In [1]:
```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score
from sklearn.metrics import ConfusionMatrixDisplay
import matplotlib.pyplot as plt
```

Own dataset

- The dataset contain year wise co2 and temperature difference data.

In [2]:
```python
df = pd.read_csv("co2_temperature.csv")
df.head()
```

Out[2]:

	Year	CO2	Temperature_change
0	1961	2580	0.0818
1	1962	2686	0.0924
2	1963	2833	0.1100
3	1964	2995	-0.1461
4	1965	3130	-0.0752

In [3]:
```python
df.shape
```

Out[3]:
```
(50, 3)
```

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 3 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Year                50 non-null     int64  
 1   CO2                 50 non-null     int64  
 2   Temperature_change  50 non-null     float64
dtypes: float64(1), int64(2)
memory usage: 1.3 KB
```

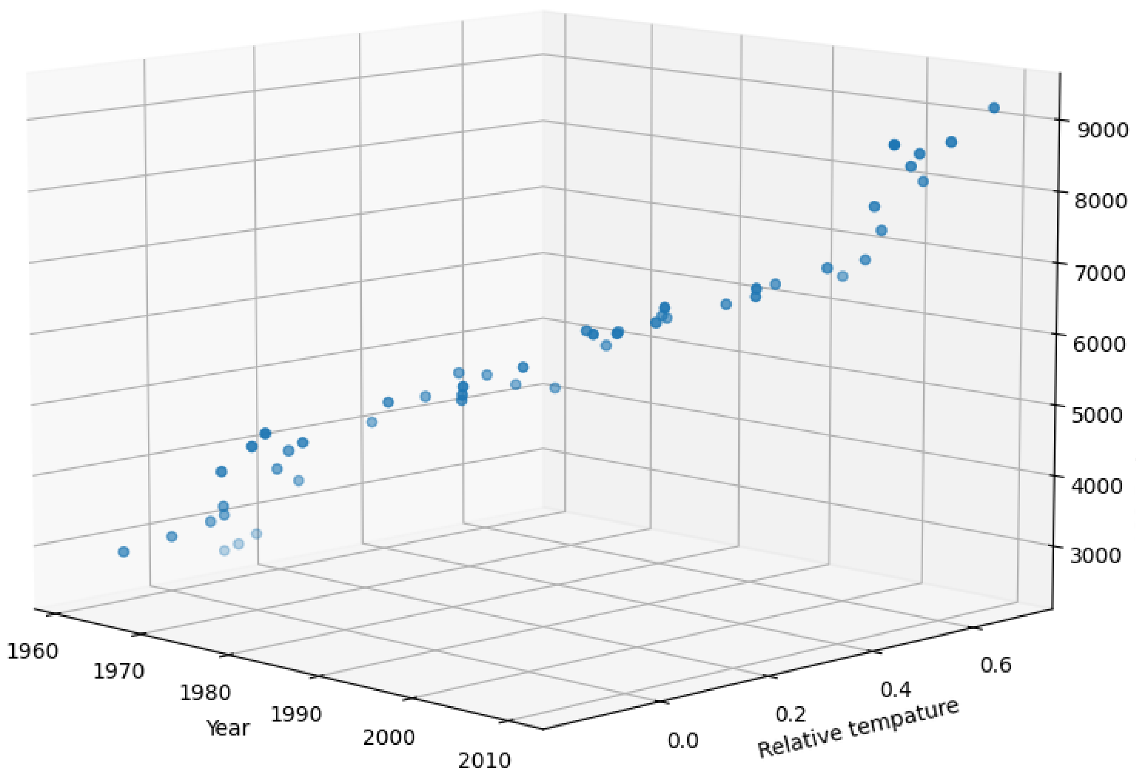
In [5]:
```python
df.describe()
```

Out[5]:

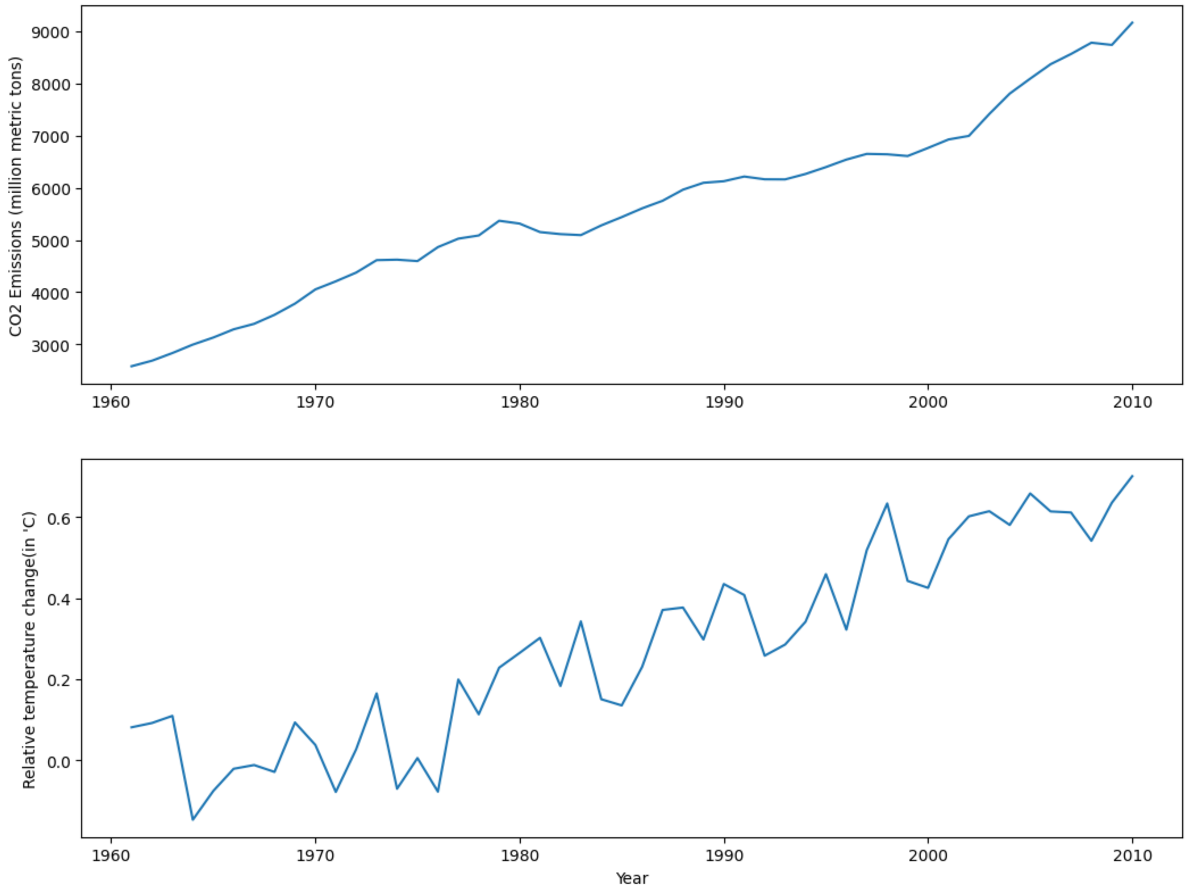
	Year	CO2	Temperature_change
count	50.00000	50.000000	50.000000
mean	1985.50000	5625.820000	0.278896
std	14.57738	1703.260675	0.240433
min	1961.00000	2580.000000	-0.146100
25%	1973.25000	4600.500000	0.092725
50%	1985.50000	5523.000000	0.275400
75%	1997.75000	6634.750000	0.455150
max	2010.00000	9167.000000	0.700800

In [6]:

