Importing the necessary libraries and mounting drive to load the dataset

```
import pandas as pd
import numpy as np
import re
from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /content/drive
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
    Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=
```

Loading the required datasets

```
da=pd.read_csv('/content/drive/MyDrive/DataAnalystJobs.csv')
de=pd.read_csv('/content/drive/MyDrive/DataEngineer.csv')
ds=pd.read_csv('/content/drive/MyDrive/DataScientist.csv')
da=da.drop(da.columns[0],axis=1)
ds=ds.drop(ds.columns[0],axis=1)
df_comb=pd.concat([da,ds,de])
df_comb=df_comb.drop_duplicates()
```

Displaying the first few rows of the combined dataset

```
df_comb.head()
```

	Job Title	Salary Estimate	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership
0	Data Analyst, Center on Immigration and Justic...	$37K-$66K (Glassdoor est.)	Are you eager to roll up your sleeves and harn...	3.2	Vera Institute of Justice\n3.2	New York, NY	New York, NY	201 to 500 employees	1961	Nonprofit Organization
1	Quality Data Analyst	$37K-$66K (Glassdoor est.)	Overview\n\nProvides analytical and technical ...	3.8	Visiting Nurse Service of New York\n3.8	New York, NY	New York, NY	10000+ employees	1893	Nonprofit Organization
2	Senior Data Analyst, Insights & Analytics Team...	$37K-$66K (Glassdoor est.)	We're looking for a Senior Data Analyst who ha...	3.4	Squarespace\n3.4	New York, NY	New York, NY	1001 to 5000 employees	2003	Company - Private
3	Data Analyst	$37K-$66K (Glassdoor est.)	Requisition NumberRR-0001939\nRemote:Yes\nWe c...	4.1	Celerity\n4.1	New York, NY	McLean, VA	201 to 500 employees	2002	Subsidiary or Business Segment
4	Reporting Data Analyst	$37K-$66K (Glassdoor est.)	ABOUT FANDUEL GROUP\n\nFanDuel Group is a worl...	3.9	FanDuel\n3.9	New York, NY	New York, NY	501 to 1000 employees	2009	Company - Private

Data Cleaning, Domain Knowledge Preprocessing, and Dimension Reduction

Feature Selection (Dimension Reduction)

```
#dropping unneccesary columns
df_comb.drop(columns = ['Competitors','Easy Apply','Industry'], inplace=True)
```

```
df_comb = df_comb.dropna()
df_comb=df_comb.drop(index=df_comb[(df_comb['Revenue']=='Unknown / Non-Applicable') | (df_comb['Size']=='Unknown')].index)
```

```
df_comb = df_comb.reset_index(drop=True)
```

```
df_comb.shape
```

```
(2742, 13)
```

```
df_comb.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Rating	2742.0	3.308862	1.484653	-1.0	3.30	3.7	4.10	5.0
Founded	2742.0	1540.315828	811.148524	-1.0	1849.00	1970.0	1999.00	2020.0
index	2742.0	2242.022611	1226.415699	11.0	1231.25	2242.5	3307.75	4379.0

```
df_comb.isnull().sum()
```

```
Job Title            0
Salary Estimate      0
Job Description      0
Rating               0
Company Name         0
Location             0
Headquarters         0
Size                 0
Founded              0
Type of ownership    0
Sector               0
Revenue              0
index                0
dtype: int64
```

Cleaning Salary Estimate column

```
df_comb.dropna(subset=['Salary Estimate'],inplace=True)
#Removing the text value from the column
df_comb['Salary Estimate'] = df_comb['Salary Estimate'].astype(str)
salary = df_comb['Salary Estimate'].apply(lambda x: x.split("(")[0])
salary
#Removing $ and K from the column
salary = salary.apply(lambda x: x.replace("$","").replace("K",""))
salary
#Creating column for per hour
df_comb['salary_per_hour'] = salary.apply(lambda x: 1 if "per hour" in x.lower() else 0)
salary = salary.apply(lambda x: x.lower().replace("per hour","").replace(" ",""))

