt.show()
```



In [15]:
```
df = df.applymap(lambda x: x.strip() if isinstance(x, str) else x)
```

In [16]:
```
df['Drug'] = df['Drug'].replace('DrugY', 0)
df['Drug'] = df['Drug'].replace('drugC', 1)
df['Drug'] = df['Drug'].replace('drugX', 2)
df['Drug'] = df['Drug'].replace('drugA', 3)
df['Drug'] = df['Drug'].replace('drugB', 4)
```

In [17]:
```
df.Cholesterol.unique()
```

Out[17]:
```
array(['HIGH', 'NORMAL'], dtype=object)
```

In [18]:
```
df.BP.unique()
```

Out[18]:
```
array(['HIGH', 'LOW', 'NORMAL'], dtype=object)
```

In [19]:
```
df.Drug.unique()
```

Out[19]:
```
array([0, 1, 2, 3, 4])
```

In [20]:
```
df[:5]
```

Out[20]:

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	0
1	47	M	LOW	HIGH	13.093	1
2	47	M	LOW	HIGH	10.114	1
3	28	F	NORMAL	HIGH	7.798	2
4	61	F	LOW	HIGH	18.043	0

In [21]:
```
X = df[['Age', 'Na_to_K']].values.reshape(-2,2)
```

In [22]:
```
X = (X - X.mean())/X.std()
```

In [23]:
```
X[:5]
```

Out[23]:
```
array([[-0.3787368 , -0.25485387],
       [ 0.88376434, -0.89988674],
       [ 0.88376434, -1.0565947 ],
       [-0.11571573, -1.17842606],
       [ 1.62022334, -0.63949588]])
```

In [24]:
```
y = df['Drug'].values
```

In [25]:
```
y
```

Out[25]:
```
array([0, 1, 1, 2, 0, 2, 0, 1, 0, 0, 1, 0, 0, 0, 2, 0, 2, 3, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 2, 0, 0, 2, 4, 2, 0, 2, 2, 3, 2, 2, 2, 0, 4, 0, 2,
       2, 2, 3, 1, 0, 0, 0, 2, 0, 0, 4, 1, 4, 0, 2, 0, 0, 3, 0, 2, 4, 0,
       3, 2, 0, 0, 4, 0, 2, 0, 0, 0, 3, 0, 3, 2, 4, 2, 1, 3, 1, 4, 2, 0,
       0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 3, 3, 1, 2, 0, 2, 2, 0, 4, 0,
       3, 2, 2, 2, 2, 0, 2, 2, 3, 0, 0, 0, 0, 0, 4, 0, 0, 2, 0, 2, 0, 0,
       2, 0, 0, 2, 4, 3, 4, 2, 3, 0, 4, 0, 3, 2, 2, 3, 2, 1, 3, 4, 2, 2,
       0, 1, 3, 0, 1, 2, 2, 4, 2, 0, 0, 0, 0, 2, 0, 3, 2, 2, 0, 0, 3, 0,
       3, 0, 0, 0, 0, 2, 2, 0, 0, 0, 4, 3, 0, 0, 0, 3, 0, 1, 0, 1, 1, 2,
       2, 2])
```

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

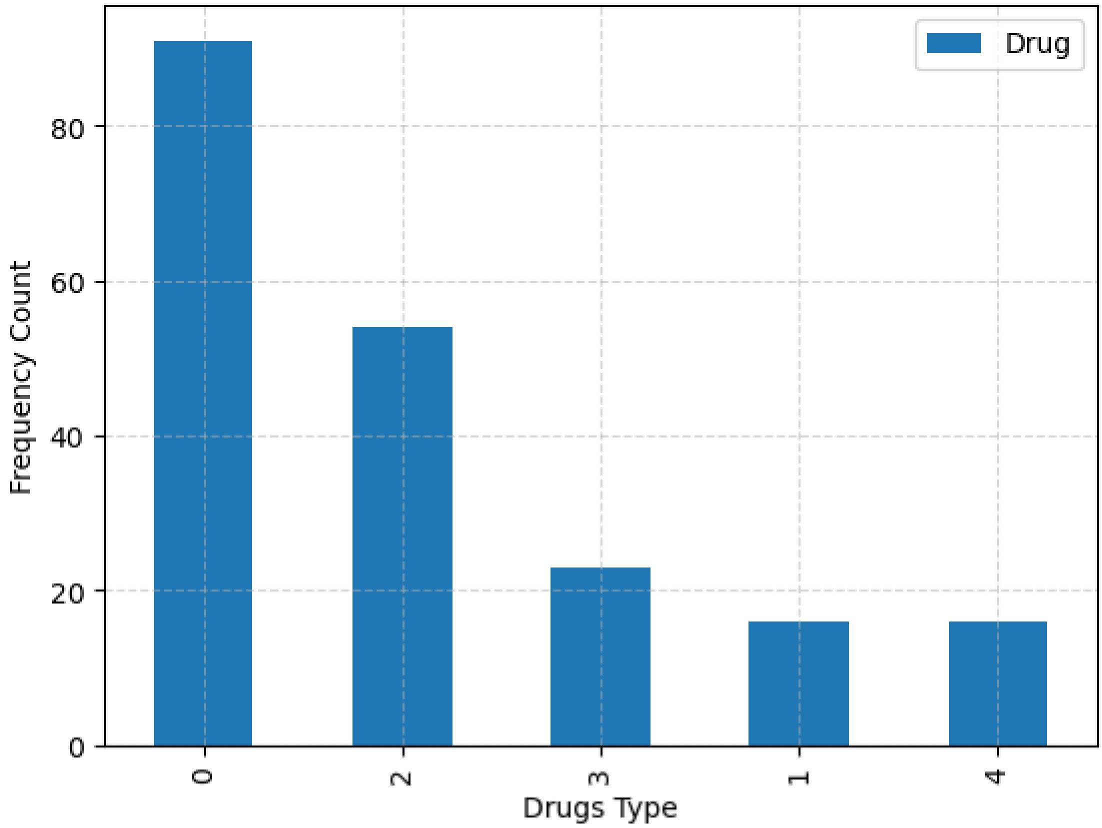
In [27]:
```
svm = SVC(kernel='linear', C=1000)
svm.fit(X_train, y_train)
```

Out[27]:
```
SVC
SVC(C=1000, kernel='linear')
```

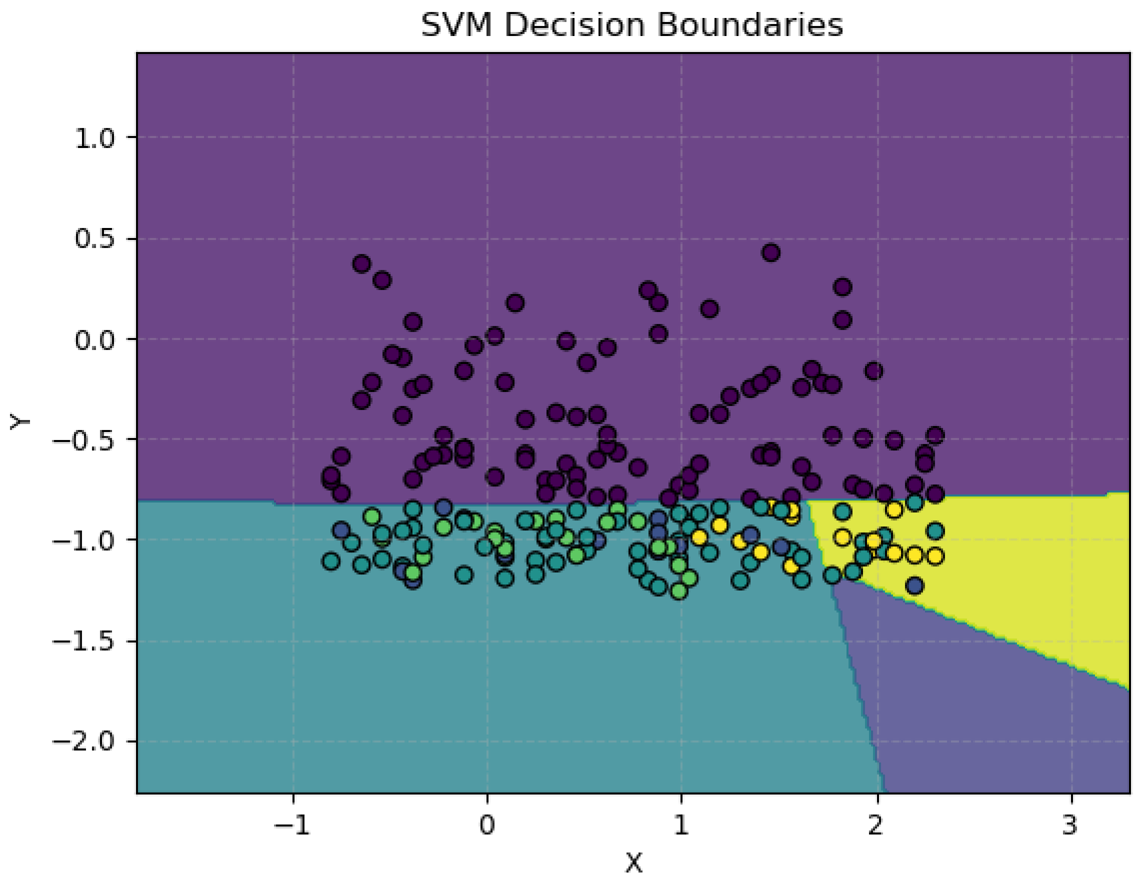
In [28]:
```
y_pred = svm.predict(X_test)
y_pred
```

Out[28]:
```
array([2, 2, 0, 0, 0, 2, 2, 2, 0, 2, 2, 0, 0, 0, 2, 2, 0, 0, 2, 0, 0, 2,
       4, 2, 0, 0, 0, 0, 0, 2, 4, 2, 2, 2, 0, 0, 2, 0, 2, 2])
```

In [29]:
```
df['Drug'].value_counts().plot(kind="bar")
plt.grid(True, linestyle="--", alpha=0.5)
plt.xlabel("Drugs Type")
plt.ylabel("Frequency Count")
plt.legend()
plt.show()
```



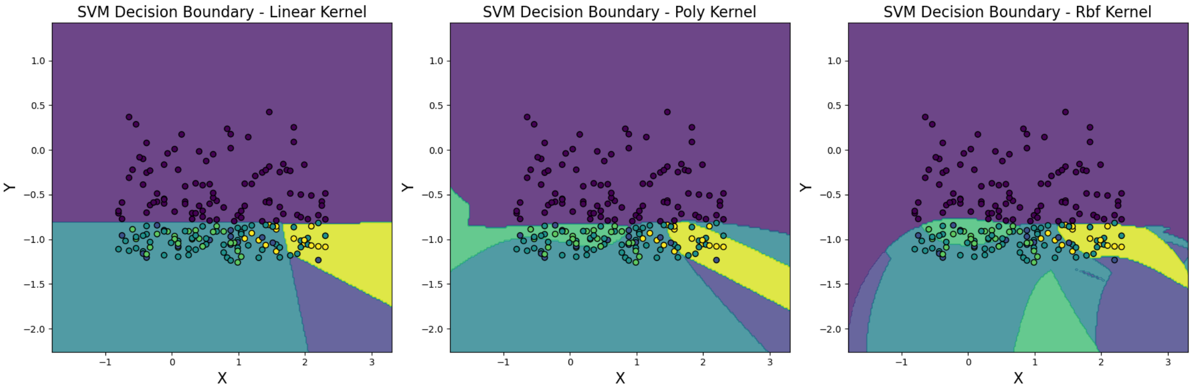
In [30]:
```
h = .02
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