```
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
fig.set_size_inches(12.5, 9.5)
ax = fig.add_subplot(111, projection='3d')
ax.scatter(xs= df['Year'],ys=df['Temperature_change'],zs = df['CO2']) # scat
ax.set_ylabel('Relative tempature'); ax.set_xlabel('Year'); ax.set_zlabel('C
ax.view_init(10, -45)
plt.show()
```



In [7]:
```
fig = plt.figure()
fig.set_size_inches(12.5, 9.5)

plt.subplot(2, 1, 1)
plt.plot(df['Year'],df['CO2'])
plt.ylabel('CO2 Emissions (million metric tons)')

plt.subplot(2, 1, 2)
plt.plot(df['Year'],df['Temperature_change'])
plt.xlabel('Year')
plt.ylabel("Relative temperature change(in 'C)")

plt.show()
```




```
In [8]: df.head()
```

Out[8]:

	Year	CO2	Temperature_change
0	1961	2580	0.0818
1	1962	2686	0.0924
2	1963	2833	0.1100
3	1964	2995	-0.1461
4	1965	3130	-0.0752

Split the dataset

```
In [9]: X = df['Year'].values
        y = df['Temperature_change'].values
```

```
In [10]: X_train,X_test,y_train,y_test = train_test_split(X.reshape(-1,1), y.reshape(
```

Linear Regression

```
In [11]: reg = LinearRegression()
```

```
In [12]: reg.fit(X_train, y_train)
```

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

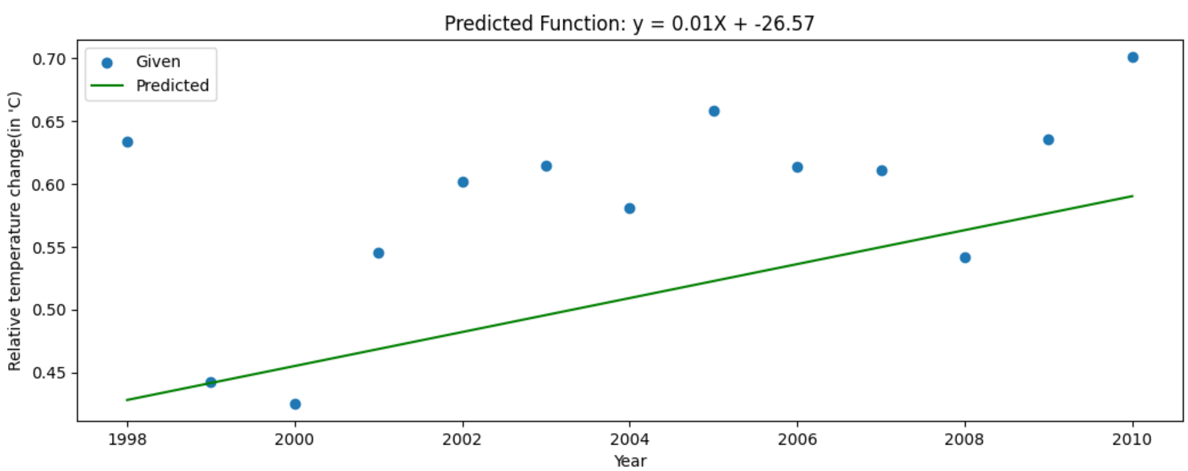
In [13]:
```
MSE = mean_squared_error(y_test, y_pred)
print(f"Mean squared error : {MSE}")
```

```
Mean squared error : 0.009763461396018537
```

In [14]:
```
r2_score_ = r2_score(y_test, y_pred)
print(f"R2 score : {r2_score_}")
```

```
R2 score : -0.6807757772371528
```

In [15]:
```
fig = plt.figure()
fig.set_size_inches(12.5, 9.5)

plt.subplot(2, 1, 1)
plt.scatter(X_test,y_test,label='Given')
plt.plot(X_test,y_pred, color='green',label='Predicted')
plt.xlabel('Year')
plt.ylabel("Relative temperature change(in 'C)")
titlestr = 'Predicted Function: y = %.2fX + %.2f' % (reg.coef_[0], reg.inter
plt.title(titlestr)
plt.legend()
plt.show()
```



Multilinear regression

In [16]:
```
X = df.drop(['Temperature_change'], axis=1)
y = df['Temperature_change'].values
```

In [17]:
```
X_train,X_test,y_train,y_test = train_test_split(X, y.reshape(-1,1), test_si
```

In [18]:
```
# Initialize the standardizer
scaler = StandardScaler()

# Fit on training set only
scaler.fit(X_train)

# Apply transform to both the training set and the test set
```

```python
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

In [19]:
```python
reg = LinearRegression()
reg.fit(X_train, y_train)
y_pred = reg.predict(X_test)
```