#minimum salary
df_comb["min_salary"] = salary.apply(lambda x: x.split("-")[0]).astype(int)
#maximum salary
df_comb["max_salary"] = salary.apply(lambda x: x.split("-")[1]).astype(int)
#converting the hourly salaries to annual salaries
df_comb['min_salary'] = df_comb.apply(lambda x: x['min_salary']*1.92 if x["salary_per_hour"]==1 else x['min_salary'], axis =1).
df_comb['max_salary'] = df_comb.apply(lambda x: x['max_salary']*1.92 if x["salary_per_hour"]==1 else x['max_salary'], axis =1).
```

Cleaning company name column

```
def clean_company_name(value):
  parts = value.split('\n')
  return parts[0].strip()
df_comb['Company Name'] = df_comb['Company Name'].astype(str)
df_comb['Company Name'] = df_comb['Company Name'].apply(clean_company_name)
```

Creating a job_state column

```
df_comb["job_state"] = df_comb["Location"].apply(lambda x: x.split(',')[1])
df_comb["job_state"] = df_comb["job_state"].apply(lambda x: x.strip() if x.strip().lower()!=("arapahoe") else 'AC')
df_comb["job_state"] = df_comb["job_state"].apply(lambda x: x.strip() if x.strip().lower()!=("united kingdom") else 'UK')
df_comb["job_state"].value_counts()
```

```
TX    920
CA    739
IL    239
AZ    226
PA    220
NY    168
OH    142
FL     55
NJ     21
DE      8
UK      4
Name: job_state, dtype: int64
```

Finding company age from founded column

```
#df_comb[df_comb['Founded']=='<NA>']
df_comb['Founded'].replace('<NA>',np.nan,inplace=True)
df_comb['Founded']=pd.to_numeric(df_comb['Founded'])
df_comb['Founded'].isna().mean()*100 # 25% missing values
#FInding company's age based on 2023
def age(value):
  if(pd.isna(value)):
    return None
  else:
    return(2023-int(value))
df_comb["Company_age"] = df_comb["Founded"].apply(age)
```

Cleaning Job-Title coloumn

```
from nltk import FreqDist
df_comb["Job Title"]=df_comb["Job Title"].apply(lambda x:x.lower())
all_jobs = (' '.join(df_comb['Job Title'])).split()
fdist = FreqDist(all_jobs)
def job_title(v):
  if(("data scientist" in v) or ("data science" in v)):
    return "data scientist"
  elif(('analyst' in v) or ("analytics" in v) or ('analysis' in v) or ("quantitative" in v) or ("visualization" in v) or ('data
    return "analyst"
  elif(("data engineer" in v) or ("big data" in v) or ("etl" in v) or ('data integration' in v) or ('data infrastructure' in v)
    return "data engineer"
  elif("machine learning" in v):
    return "machine learning engineer"
  elif(("artificial intelligence" in v) or ("ai" in v)):
    return "AI engineer"
  elif("cloud engineer" in v):
    return "cloud engineer"
  elif("manager" in v):
    return "manager"
  elif("director" in v):
    return "director"
  else:
    return "others"
df_comb["job_desc_simp"]=df_comb['Job Title'].apply(job_title)
df_comb[(df_comb['job_desc_simp']=="others") & (df_comb['Job Title'].str.contains('data', case=False))]
df_comb['job_desc_simp'].value_counts()
```

```
data scientist               782
analyst                      730
others                       595
data engineer                534
machine learning engineer     79
AI engineer                   15
director                       4
manager                        3
Name: job_desc_simp, dtype: int64
```

Adding a seniority column

```
def seniority(v):
  if(("sr." in v) or ("senior" in v) or ('sr' in v) or ("lead" in v)):
    return "senior"
  elif(("jr." in v) or ("junior" in v) or ('jr' in v) or ('entry' in v)):
    return "junior"
  else:
    return 'na'
```

```
df_comb['seniority']=df_comb['Job Title'].apply(seniority)
df_comb['seniority'].value_counts()
```

```
na        2143
senior     558
junior      41
Name: seniority, dtype: int64
```

Preprocessing Type of ownership column

```
def ownership(v):
  if((pd.isna(v)) or v==-1):
    return "other organisations"
  if(('private' in v.lower()) or ('franchise' in v.lower()) or ('self-employed' in v.lower())):
    return "private"
  elif(('public' in v.lower())):
    return "public"
  elif(("school" in v.lower()) or ("college" in v.lower()) or ('university' in v.lower())):
    return "education_institution"
  elif("government" in v.lower()):
    return("government")
  else:
    return "other organisations"
df_comb['Type of ownership']= df_comb['Type of ownership'].apply(ownership)
```

Preprocessing Company Size column