plt.contourf(xx, yy, Z, alpha=0.8)
plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('SVM Decision Boundaries')
plt.grid(True, linestyle="--", alpha=0.3)
plt.show()
```



In [31]:
```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.775
```

In [32]:
```
h = .02
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

kernels = ['linear', 'poly', 'rbf']
colors = ['red', 'blue', 'green']

fig, axs = plt.subplots(1, 3, figsize=(18, 6))
for idx, kernel in enumerate(kernels):
    svm = SVC(kernel=kernel, C=100)
    svm.fit(X_train, y_train)

    Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    axs[idx].contourf(xx, yy, Z, alpha=0.8)
    axs[idx].scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o')
    axs[idx].set_xlabel('X', fontsize=16)
    axs[idx].set_ylabel('Y', fontsize=16)
    axs[idx].set_title(f'SVM Decision Boundary - {kernel.capitalize()} Kerne
plt.tight_layout()
plt.show()
```



4. SUPPORT VECTOR CLASSIFIER PART 2

In [33]:
```
dataset = {
    'age': [25, 45, 30, 50, 40, 60, 20, 55, 32, 38, 28, 48, 22, 29, 51, 59,
            34, 47, 31, 49, 39, 61, 21, 56, 33, 37, 29, 49, 23, 30, 52, 60,
            44, 36, 54, 58, 37, 62, 19, 57, 35, 39, 30, 50, 26, 33, 53, 61,
            46, 37, 55, 63, 29, 58, 18, 59, 31, 34, 26, 51, 24, 32, 54, 62,
            43, 35, 53, 64, 28, 63, 17, 60, 30, 35, 27, 52, 26, 31, 55, 65,
    'salary': [50000, 75000, 60000, 100000, 80000, 120000, 45000, 110000, 55
               90000, 48000, 53000, 95000, 105000, 49000, 60000, 70000, 5100
               73000,59000, 98000, 78000, 122000, 44000, 112000, 54000, 6300
               93000, 46000, 54000, 97000, 108000, 50000, 61000, 72000, 5300
               66000,55000, 105000, 62000, 125000, 43000, 115000, 57000, 670
               95000, 49000, 56000, 104000, 118000, 47000, 59000, 69000, 520
               58000,110000, 130000, 64000, 128000, 42000, 112000, 58000, 61
               100000, 46000, 54000, 107000, 125000, 45000, 62000, 72000, 50
               55000,108000, 135000, 58000, 130000, 41000, 115000, 55000, 58
               105000, 44000, 52000, 115000, 140000, 43000, 57000, 66000, 51
    'purchased': [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0
                   0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1,
                   1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1,
                   0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1,
                 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0]
}
```

In [34]:
```
plt.figure(figsize=(15, 6))
sns.scatterplot(x='age', y='salary', data=dataset, s=100)
plt.grid(True)
plt.ylabel("Salary")
plt.xlabel("Age")
plt.title("Age & Salary")
plt.show()
```

SVR

In [35]:
```
LinearModel = SVR(kernel='linear', C=1000)
LinearModel
```

Out[35]:
```
SVR
SVR(C=1000, kernel='linear')
```

In [36]:
```
X = dataset['age']
X = np.array([X])
X = X.reshape(-1,1)
y = dataset['salary']
```

In [37]:
```
LinearModel.fit(X,y)
```

Out[37]:
```
SVR
SVR(C=1000, kernel='linear')
```

In [38]:
```
y_pred = LinearModel.predict(X)
```

In [39]:
```
plt.figure(figsize=(15, 6))
sns.scatterplot(x='age', y='salary', data=dataset, s=150)
plt.plot(X, y_pred, color="red")
plt.grid(True)
plt.ylabel("Salary")
plt.xlabel("Age")
plt.title("Age & Salary")
plt.show()
```

In [40]:
```
from sklearn.metrics import r2_score
```

In [41]:
```
r2_score(y, y_pred)
```

Out[41]:
```
0.8880924392188275
```

SVC

In [42]:
```
df = pd.DataFrame(dataset)
```

In [43]:
```
X = df.iloc[:, 0:2].values
X = X.reshape(-1, 2)
```

In [44]:
```
X[:5]
```

Out[44]:
```
array([[    25,  50000],
       [    45,  75000],
       [    30,  60000],
       [    50, 100000],
       [    40,  80000]])
```

In [45]:
```
y = df['purchased']
y = y.values
y
```

Out[45]:
```
array([0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1,
       0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
       0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1,
       0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0])
```

In [46]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran
```