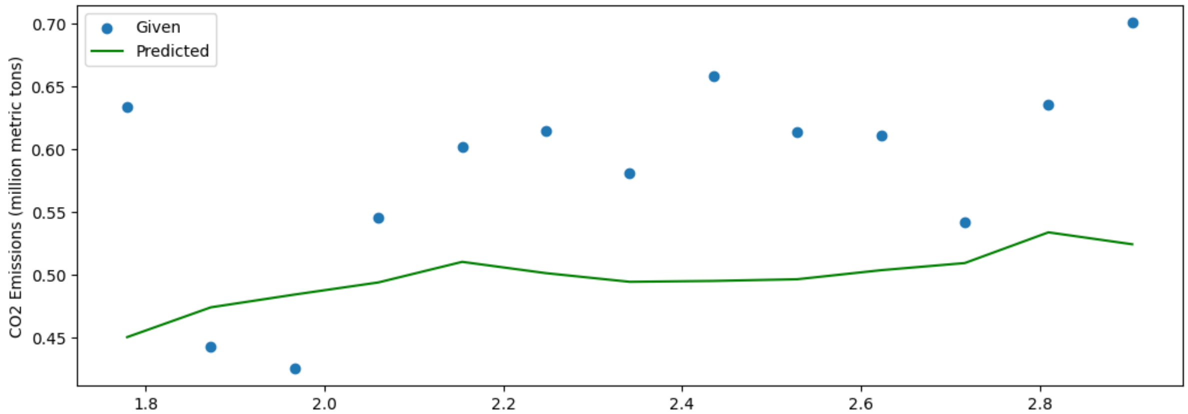
In [20]:
```python
MSE = mean_squared_error(y_test, y_pred)
print(f"Mean squared error : {MSE}")
```

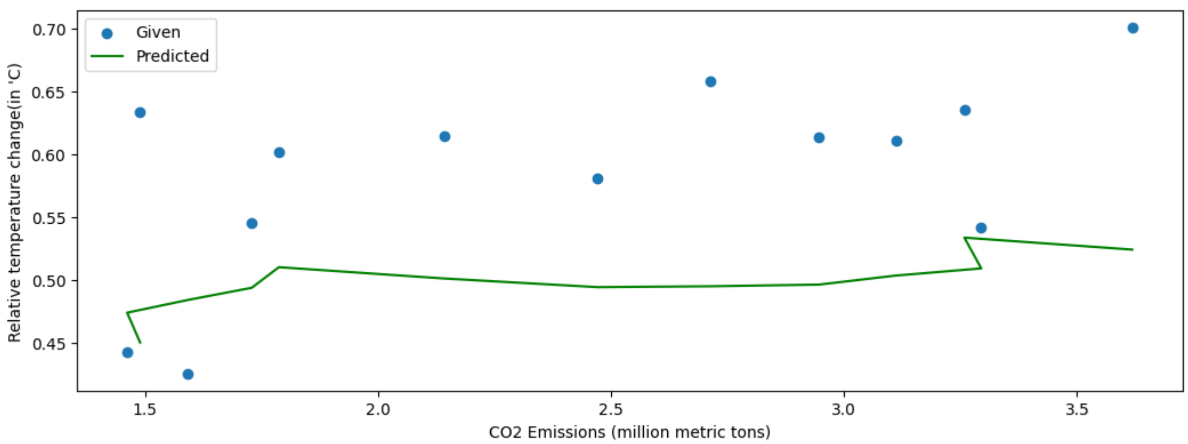
```
Mean squared error : 0.012639292655687593
```

In [21]:
```python
r2_score_ = r2_score(y_test, y_pred)
print(f"R2 score : {r2_score_}")
```

```
R2 score : -1.1758489203177684
```

In [22]:
```python
fig = plt.figure()
fig.set_size_inches(12.5, 9.5)

plt.subplot(2, 1, 1)
plt.scatter(X_test[:,0], y_test, label='Given')
plt.plot(X_test[:,0], y_pred, color='green', label='Predicted')
plt.ylabel('CO2 Emissions (million metric tons)')
plt.legend()


plt.subplot(2, 1, 2)
plt.scatter(X_test[:,1], y_test, label='Given')
plt.plot(X_test[:,1], y_pred, color='green', label='Predicted')
plt.xlabel('CO2 Emissions (million metric tons)')
plt.ylabel("Relative temperature change(in 'C)")
plt.legend()

plt.show()
```





Given Dataset

In [23]:
```
df = pd.read_csv("Admission_Predict_Ver1.1_small_data_set_for_Linear_Regress
```

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

Out[24]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

In [25]:
```
df.shape
```

Out[25]:
```
(500, 9)
```

In [26]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Serial No.         500 non-null    int64  
 1   GRE Score          500 non-null    int64  
 2   TOEFL Score        500 non-null    int64  
 3   University Rating  500 non-null    int64  
 4   SOP                500 non-null    float64
 5   LOR                500 non-null    float64
 6   CGPA               500 non-null    float64
 7   Research           500 non-null    int64  
 8   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 35.3 KB
```

In [27]:
```
df.describe()
```

Out[27]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CG
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.0000
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.5764
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.6048
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.8000
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.1275
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.5600
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.0400
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.9200

In [28]:
```
df = df.drop(['Serial No.'], axis=1)
```

In [29]:
```
X = df.drop(['Chance of Admit '],axis=1)
y = df['Chance of Admit ']
```

In [30]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

print(f"Number of training examples: {X_train.shape[0]}")
print(f"Number of testing examples: {X_test.shape[0]}")
```

```
Number of training examples: 400
Number of testing examples: 100
```