```
size_mapping = {
    '1 to 50 employees': 'Small',
    '51 to 200 employees': 'Small',
    '201 to 500 employees': 'Small',
    '501 to 1000 employees': 'Medium',
    '1001 to 5000 employees': 'Medium',
    '5001 to 10000 employees': 'Large',
    '10000+ employees': 'Large'
}
df_comb['size_category'] = df_comb['Size'].map(size_mapping)
df_comb['size_category'].value_counts()
```

```
Large     1064
Small      876
Medium     573
Name: size_category, dtype: int64
```

Preprocessing Revenue Column

```
revenue_mapping = {
    'Less than $1 million (USD)': 'Low',
    '$1 to $5 million (USD)': 'Low',
    '$5 to $10 million (USD)': 'Low',
    '$10 to $25 million (USD)': 'Medium',
    '$25 to $50 million (USD)': 'Medium',
    '$50 to $100 million (USD)': 'Medium',
    '$100 to $500 million (USD)': 'High',
    '$500 million to $1 billion (USD)': 'High',
    '$1 to $2 billion (USD)': 'High',
    '$2 to $5 billion (USD)': 'Very High',
    '$5 to $10 billion (USD)': 'Very High',
    '$10+ billion (USD)': 'Very High'
}
df_comb['revenue_category'] = df_comb['Revenue'].map(revenue_mapping)
df_comb['revenue_category'].value_counts()
```

```
Very High    943
High         632
Medium       546
Low          392
Name: revenue_category, dtype: int64
```

Preprocessing Job description column based on the skills present in the JD

```
ds0=[
 'excel',
```

```
 'python',
 'sql',
 'machine learning','spark',
 'aws']
ski = pd.DataFrame(0, index=range(len(df_comb)), columns=ds0)
for i in range(len(df_comb)):
  tt=df_comb.iloc[i,2]
  ss=str(tt)
  for j in ds0:
    if ss.lower().find(j.lower()) != -1:
      ski.loc[i,j]=1
    else:
      continue
#df_comb=pd.concat([df_comb, ski], axis=1)
```

```
ski
```

	excel	python	sql	machine learning	spark	aws
0	0	1	0	1	1	0
1	0	1	1	1	0	1
2	0	1	1	0	0	0
3	0	1	1	1	1	0
4	0	1	1	0	0	0
...	...	...	...	...	...	...
2737	0	0	0	0	0	1
2738	1	0	1	0	0	0
2739	1	1	1	1	0	0
2740	1	1	1	1	0	0
2741	1	0	0	0	0	0

2742 rows × 6 columns

```
ski.sum()
```

```
excel               1333
python              1421
sql                 1422
machine learning     897
spark                689
aws                  677
dtype: int64
```

Preprocessing Job State column

```
(df_comb['job_state'].unique())
```

```
array(['NY', 'NJ', 'CA', 'IL', 'TX', 'AZ', 'DE', 'PA', 'UK', 'FL', 'OH'],
      dtype=object)
```

```
st=pd.DataFrame(df_comb['job_state'].value_counts())
st['name']=st.index
st.index=range(0,len(st))
st=st.head(9)
sts=list(st['name'].values)
def states(v):
  if v not in sts:
    return "Others"
  else:
    return v
df_comb["job_state"]=df_comb['job_state'].apply(states)
df_comb['job_in_hq']=df_comb.apply(lambda x: 1 if x['Location']==x['Headquarters'] else 0, axis=1)
```