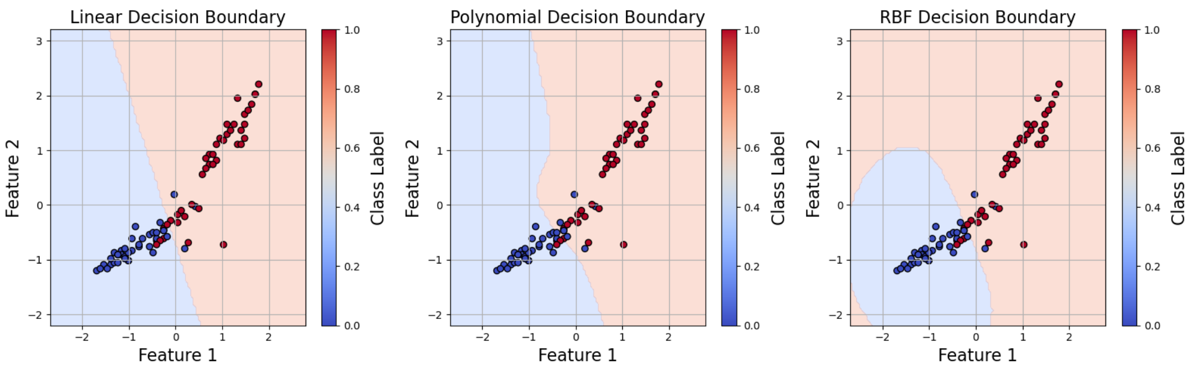
In [47]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [48]:
```
svm_linear = SVC(kernel='linear', C=1).fit(X_train_scaled, y_train)
y_pred_linear = svm_linear.predict(X_test_scaled)
accuracy_linear = accuracy_score(y_test, y_pred_linear)
print("Accuracy (Linear Kernel):", accuracy_linear)

svm_poly = SVC(kernel='poly', C=1, degree=3).fit(X_train_scaled, y_train)
y_pred_poly = svm_poly.predict(X_test_scaled)
accuracy_poly = accuracy_score(y_test, y_pred_poly)
print("Accuracy (Polynomial Kernel):", accuracy_poly)

svm_rbf = SVC(kernel='rbf', C=1).fit(X_train_scaled, y_train)
y_pred_rbf = svm_rbf.predict(X_test_scaled)
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
print("Accuracy (RBF Kernel):", accuracy_rbf)
```

```
Accuracy (Linear Kernel): 0.95
Accuracy (Polynomial Kernel): 0.95
Accuracy (RBF Kernel): 0.95
```

In [49]:
```
xx, yy = np.meshgrid(np.linspace(X_train_scaled[:, 0].min() - 1, X_train_sca
                     np.linspace(X_train_scaled[:, 1].min() - 1, X_train_sca

Z_linear = svm_linear.predict(np.c_[xx.ravel(), yy.ravel()])
Z_linear = Z_linear.reshape(xx.shape)

Z_poly = svm_poly.predict(np.c_[xx.ravel(), yy.ravel()])
Z_poly = Z_poly.reshape(xx.shape)

Z_rbf = svm_rbf.predict(np.c_[xx.ravel(), yy.ravel()])
Z_rbf = Z_rbf.reshape(xx.shape)

plt.figure(figsize=(16, 5))
plt.subplot(131)
plt.contourf(xx, yy, Z_linear, levels=1, cmap=plt.cm.coolwarm, alpha=0.3)
```

```
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train, cmap=plt.
plt.xlabel("Feature 1", fontsize=16)
plt.ylabel("Feature 2", fontsize=16)
plt.title("Linear Decision Boundary", fontsize=16)
plt.grid(True)
color_bar_linear = plt.colorbar()
color_bar_linear.set_label("Class Label", labelpad=10, fontsize=16)

plt.subplot(132)
plt.contourf(xx, yy, Z_poly, levels=1, cmap=plt.cm.coolwarm, alpha=0.3)
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train, cmap=plt.
plt.xlabel("Feature 1", fontsize=16)
plt.ylabel("Feature 2", fontsize=16)
plt.title("Polynomial Decision Boundary", fontsize=16)
plt.grid(True)
color_bar_poly = plt.colorbar()
color_bar_poly.set_label("Class Label", labelpad=10, fontsize=16)

plt.subplot(133)
plt.contourf(xx, yy, Z_rbf, levels=1, cmap=plt.cm.coolwarm, alpha=0.3)
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train, cmap=plt.
plt.xlabel("Feature 1", fontsize=16)
plt.ylabel("Feature 2", fontsize=16)
plt.title("RBF Decision Boundary", fontsize=16)
plt.grid(True)
color_bar_rbf = plt.colorbar()
color_bar_rbf.set_label("Class Label", labelpad=10, fontsize=16)

plt.tight_layout()
plt.show()
```



THREE DIMENSIONAL HYPER PLANE

In [50]:
```
df[:10]
```

Out[50]:

	age	salary	purchased
0	25	50000	0
1	45	75000	1
2	30	60000	0
3	50	100000	1
4	40	80000	0
5	60	120000	1
6	20	45000	0
7	55	110000	1
8	32	55000	0
9	38	65000	1

In [51]:

```
X = df[['age', 'salary']].values
y = df['purchased'].values
```

In [52]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran
```

LINEAR

In [53]:

```
svm = SVC(kernel='linear', C=1000)
svm.fit(X_train, y_train)
```

Out[53]:

```
▾ SVC
SVC(C=1000, kernel='linear')
```

In [54]:

```
y_pred = svm.predict(X_test)
```

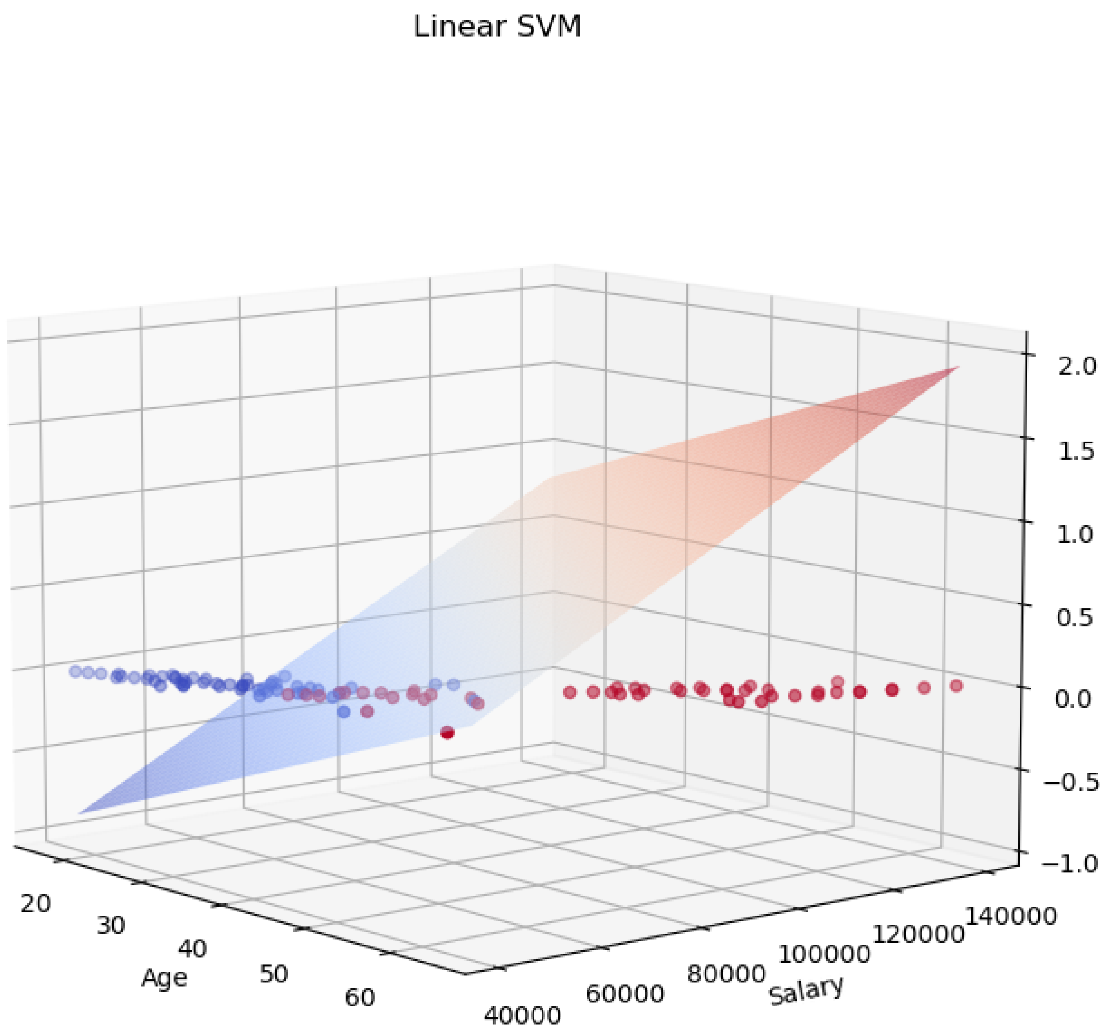
In [55]:

```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy (Linear SVM):", accuracy)
```

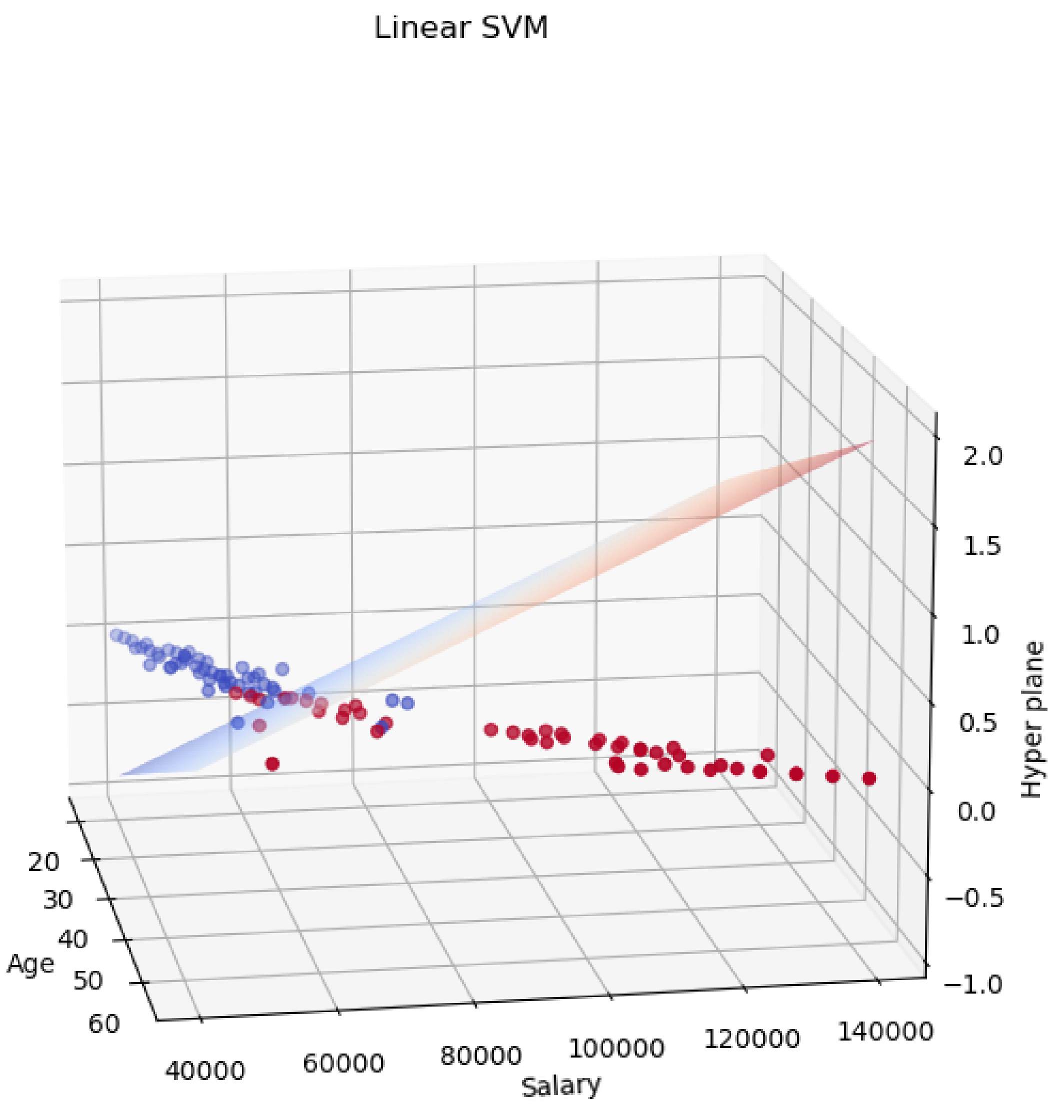
```
Accuracy (Linear SVM): 0.95
```

In [56]:

```
age_range = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_range = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_values, salary_values = np.meshgrid(age_range, salary_range)
mesh_points = np.c_[age_values.ravel(), salary_values.ravel()]

decision_values = svm.decision_function(mesh_points)
decision_values = decision_values.reshape(age_values.shape)

fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values, cmap='coolwarm'
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyper plane')
ax1.view_init(elev=10, azim=320)
ax1.grid(True, linestyle='dashed', alpha=0.5)
y_pred = svm.predict(X_test)
```

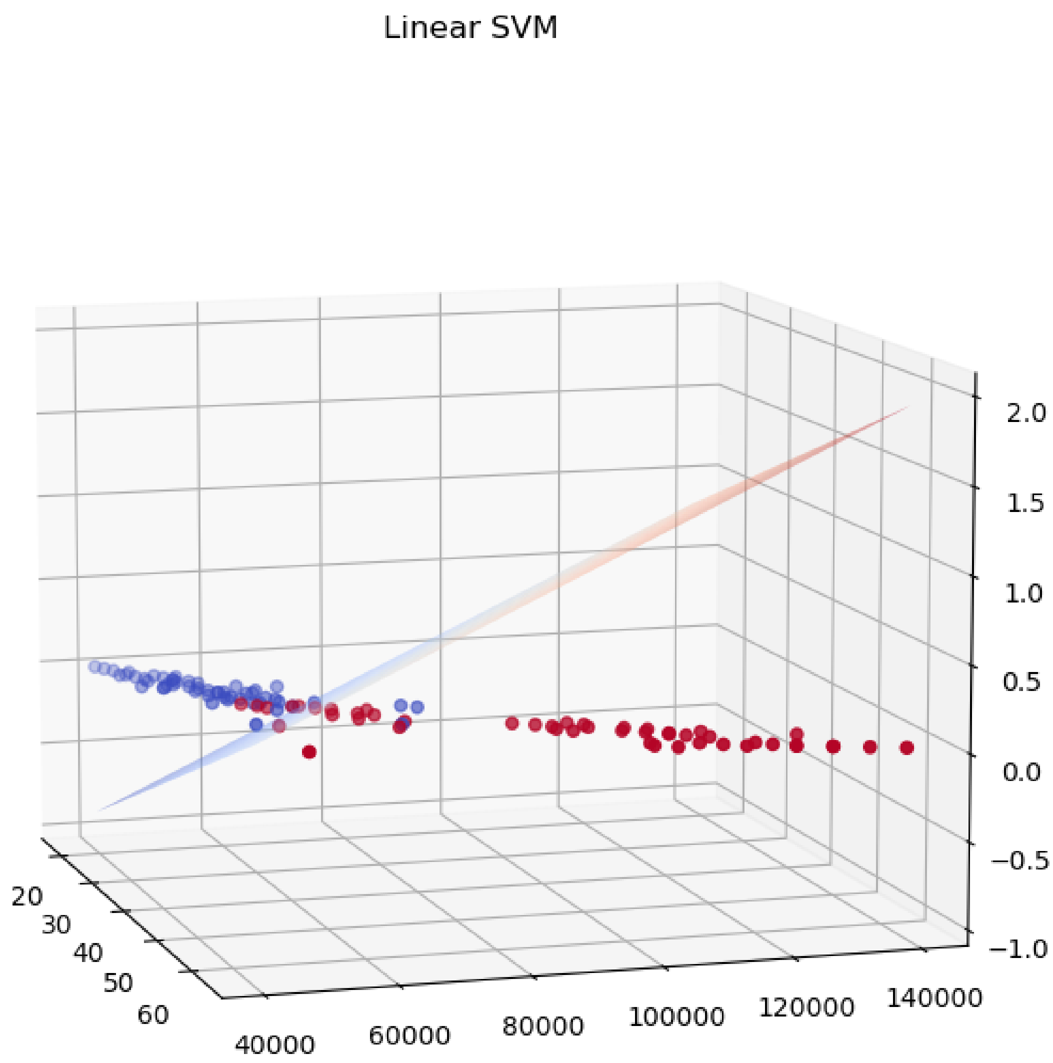


In [57]:
```
age_range = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_range = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_values, salary_values = np.meshgrid(age_range, salary_range)
mesh_points = np.c_[age_values.ravel(), salary_values.ravel()]