Linear Regression

In [31]:
```
reg = LinearRegression()
```

In [32]:
```
reg.fit(X_train['CGPA'].values.reshape(-1,1), y_train)
```

Out[32]:

```
▾ LinearRegression
LinearRegression()
```

In [33]:

```
y_pred = reg.predict(X_test['CGPA'].values.reshape(-1,1))
```

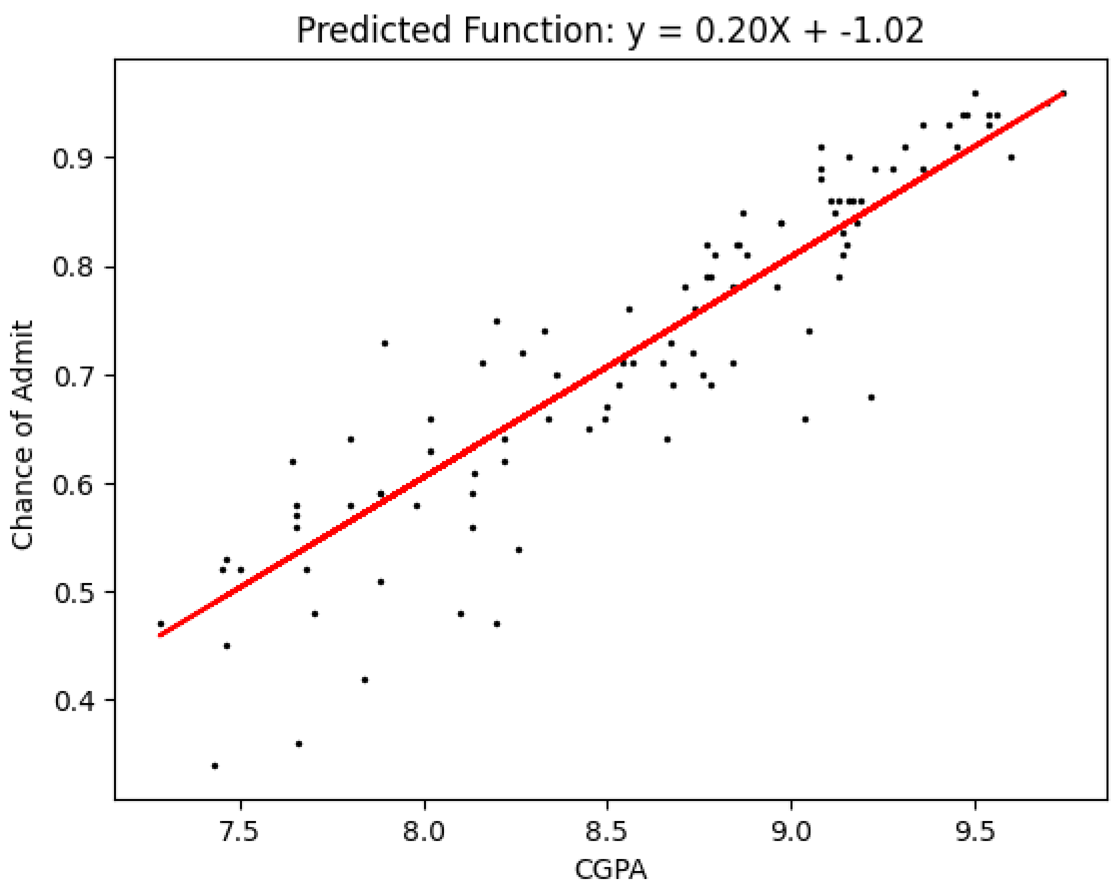
In [34]:

```
reg.intercept_
```

Out[34]: -1.0182042839120313

In [35]:

```
plt.scatter(X_test['CGPA'], y_test,  color='black',s=2)
plt.xlabel('CGPA')
plt.ylabel('Chance of Admit ')
plt.plot(X_test['CGPA'], y_pred, color='red')
titlestr = 'Predicted Function: y = %.2fX + %.2f' % (reg.coef_[0], reg.inter
plt.title(titlestr)
plt.show()
```



In [36]:

```
MSE = mean_squared_error(y_test, y_pred)
print(f"Mean squared error : {MSE}")
```

Mean squared error : 0.00387225142355091

In [37]:

```
r2_score_ = r2_score(y_test, y_pred)
print(f"R2 score : {r2_score_}")
```

R2 score : 0.8290680477081549

Multiple Linear Regression

In [38]:
```
X = df.drop(['Chance of Admit '],axis=1)
y = df['Chance of Admit ']
```

In [39]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

print(f"Number of training examples: {X_train.shape[0]}")
print(f"Number of testing examples: {X_test.shape[0]}")
```

```
Number of training examples: 400
Number of testing examples: 100
```

In [40]:
```
# Initialize the standardizer
scaler = StandardScaler()

# Fit on training set only
scaler.fit(X_train)

# Apply transform to both the training set and the test set
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

In [41]:
```
reg = LinearRegression()
```

In [42]:
```
reg.fit(X_train, y_train)
```

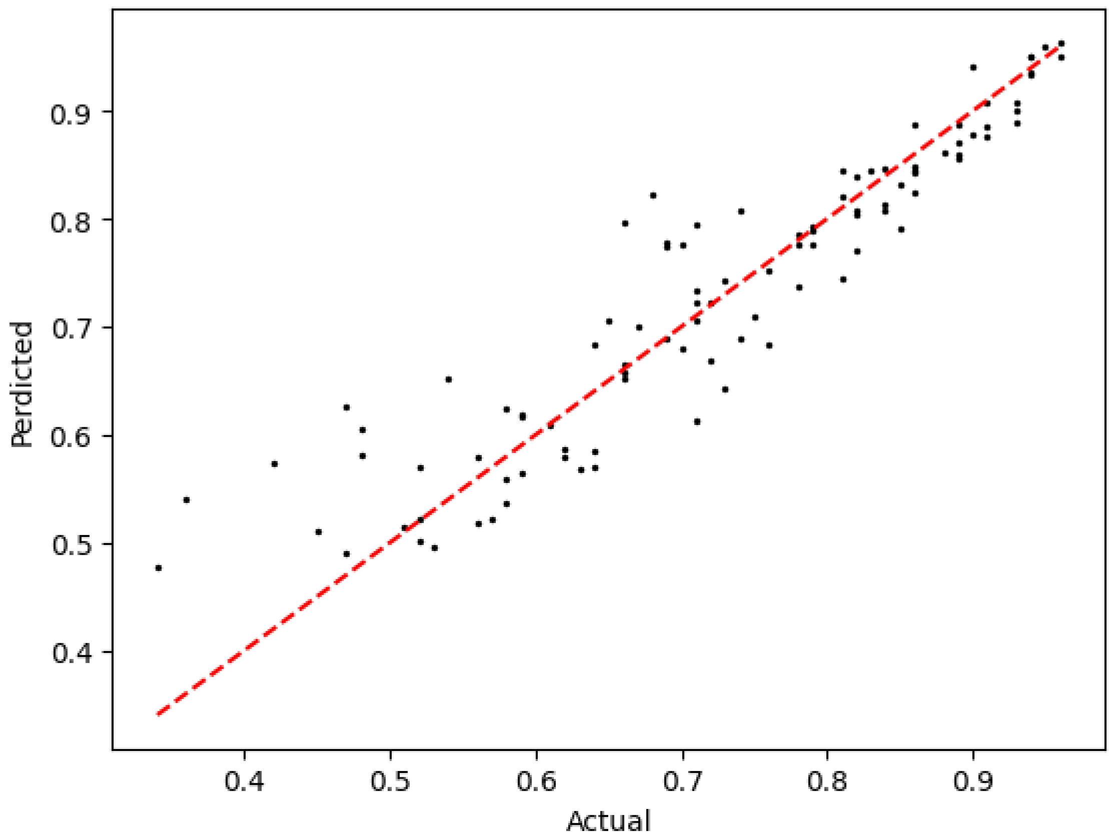
Out[42]:
```
▾ LinearRegression
LinearRegression()
```