```
df_comb
```

	Job Title	Salary Estimate	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership	.
0	data scientist/machine learning	$111K-$181K (Glassdoor est.)	PulsePoint™, a global programmatic advertising...	4.4	PulsePoint	New York, NY	New York, NY	51 to 200 employees	2011	private	
1	data scientist, acorn ai labs	$111K-$181K (Glassdoor est.)	Medidata: Conquering Diseases Together\n\nMedi...	4.3	Medidata Solutions	New York, NY	New York, NY	1001 to 5000 employees	1999	public	
2	data scientist, analytics	$111K-$181K (Glassdoor est.)	Company DescriptionAs an Etsy employee, you ca...	3.6	Etsy	Brooklyn, NY	Brooklyn, NY	501 to 1000 employees	2005	public	
3	data scientist/ml engineer	$111K-$181K (Glassdoor est.)	Data Scientist/ML Engineer\n\nApply Now\n\nBec...	3.3	PA Consulting	New York, NY	London, United Kingdom	1001 to 5000 employees	1943	private	
4	data scientist	$111K-$181K (Glassdoor est.)	Job Description\nCompany Description\n\nAs an ...	3.6	Etsy	New York, NY	Brooklyn, NY	501 to 1000 employees	2005	public	
...	...	...	...	...	...	...	...	...	...	...	
2737	aws data engineer	$55K-$112K (Glassdoor est.)	About Us\n\nTachyon Technologies is a Digital ...	4.4	Tachyon Technologies	Dublin, OH	Irving, TX	201 to 500 employees	2011	private	
2738	data analyst â junior	$55K-$112K (Glassdoor est.)	Job description\nInterpret data, analyze resul...	5.0	Staffigo Technical Services, LLC	Columbus, OH	Woodridge, IL	51 to 200 employees	2008	private	
2739	security analytics data engineer	$55K-$112K (Glassdoor est.)	Job DescriptionThe Security Analytics Data Eng...	3.8	PDS Tech, Inc.	Dublin, OH	Irving, TX	5001 to 10000 employees	1977	private	
2740	security analytics data engineer	$55K-$112K (Glassdoor est.)	The Security Analytics Data Engineer will inte...	4.0	Data Resource Technologies	Dublin, OH	Omaha, NE	1 to 50 employees	-1	private	
2741	patient safety physician or safety scientist -	$55K-$112K (Glassdoor est.)	Help us transform patients' lives.\nAt UCB, we...	3.7	UCB	Slough, OH	Brussel, Belgium	5001 to 10000 employees	-1	public	

Creating Seniority Rank column by further preprocessing seniority column

```
seniority_map={'na':0,'junior':1,'senior':2}
df_comb['seniority_rank']=df_comb['seniority'].map(seniority_map)
```

```
df_comb['seniority_rank'].value_counts()
```

```
0    2143
2     558
1      41
Name: seniority_rank, dtype: int64
```

One hot encoding of categorical columns (dimension reduction)

```
sect_encoded = pd.get_dummies(df_comb['Sector'])
owner_encoded=pd.get_dummies(df_comb['Type of ownership'])
sts_encoded=pd.get_dummies(df_comb['job_state'])
title_encoded=pd.get_dummies(df_comb['job_desc_simp'])
revenue_cat=pd.get_dummies(df_comb['revenue_category'])
size_cat=pd.get_dummies(df_comb['size_category'])
drop_column=['Company Name','job_desc_simp','job_state','Location','Job Description', 'salary_per_hour','Headquarters', 'Job Ti
model=df_comb.drop(labels=drop_column,axis=1)
df_mod=pd.concat([model,sect_encoded,owner_encoded,sts_encoded,title_encoded,revenue_cat,size_cat,ski],axis=1)
```

Final modified dataset after data cleaning and preprocessing

```
df_mod
```

	Rating	index	min_salary	max_salary	Company_age	job_in_hq	seniority_rank	-1	Accounting & Legal	Aerospace & Defense	...	Very High	Lar
0	4.4	11.0	111000.0	181000.0	12	1	0	0	0	0	...	0	
1	4.3	12.0	111000.0	181000.0	24	1	0	0	0	0	...	0	
2	3.6	16.0	111000.0	181000.0	18	1	0	0	0	0	...	0	
3	3.3	17.0	111000.0	181000.0	80	0	0	0	0	0	...	0	
4	3.6	18.0	111000.0	181000.0	18	0	0	0	0	0	...	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
2737	4.4	4375.0	55000.0	112000.0	12	0	0	0	0	0	...	0	
2738	5.0	4376.0	55000.0	112000.0	15	0	1	0	0	0	...	0	
2739	3.8	4377.0	55000.0	112000.0	46	0	0	0	0	0	...	0	
2740	4.0	4378.0	55000.0	112000.0	2024	0	0	0	1	0	...	0	

Data Modeling

Data set split into test train, predictors and response variable

```
y1=df_mod['min_salary'].values
y2=df_mod['max_salary'].values
x=df_mod.drop(labels=['min_salary','max_salary'],axis=1)
```

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

#fit and transform the dataframe using MinMaxScaler
x_normalized = (pd.DataFrame(scaler.fit_transform(x), columns=x.columns)).round(3)

x_normalized
```