decision_values = svm.decision_function(mesh_points)
decision_values = decision_values.reshape(age_values.shape)

fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values, cmap='coolwarm'
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyper plane')
ax1.view_init(elev=15, azim=350)
ax1.grid(True, linestyle='dashed', alpha=0.5)
y_pred = svm.predict(X_test)
```



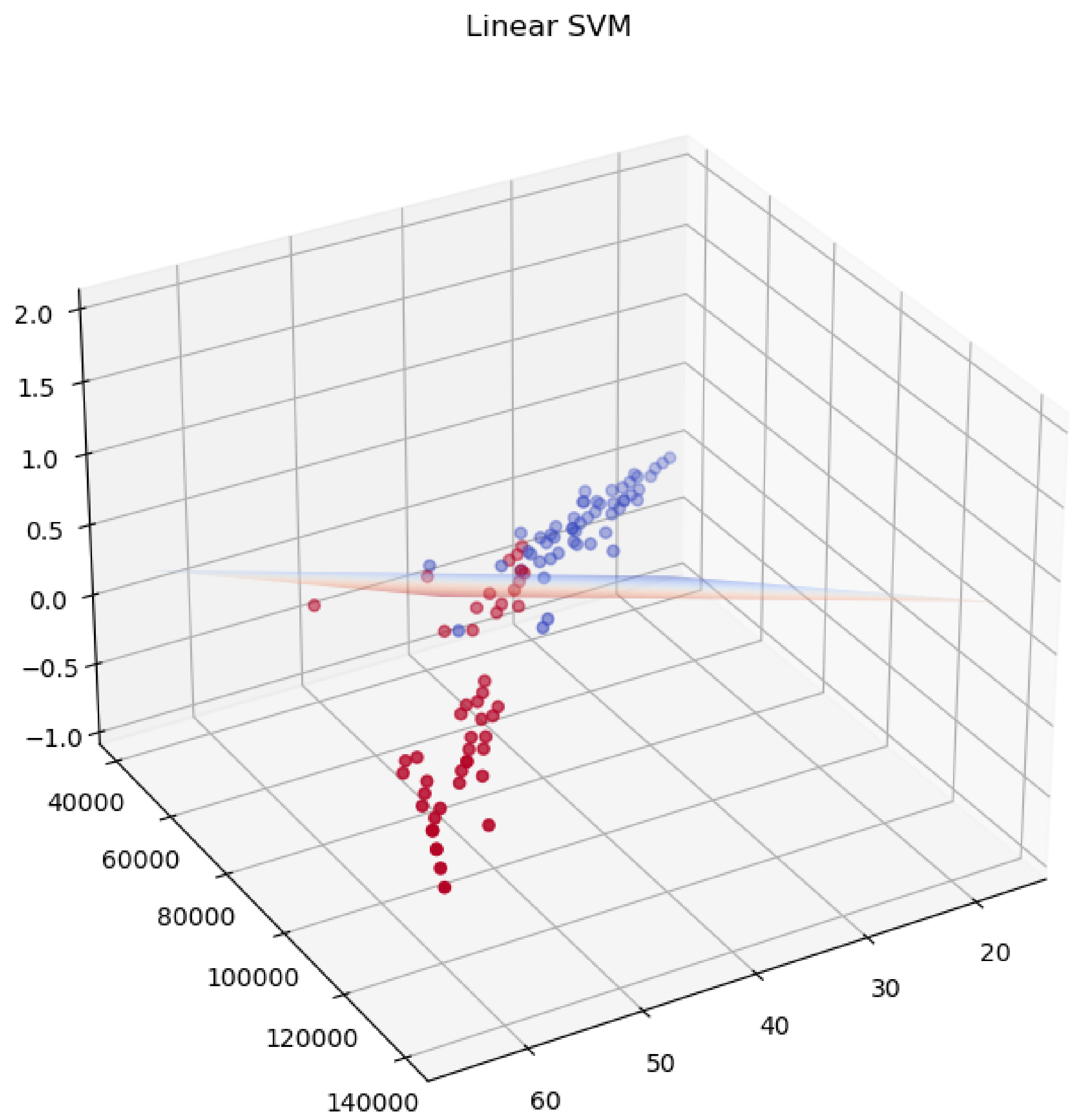
In [58]:

```
age_range = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_range = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_values, salary_values = np.meshgrid(age_range, salary_range)
mesh_points = np.c_[age_values.ravel(), salary_values.ravel()]

decision_values = svm.decision_function(mesh_points)
decision_values = decision_values.reshape(age_values.shape)

fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values, cmap='coolwarm'
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyper plane')
ax1.view_init(elev=10, azim=-17)
ax1.dist = 10
ax1.zaxis.labelpad = 90
ax1.xaxis.labelpad = 90
ax1.yaxis.labelpad = 90