In [43]:
```
y_pred = reg.predict(X_test)
```

In [44]:
```
X_test[:,-2].shape
```

Out[44]:
```
(100,)
```

In [45]:
```
plt.scatter(y_test, y_pred,  color='black',s=2)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red'
plt.xlabel('Actual')
plt.ylabel('Perdicted')
plt.show()
```



In [46]:
```
MSE = mean_squared_error(y_test, y_pred)
print(f"Mean squared error : {MSE}")
```

```
Mean squared error : 0.0030965712093589813
```

In [47]:
```
r2_score_ = r2_score(y_test, y_pred)
print(f"R2 score : {r2_score_}")
```

```
R2 score : 0.8633087306761005
```

Classification

In [48]:
```
df = pd.read_csv("Admission_Predict_Ver1.1_small_data_set_for_Linear_Regress
df.head()
```

Out[48]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

In [49]:
```
df.isna().sum()
```

Out[49]:
```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

In [50]:
```
df = df.drop(['Serial No.'], axis=1)
```

In [51]:
```
df['University Rating'].value_counts()
```

Out[51]:
```
University Rating
3    162
2    126
4    105
5     73
1     34
Name: count, dtype: int64
```

In [52]:
```
df.columns
```

Out[52]:
```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGP
A',
       'Research', 'Chance of Admit '],
      dtype='object')
```

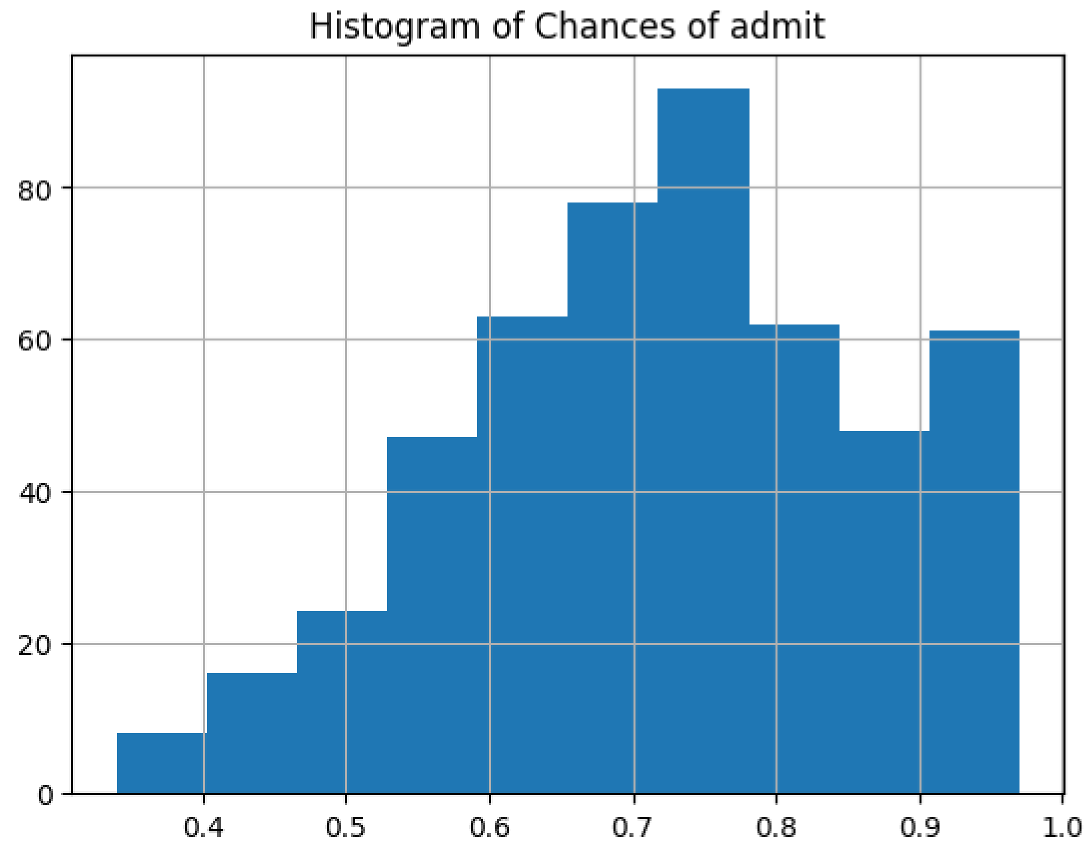
In [53]:
```
# columns_for_transformation = ['GRE Score', 'TOEFL Score', 'SOP', 'LOR ', '
# # Initialize the MinMaxScaler
# scaler = MinMaxScaler()