	Rating	index	Company_age	job_in_hq	seniority_rank	-1	Accounting & Legal	Aerospace & Defense	Arts, Entertainment & Recreation	Biotech & Pharmaceuticals	...
0	0.900	0.000	0.004	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1	0.883	0.000	0.010	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2	0.767	0.001	0.007	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
3	0.717	0.001	0.038	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
4	0.767	0.002	0.007	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
2737	0.900	0.999	0.004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2738	1.000	0.999	0.006	0.0	0.5	0.0	0.0	0.0	0.0	0.0	...
2739	0.800	1.000	0.021	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
2740	0.833	1.000	1.000	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...
2741	0.783	1.000	1.000	0.0	0.0	0.0	0.0	0.0	0.0	1.0	...

2742 rows × 66 columns

```
from sklearn.model_selection import train_test_split
x_train,x_test,y1_train,y1_test=train_test_split(x_normalized,y1,test_size=0.20,random_state=42)
x_train,x_test,y2_train,y2_test=train_test_split(x_normalized,y2,test_size=0.20,random_state=42)
```

Prediction Models

Linear Regression

```
from sklearn.linear_model import LinearRegression
lr_model1=LinearRegression()
lr_model1.fit(x_train,y1_train)
```

```
lr_model2=LinearRegression()
lr_model2.fit(x_train,y2_train)
y_pred_lr1 = lr_model1.predict(x_test)
y_pred_lr2 = lr_model2.predict(x_test)


from sklearn.metrics import r2_score, mean_squared_error

# Create a data frame to store the performance metrics
lr_df1 = pd.DataFrame({'Accuracy_training': [lr_model1.score(x_train, y1_train)], 'R2 Score_training': [r2_score(y1_train, lr_m

# Print the data frame
print("Training vs Testing Score for Linear regression for min_salary")
lr_df1
```

Training vs Testing Score for Linear regression for min_salary

	Accuracy_training	R2 Score_training	RMSE_training	Accuracy_test	R2 Score_test	RMSE_test
0	0.341448	0.341448	27878.544454	0.282702	0.282702	27924.942326

```
# Create a data frame to store the performance metrics
lr_df2 = pd.DataFrame({'Accuracy_training': [lr_model2.score(x_train, y2_train)], 'R2 Score_training': [r2_score(y2_train, lr_m

# Print the data frame
print("Testing Score for Linear regression for max_salary")
lr_df2
```

Testing Score for Linear regression for max_salary

	Accuracy_training	R2 Score_training	RMSE_training	Accuracy_test	R2 Score	RMSE
0	0.275463	0.275463	38016.807783	0.225626	0.225626	39786.189849

Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor
decision_model1=DecisionTreeRegressor(criterion='squared_error',max_depth=4,random_state=42)
decision_model2=DecisionTreeRegressor(criterion='squared_error',max_depth=4,random_state=42)
decision_model1.fit(x_train,y1_train)
decision_model2.fit(x_train,y2_train)

y_dt1=decision_model1.predict(x_test)
y_dt2=decision_model2.predict(x_test)

dt_df1 = pd.DataFrame({'Accuracy train': [decision_model1.score(x_train, y1_train)], 'R2 Score train': [r2_score(y1_train, deci

# Print the data frame
print("Training VS Testing Score for decision tree regressor for minimum salary")
dt_df1
```

Training VS Testing Score for decision tree regressor for minimum salary

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.483564	0.483564	24687.860538	0.431993	0.431993	24849.592498

```
dt_df2 = pd.DataFrame({'Accuracy train': [decision_model2.score(x_train, y2_train)], 'R2 Score train': [r2_score(y2_train, deci

# Print the data frame
print("Training VS Testing Score for decision tree regressor for maximum salary")
dt_df2
```

Training VS Testing Score for decision tree regressor for maximum salary

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.434335	0.434335	33591.170519	0.440809	0.440809	33809.376441

Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
forest_model1=RandomForestRegressor(n_estimators=100,criterion="squared_error",random_state=42)
forest_model2=RandomForestRegressor(n_estimators=100,criterion="squared_error",random_state=42)
forest_model1.fit(x_train,y1_train)
forest_model2.fit(x_train,y2_train)

y_rf1=forest_model1.predict(x_test)
y_rf2=forest_model2.predict(x_test)
```

```
rf_df1 = pd.DataFrame({'Accuracy train': [forest_model1.score(x_train, y1_train)], 'R2 Score train': [r2_score(y1_train, forest_

# Print the data frame
print("Training vs Testing Score for Random Forest regressor for minimum salary")
rf_df1
```