ax1.grid(True, linestyle='dashed', alpha=0.5)
```



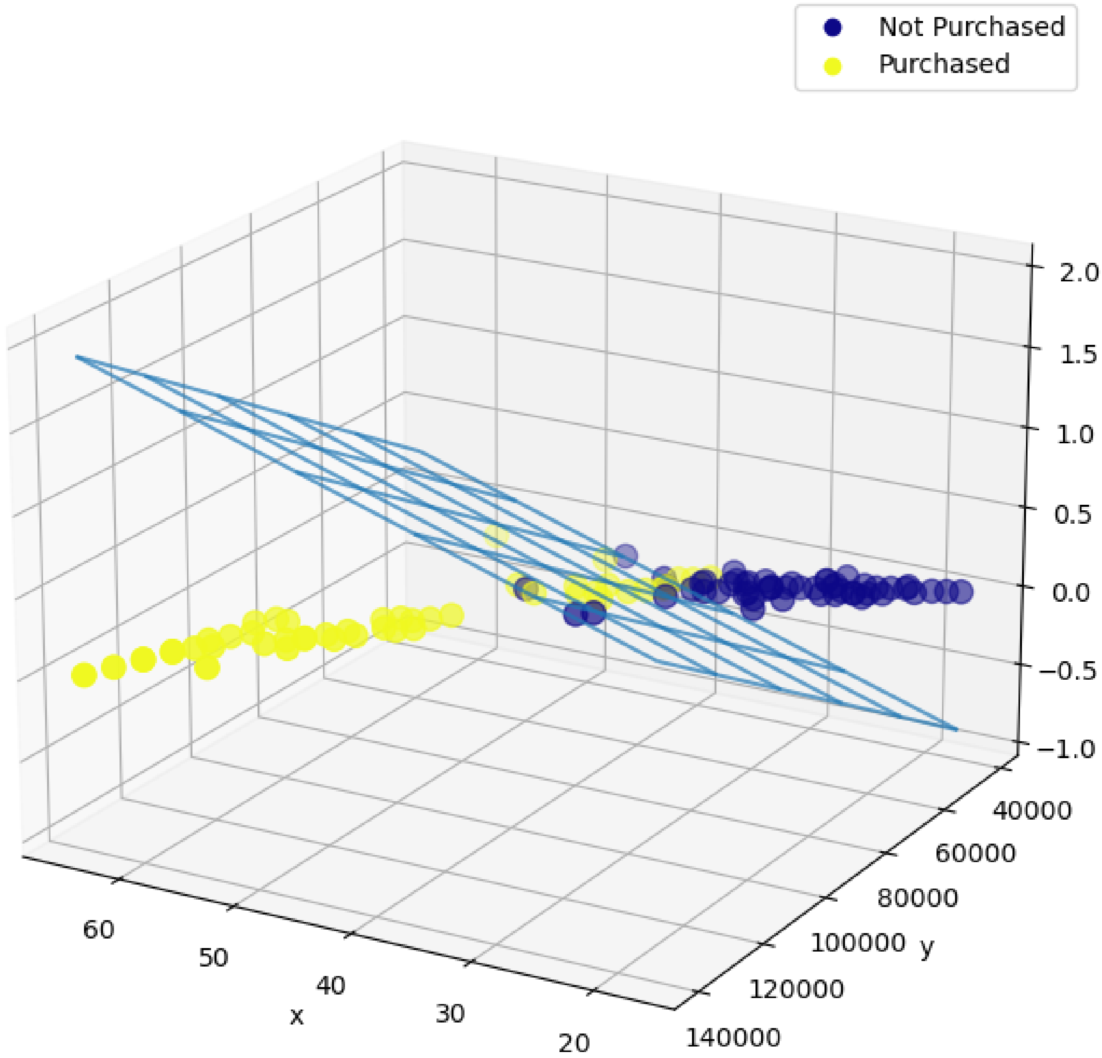
In [59]:

```
age_range = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_range = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_values, salary_values = np.meshgrid(age_range, salary_range)
mesh_points = np.c_[age_values.ravel(), salary_values.ravel()]

decision_values = svm.decision_function(mesh_points)
decision_values = decision_values.reshape(age_values.shape)

fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values, cmap='coolwarm'
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyper plane')
ax1.view_init(elev=30, azim=60)
ax1.dist = 10
ax1.zaxis.labelpad = 90
ax1.xaxis.labelpad = 90
ax1.yaxis.labelpad = 90

ax1.grid(True, linestyle='dashed', alpha=0.5)
```



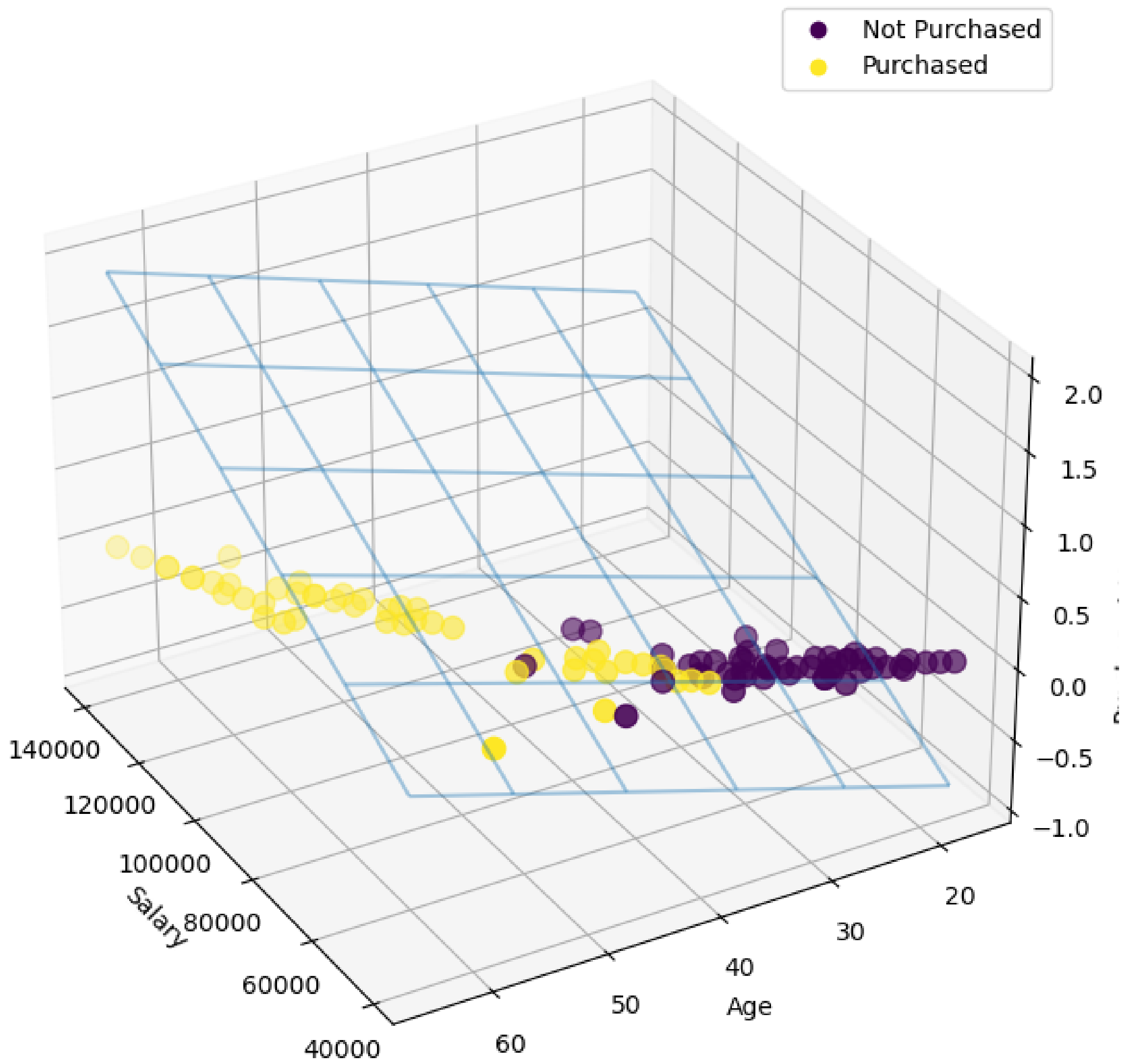
In [60]:

```
fig = plt.figure(figsize=(12, 8))
ax = fig.add_subplot(111, projection='3d')
ax.plot_wireframe(age_values, salary_values,
                  decision_values, rstride=10,
                  cstride=10, alpha=0.7, cmap='coolwarm')
scatter = ax.scatter(X[:, 0], X[:, 1], y, c=y, cmap='plasma', marker='o', s=
ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z')
ax.view_init(elev=20, azim=120)
handles, labels = scatter.legend_elements()
legend_labels = ['Not Purchased', 'Purchased']
ax.legend(handles, legend_labels, loc='upper right')
ax.grid(True, linestyle='dashed', alpha=0.5)
plt.show()
```



In [61]:

```
fig = plt.figure(figsize=(12, 8))
ax = fig.add_subplot(111, projection='3d')
ax.plot_wireframe(salary_values, age_values, decision_values,
                  rstride=10, cstride=10, alpha=0.4,
                  cmap='coolwarm')
scatter = ax.scatter(X[:, 1], X[:, 0], y, c=y, cmap='viridis', marker='o', s
ax.set_xlabel('Salary')
ax.set_ylabel('Age')
ax.set_zlabel('Purchased (0 or 1)')
ax.view_init(elev=30, azim=150)
handles, labels = scatter.legend_elements()
legend_labels = ['Not Purchased', 'Purchased']
ax.legend(handles, legend_labels, loc='upper right')
ax.grid(True, linestyle='dashed', alpha=0.5)
plt.show()
```



5. SUPPORT VECTOR CLASSIFIER PART 3

In [62]:
```
dataset = {
    'age': [25, 45, 30, 50, 40, 60, 20, 55, 32, 38, 28, 48, 22, 29, 51, 59,
    'salary': [50000, 75000, 60000, 100000, 80000, 120000, 45000, 110000, 55
               52000, 90000, 48000, 53000, 95000, 105000, 49000, 60000, 7000
    'purchased': [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0
}
```

In [63]:
```
df = pd.DataFrame(dataset)
X = df[['age', 'salary']].values.reshape(-1, 2)
y = df['purchased'].values
```

In [64]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran
```

In [65]:
```
X_train
```

Out[65]:
```
array([[    28,  52000],
       [    33,  60000],
       [    20,  45000],
       [    29,  53000],
       [    40,  80000],
       [    30,  60000],
       [    60, 120000],
       [    51,  95000],
       [    38,  65000],
       [    55, 110000],
       [    23,  49000],
       [    48,  90000],
       [    50, 100000],
       [    25,  50000],
       [    59, 105000],
       [    22,  48000]])
```

In [66]:
```python
svm_linear = SVC(kernel='linear', C=1000)
svm_poly = SVC(kernel='poly',degree=3, C=1000)
```

In [67]:
```python
svm_linear.fit(X_train, y_train)
```

Out[67]:
```
▾ SVC
SVC(C=1000, kernel='linear')
```

In [68]:
```python
svm_poly.fit(X_train, y_train)
```

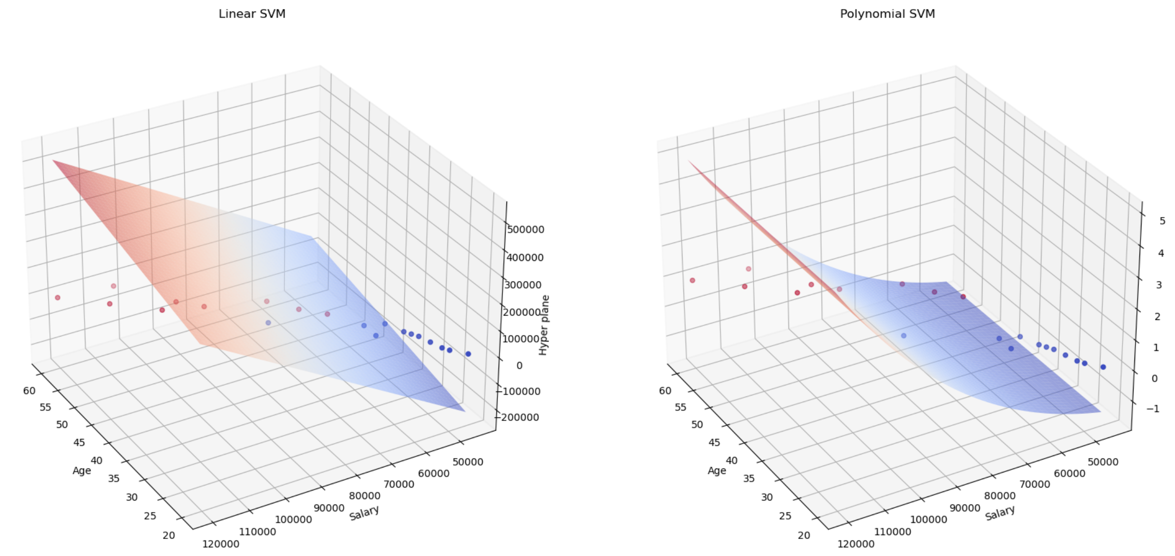
Out[68]:
```
▾ SVC
SVC(C=1000, kernel='poly')
```

In [69]:
```python
y_pred_linear = svm_linear.predict(X_test)
y_pred_poly = svm_poly.predict(X_test)
accuracy_linear = accuracy_score(y_test, y_pred_linear)
accuracy_poly = accuracy_score(y_test, y_pred_poly)
print("Linear SVM Accuracy:", accuracy_linear)
print("Polynomial SVM Accuracy:", accuracy_poly)
```

```
Linear SVM Accuracy: 1.0
Polynomial SVM Accuracy: 0.5
```

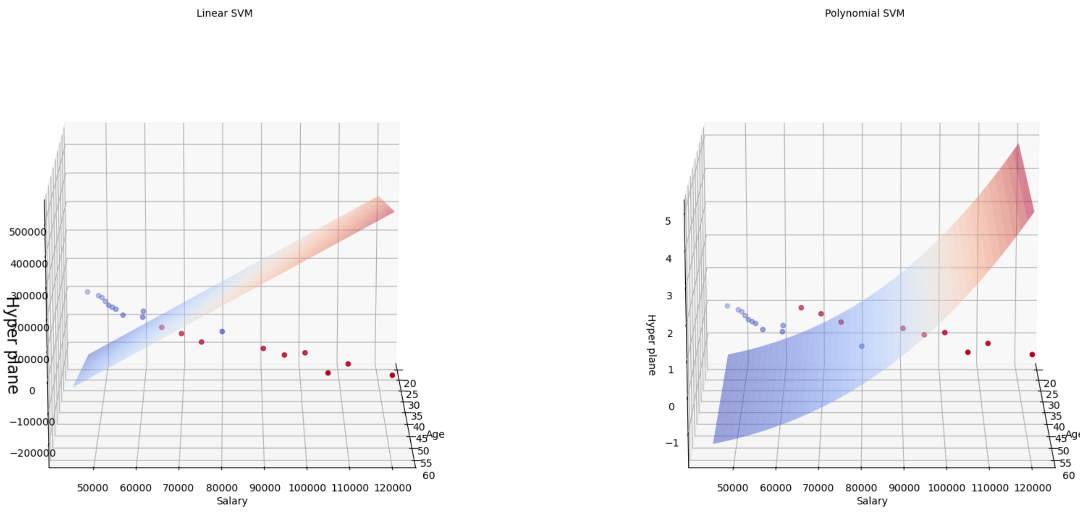
In [70]:
```python
age_range = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_range = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_values, salary_values = np.meshgrid(age_range, salary_range)
mesh_points = np.c_[age_values.ravel(), salary_values.ravel()]

decision_values_linear = svm_linear.decision_function(mesh_points)
decision_values_linear = decision_values_linear.reshape(age_values.shape)

decision_values_poly = svm_poly.decision_function(mesh_points)
decision_values_poly = decision_values_poly.reshape(age_values.shape)

fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values_linear, cmap='cc
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyper plane')
ax1.view_init(elev=30, azim=150)
```

```
ax1.grid(True, linestyle='dashed', alpha=0.5)

ax2 = fig.add_subplot(122, projection='3d')
ax2.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax2.plot_surface(age_values, salary_values, decision_values_poly, cmap='cool
ax2.set_title('Polynomial SVM')
ax2.set_xlabel('Age')
ax2.set_ylabel('Salary')
ax2.set_zlabel('Purchased (0 or 1)')
ax2.view_init(elev=30, azim=150)
ax2.grid(True, linestyle='dashed', alpha=0.5)
plt.tight_layout()
plt.show()
```