# # Apply the scaler to the numerical columns
# df[columns_for_transformation] = scaler.fit_transform(df[columns_for_trans
```

In [54]:
```
df.head()
```

Out[54]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65

In [55]:
```
df['Chance of Admit '].hist(bins=10)
plt.title("Histogram of Chances of admit")
plt.show()
```

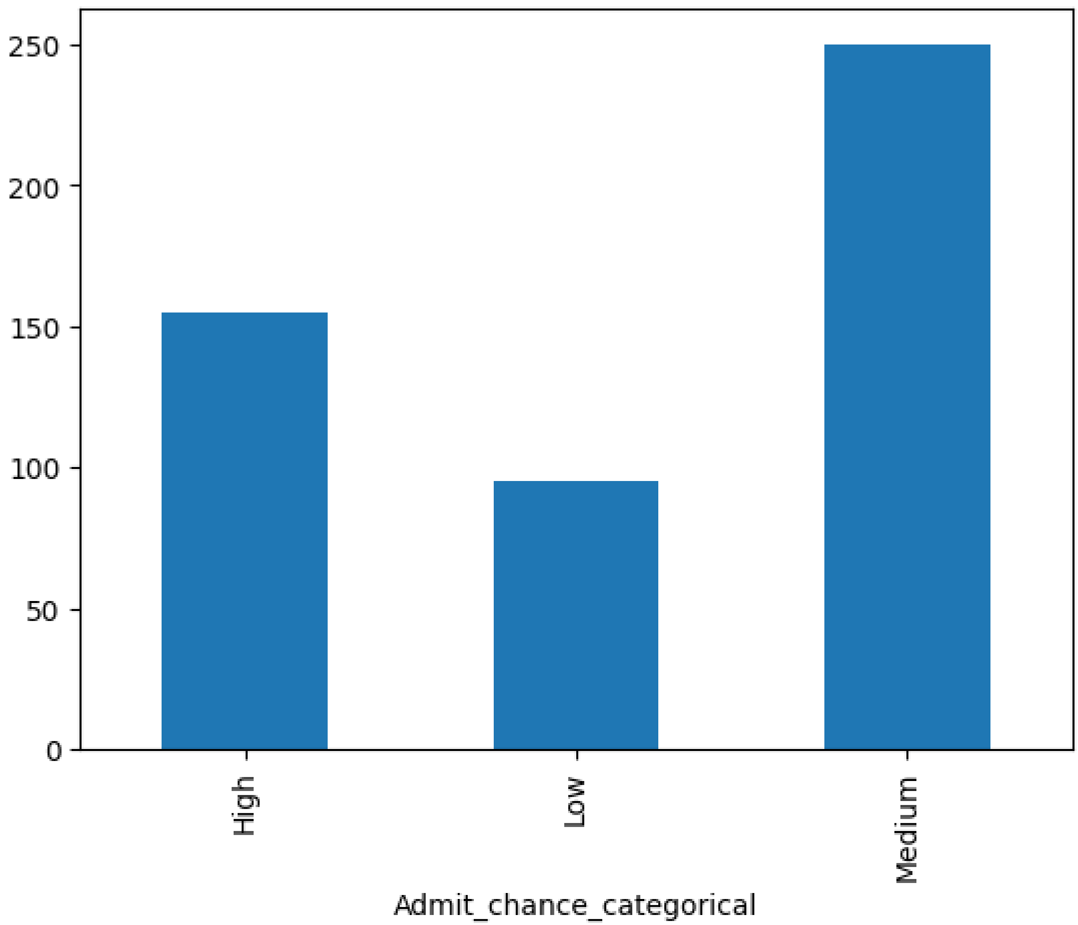


In [56]:
```
def convert_to_categorical(chance_probability):
    if chance_probability >= 0.8:
        return "High"
    elif chance_probability >= 0.6:
        return "Medium"
    else:
        return "Low"

df['Admit_chance_categorical'] = df['Chance of Admit '].apply(convert_to_cat
df.drop(['Chance of Admit '],axis=1, inplace=True)
df.head()
```

Out[56]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Admit_chance_categorical
0	337	118	4	4.5	4.5	9.65	1	High
1	324	107	4	4.0	4.5	8.87	1	Medium
2	316	104	3	3.0	3.5	8.00	1	Medium
3	322	110	3	3.5	2.5	8.67	1	High
4	314	103	2	2.0	3.0	8.21	0	Medium

In [57]:
```
df['Admit_chance_categorical'].value_counts().sort_index().plot(kind='bar')
plt.show()
```



Split the dataset

In [58]:
```
X = df.drop(['Admit_chance_categorical'],axis=1)
y = df['Admit_chance_categorical']
```

In [59]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

print(f"Number of training examples: {X_train.shape[0]}")
print(f"Number of testing examples: {X_test.shape[0]}")
```

```
Number of training examples: 400
Number of testing examples: 100
```

In [60]:
```
clf = DecisionTreeClassifier(max_depth=3, random_state = 0)
clf.fit(X_train, y_train)
```

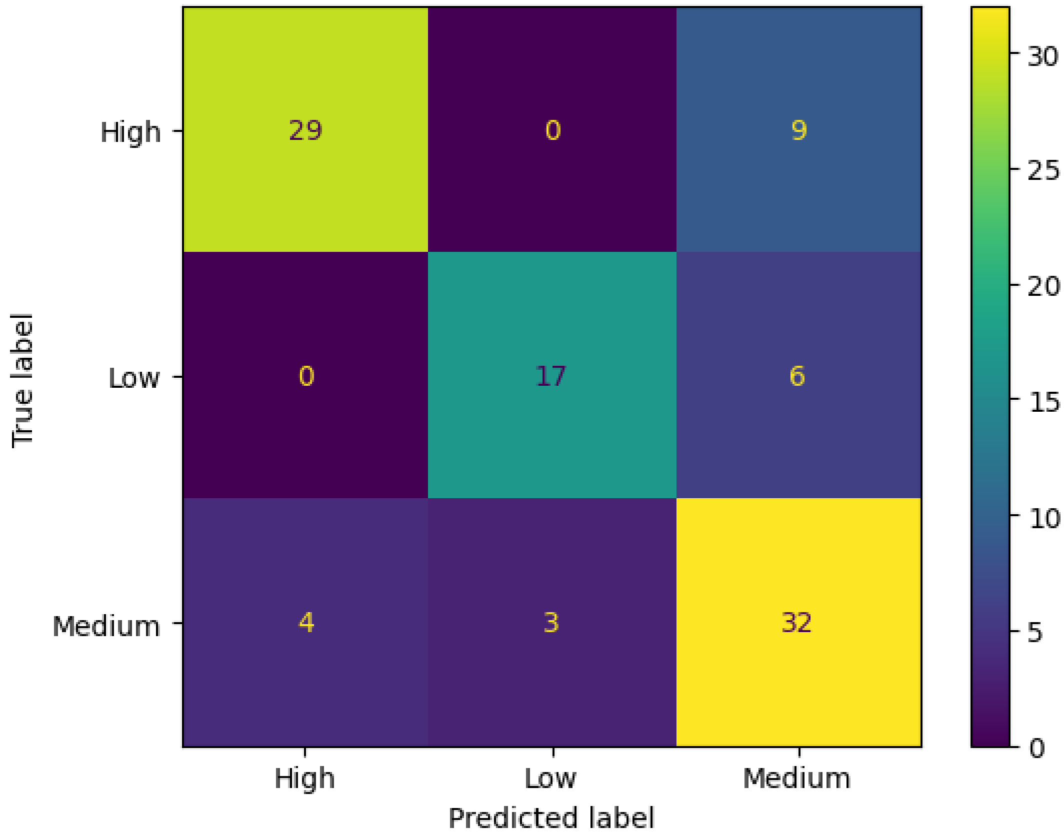
Out[60]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3, random_state=0)
```

In [61]:
```
y_pred = clf.predict(X_test)
```

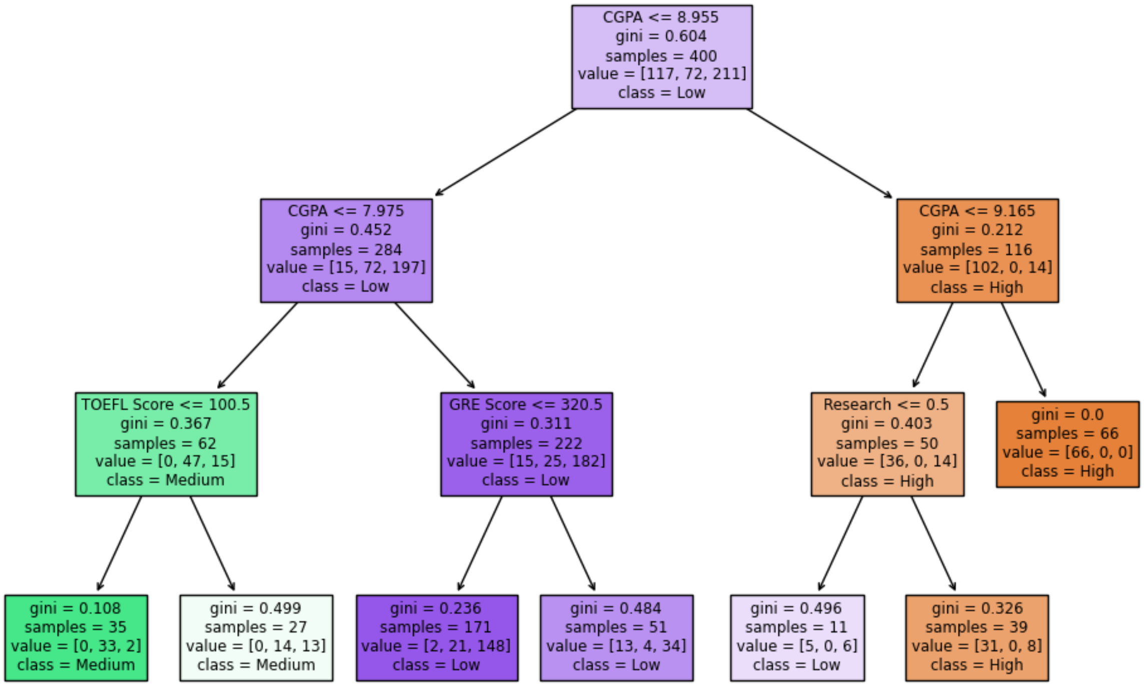
In [62]:
```
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy : {accuracy}")
```