Training vs Testing Score for Random Forest regressor for minimum salary

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.991921	0.991921	3087.907958	0.927122	0.927122	8901.02863

```
rf_df2 = pd.DataFrame({'Accuracy train': [forest_model2.score(x_train, y2_train)], 'R2 Score train': [r2_score(y2_train, forest_

# Print the data frame
print("Training vs Testing Score for Random Forest regressor for maximum salary")
rf_df2
```

Training vs Testing Score for Random Forest regressor for maximum salary

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.978316	0.978316	6576.864288	0.855392	0.855392	17193.043761

AdaBoostRegressor

```
from sklearn.ensemble import AdaBoostRegressor
adb_model1=AdaBoostRegressor(base_estimator=decision_model1,n_estimators=250,learning_rate=2,random_state=42)
adb_model2=AdaBoostRegressor(base_estimator=decision_model2,n_estimators=250,learning_rate=2,random_state=42)
adb_model1.fit(x_train,y1_train)
adb_model2.fit(x_train,y2_train)

y_adb1=adb_model1.predict(x_test)
y_adb2=adb_model2.predict(x_test)

adb_df1= pd.DataFrame({'Accuracy train': [adb_model1.score(x_train, y1_train)], 'R2 Score train': [r2_score(y1_train, adb_model

print("Training vs Testing Score for Adaboost regressor for min salary")
adb_df1
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/ensemble/_base.py:166: FutureWarning: `base_estimator` was renamed to `esti
  warnings.warn(
/usr/local/lib/python3.9/dist-packages/sklearn/ensemble/_base.py:166: FutureWarning: `base_estimator` was renamed to `esti
  warnings.warn(
Training vs Testing Score for Adaboost regressor for min salary
```

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.623991	0.623991	21065.616116	0.568453	0.568453	21659.908526

```
adb_df2= pd.DataFrame({'Accuracy train': [adb_model2.score(x_train, y2_train)], 'R2 Score train': [r2_score(y2_train, adb_model

print("Training vs Testing Score for Adaboost regressor for max salary")
adb_df2
```

Training vs Testing Score for Adaboost regressor for max salary

	Accuracy train	R2 Score train	RMSE train	Accuracy_test	R2 Score test	RMSE test
0	0.509741	0.509741	31272.190385	0.48286	0.48286	32513.310565

Classification Models

```
avg=(y1+y2)/2
median_salary = sorted(avg)[len(avg)//2]

# calculate the low and high threshold salaries
low = median_salary * 0.6
high = median_salary * 1.2
```

```
# 0 --> Low
# 1 --> Average
# 2 --> High

def map_salaries(salaries, threshold1, threshold2):
    categories = []
```

```
    for salary in salaries:
        if salary < threshold1:
            categories.append(0)
        elif ((salary <= threshold2) and (salary >= threshold1)) :
            categories.append(1)
        else:
            categories.append(2)
    return categories
y = np.array(map_salaries(avg, low, high))
y
```

```
array([2, 2, 2, ..., 1, 1, 1])
```

Train Test Split

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x_normalized,y,test_size=0.23,random_state=42)
```