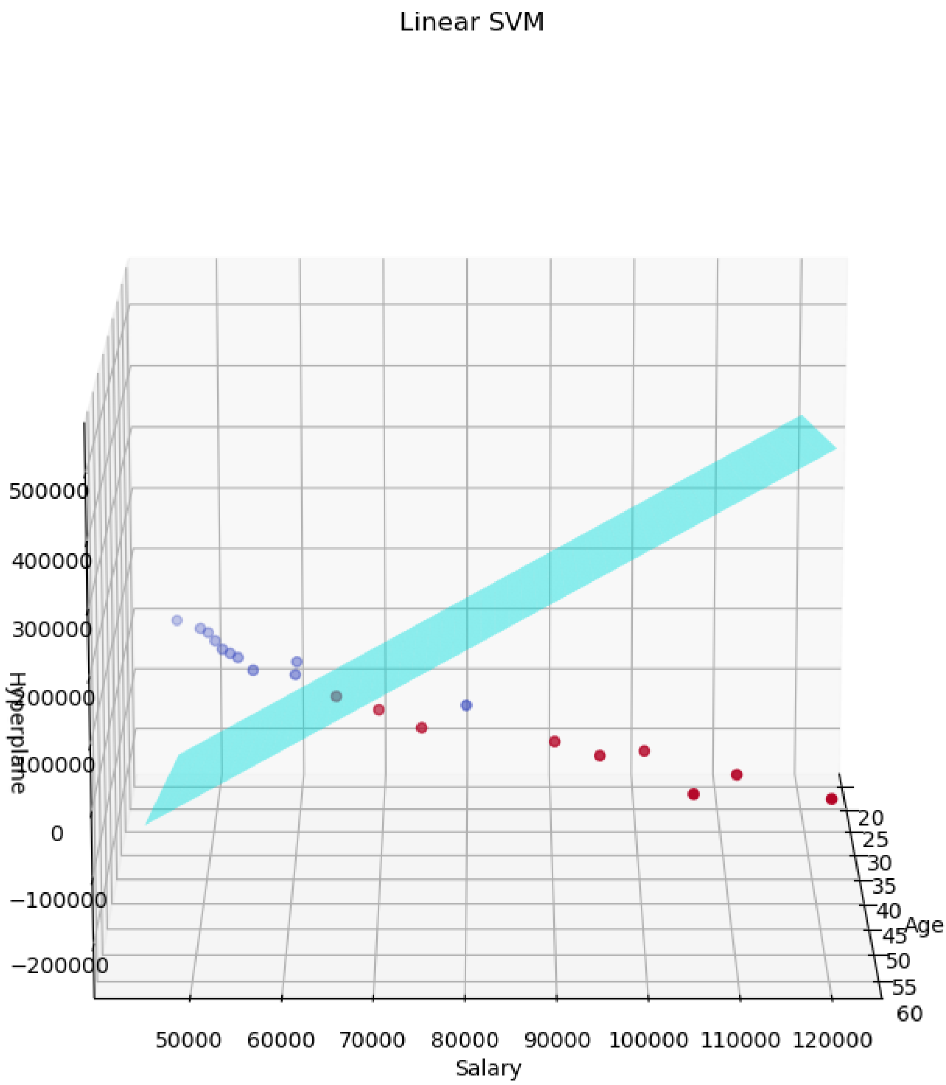


In [71]:

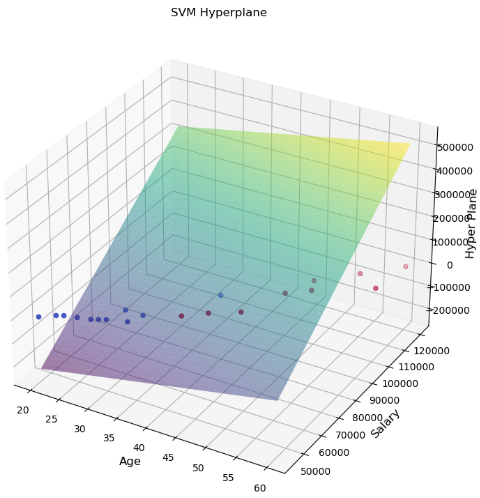
```
fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values_linear, cmap='cc
ax1.set_title('Linear SVM', fontsize=10)
ax1.set_xlabel('Age', fontsize=10)
ax1.set_ylabel('Salary', fontsize=10)
ax1.set_zlabel('Hyper plane', fontsize=16)
ax1.view_init(elev=15, azim=360)
ax1.grid(True, linestyle='dashed', alpha=0.5)

ax2 = fig.add_subplot(122, projection='3d')
ax2.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax2.plot_surface(age_values, salary_values, decision_values_poly, cmap='cool
ax2.set_title('Polynomial SVM', fontsize=10)
ax2.set_xlabel('Age', fontsize=10)
ax2.set_ylabel('Salary', fontsize=10)
ax2.set_zlabel('Hyper plane', fontsize=10)
ax2.view_init(elev=15, azim=360)
ax2.grid(True, linestyle='dashed', alpha=0.5)
plt.tight_layout()
plt.show()
```

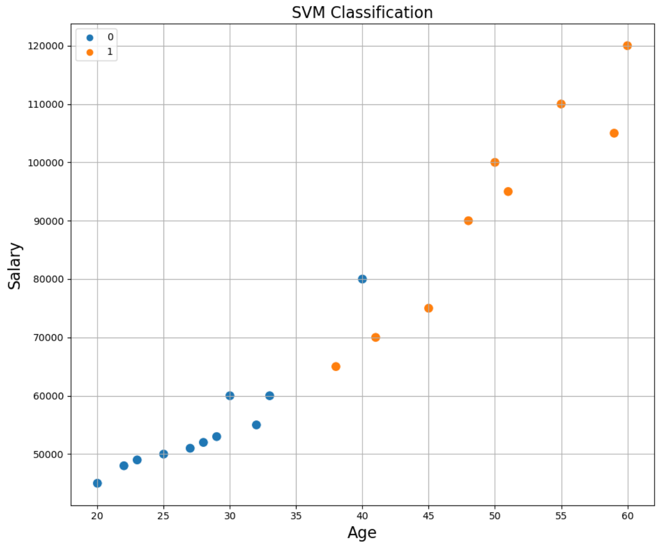


In [72]:
```
fig = plt.figure(figsize=(18, 8))
ax1 = fig.add_subplot(121, projection='3d')
ax1.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax1.plot_surface(age_values, salary_values, decision_values_linear, color='c
ax1.set_title('Linear SVM')
ax1.set_xlabel('Age')
ax1.set_ylabel('Salary')
ax1.set_zlabel('Hyperplane')
ax1.view_init(elev=15, azim=360)
ax1.grid(True, linestyle='dashed', alpha=0.5)
plt.tight_layout()
plt.show()
```



In [73]:
```
age_values = np.linspace(min(X[:, 0]), max(X[:, 0]), 50)
salary_values = np.linspace(min(X[:, 1]), max(X[:, 1]), 50)
age_mesh, salary_mesh = np.meshgrid(age_values, salary_values)
decision_values_linear = svm_linear.decision_function(np.c_[age_mesh.ravel()
decision_values_linear = decision_values_linear.reshape(age_mesh.shape)

fig = plt.figure(figsize=(18, 8))
ax = fig.add_subplot(121, projection='3d')
ax.plot_surface(age_mesh, salary_mesh, decision_values_linear, cmap='viridis
ax.scatter(X[:, 0], X[:, 1], y, c=y, cmap='coolwarm', marker='o')
ax.set_title('SVM Hyperplane', fontsize=12)
ax.set_xlabel('Age', fontsize=12)
ax.set_ylabel('Salary', fontsize=12)
ax.set_zlabel('Hyper Plane', fontsize=12)
ax2 = fig.add_subplot(122)
sns.scatterplot(x=X[:, 0], y=X[:, 1], hue=y, marker='o', ax=ax2, s=100, alph
ax2.set_xlabel('Age', fontsize=16)
ax2.set_ylabel('Salary', fontsize=16)
ax2.set_title('SVM Classification', fontsize=16)
ax2.grid(True)
ax2.legend()

plt.tight_layout()
plt.show()
```





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