```
Accuracy : 0.78
```

In [63]:
```python
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.show()
```



In [64]:
```python
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Plot the decision tree
plt.figure(figsize=(12, 8))  # Set the size of the figure
plot_tree(clf, filled=True, feature_names=X_test.columns, class_names=["High
plt.show()
```



In [65]:
```python
from sklearn.tree import export_text

tree_rules = export_text(clf, feature_names=list(X_test.columns))
print(tree_rules)
```

```
|--- CGPA <= 8.95
|   |--- CGPA <= 7.97
|   |   |--- TOEFL Score <= 100.50
|   |   |   |--- class: Low
|   |   |--- TOEFL Score >  100.50
|   |   |   |--- class: Low
|   |--- CGPA >  7.97
|   |   |--- GRE Score <= 320.50
|   |   |   |--- class: Medium
|   |   |--- GRE Score >  320.50
|   |   |   |--- class: Medium
|--- CGPA >  8.95
|   |--- CGPA <= 9.16
|   |   |--- Research <= 0.50
|   |   |   |--- class: Medium
|   |   |--- Research >  0.50
|   |   |   |--- class: High
|   |--- CGPA >  9.16
|   |   |--- class: High
```

Conclusion

- From the above rule it is pretty much clear that above CGPA 9.16, the chance of admission is high.

- If the CGPA is above 8.95 and less than 9.16 and someone has an experience in research then also the chance of admission is high.
- If CGPA score more than 7.97 and less than 8.95 then the chances are medium.
- Similarly if CGPA is less than 7.97, than chances are Low.

C: Classification Tree Part

In [66]:
```
import pandas as pd
import numpy as np
```

- We copy the data from pdf to a csv file.

In [67]:
```
df = pd.read_csv("task3.csv")
df
```

Out[67]:

	color	shape	size	class
0	red	square	big	+
1	blue	square	big	+
2	red	round	small	-
3	green	square	small	-
4	red	round	big	+
5	green	round	big	-

Calculating Initial Entropy

In [68]:
```
def calculate_intial_entropy(dataset, target_column, unique_classes):
    total_entries = dataset[target_column].shape[0]
    class_counts = dataset[target_column].value_counts()
    entropy = -(class_counts / total_entries) * np.log2((total_entries - cla
    total_entropy = entropy.sum()
    return total_entropy
```

In [69]:
```
class_entropy = calculate_intial_entropy(df, 'class', ['+','-']) #Class
print(class_entropy)
```

```
1.0
```

entropy and information gain

In [70]:
```
import numpy as np
import pandas as pd

def calculate_average_entropy(dataset, target_attr, unique_classes):
    total_entries = dataset.shape[0]
    average_entropy = 0
```

```
    for class_value in unique_classes:
        class_subset = dataset[dataset[target_attr] == class_value]
        class_count = class_subset.shape[0]

        if class_count == 0:
            continue

        positive_count = class_subset[class_subset['class'] == '+'].shape[0]
        negative_count = class_count - positive_count

        # Calculate entropy for both positive and negative instances
        positive_entropy = -(positive_count / class_count) * np.log2(positiv
        negative_entropy = -(negative_count / class_count) * np.log2(negativ

        # Total entropy for the class
        class_entropy = positive_entropy + negative_entropy

        # Weighted average entropy
        average_entropy += (class_count / total_entries) * class_entropy

    return round(average_entropy, 2)
```

In [71]:

```
color_entropy = calculate_average_entropy(df,'color', ['red','green','blue']
print("Color-> entropy: ",color_entropy, ", information gain: ", 1-color_ent
shape_entropy = calculate_average_entropy(df,'shape', ['square','round'])
print("Shape-> entropy: ",shape_entropy, ", information gain: ", round(1-sha
size_entropy = calculate_average_entropy(df, 'size', ['big','small'])
print("Size-> entropy: ", size_entropy, ", information gain: ", round(1-size
```

```
Color-> entropy:  0.46 , information gain:  0.54
Shape-> entropy:  0.92 , information gain:  0.08
Size-> entropy:  0.54 , information gain:  0.46
```

Decision Tree

In [72]:

```
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

le = LabelEncoder()

for column in df.columns:
    df[column] = le.fit_transform(df[column])

df
```

Out[72]:

	color	shape	size	class
0	2	1	0	0
1	0	1	0	0
2	2	0	1	1
3	1	1	1	1
4	2	0	0	0
5	1	0	0	1

In [73]:

```
X = df[['color', 'shape', 'size']]
y = df['class']
```

In [74]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25, ran
```

In [75]:

```
clf_entropy = DecisionTreeClassifier(random_state=10)
clf_entropy.fit(X_train, y_train)
```

Out[75]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=10)
```

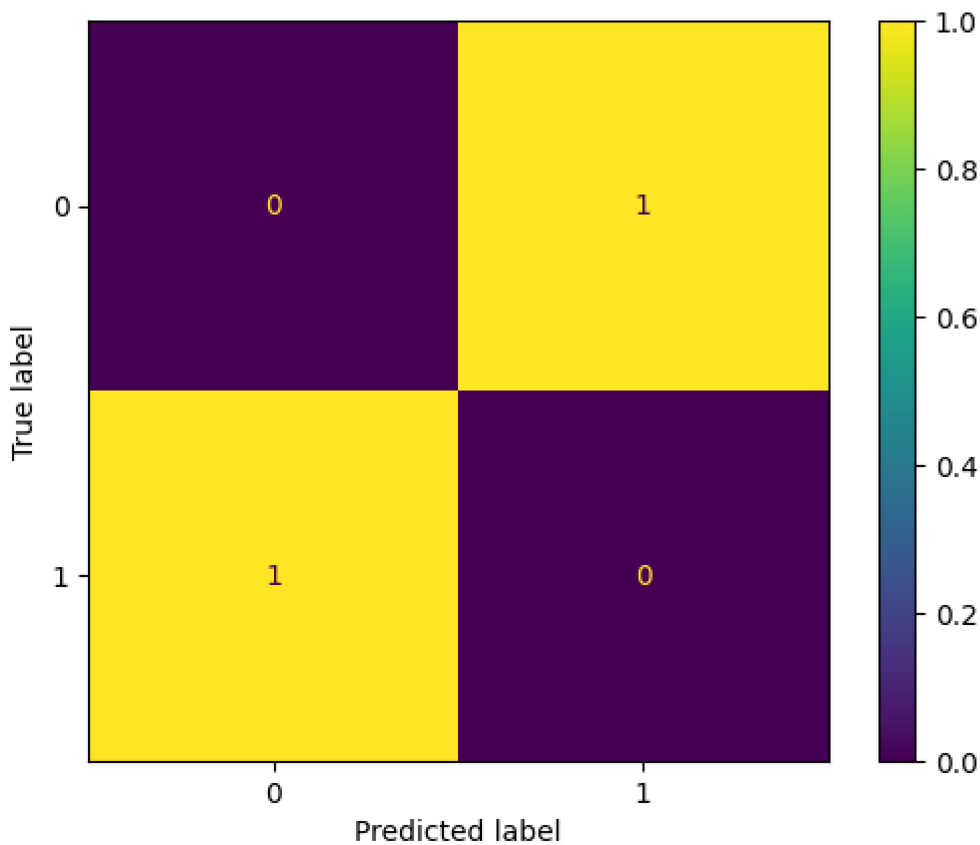
In [76]:

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

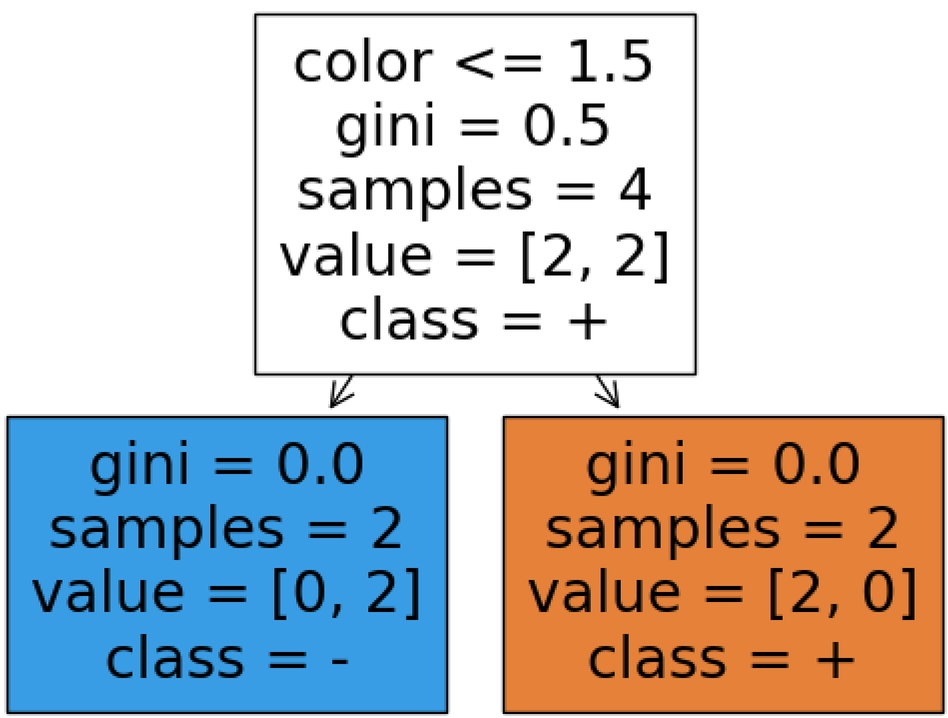
In [77]:

```
from sklearn.metrics import ConfusionMatrixDisplay
print("Accuracy score on test: ", clf_entropy.score(X_test, y_test))
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.show()
```

```
Accuracy score on test:  0.0
```



In [78]:
```
plot_tree(clf_entropy, filled=True, feature_names=X_test.columns, class_name
plt.show()
```



In [79]:
```
from sklearn.tree import export_text
```

```
tree_rules = export_text(clf_entropy, feature_names=list(X_test.columns))
print(tree_rules)
```

```
|--- color <= 1.50
|   |--- class: 1
|--- color >  1.50
|   |--- class: 0
```

Conclusion

- As we can clearly see that the color is splitted to make the tree as it has the highest information gain.

In [ ]:

```
```