```
from sklearn.metrics import confusion_matrix, accuracy_score, recall_score, precision_score, f1_score, roc_auc_score, roc_curve
from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
```

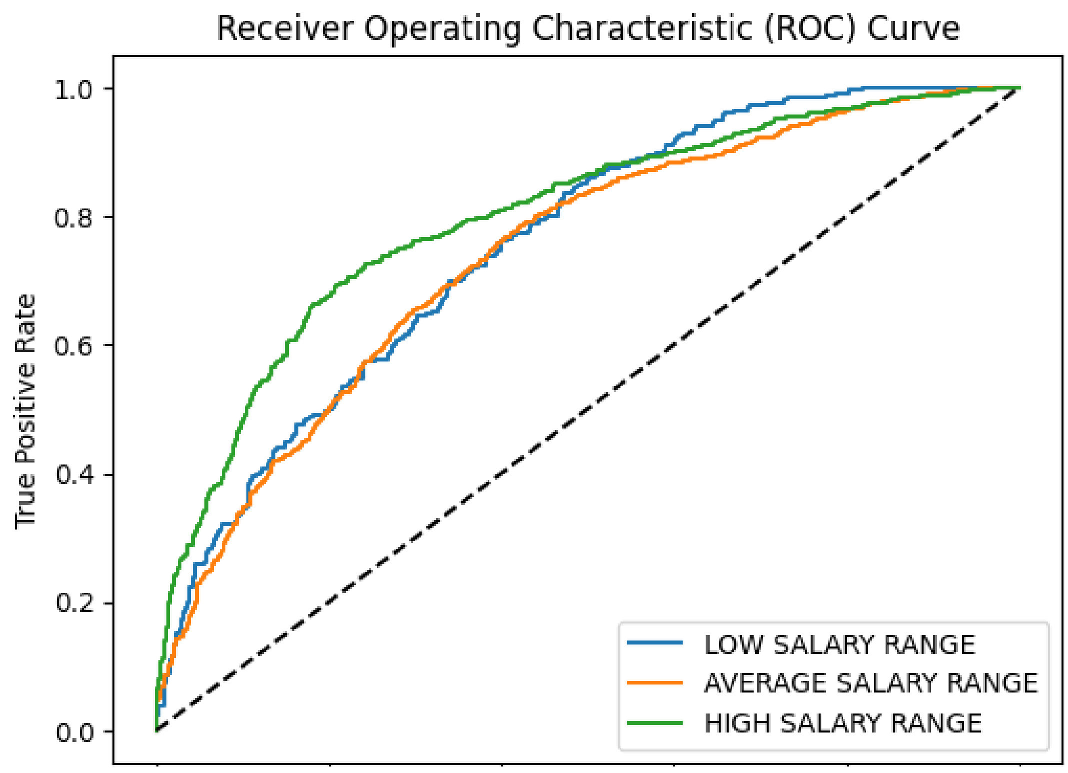
```
def train_scores(model, model_name, n_classes, proba=True):
    pred = model.predict(x_train)
    print('****** For Training on ', model_name, 'Model ******\n')

    # Print confusion matrix
    print('The Confusion Matrix:\n', confusion_matrix(y_train, pred))

    # Print accuracy score
    acc_score = accuracy_score(y_train, pred)
    print('\n The Accuray Score:', acc_score)

    # Print recall score
    recall = recall_score(y_train==2, pred==2)
    print('\n The Recall Score:', recall)

    # Print precision score
    precision = precision_score(y_train==2, pred==2)
    print('\n The Precision Score:', precision)

    # Print F1 score
    f1 = f1_score(y_train==2, pred==2)
    print('\n The F1 Score:', f1)

    # Compute and print ROC AUC score for multiclass classification
    y_train_binarized = label_binarize(y_train, classes=range(n_classes))
    y_pred_binarized = label_binarize(pred, classes=range(n_classes))
    roc_auc = roc_auc_score(y_train_binarized, y_pred_binarized, multi_class='ovr')
    print('\n The ROC AUC Score:', roc_auc)


    if(proba==False):
        return
    y_pred_prob=model.predict_proba(x_train)

    fpr = {}
    tpr = {}
    thresholds = {}
    roc_auc = {}
    for i in range(y_pred_prob.shape[1]):
        fpr[i], tpr[i], thresholds[i] = roc_curve(y_train, y_pred_prob[:, i], pos_label=i)
        roc_auc[i] = auc(fpr[i], tpr[i])

    # plot ROC curve for each class
    plt.figure()
    for i in range(y_pred_prob.shape[1]):
        plt.plot(fpr[i], tpr[i], label='Class {} (AUC = {:0.2f})'.format(i, roc_auc[i]))

    # plot the random guessing line
    plt.plot([0, 1], [0, 1], 'k--')
    print('\n')
    print("Class 0 Corresponds to LOW SALARY RANGE")
    print("Class 1 Corresponds to AVERAGE SALARY RANGE")
    print("Class 2 Corresponds to HIGH SALARY RANGE")
    print('\n')
    # format the plot
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

```
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    new_labels = ['LOW SALARY RANGE', 'AVERAGE SALARY RANGE', 'HIGH SALARY RANGE']
    plt.legend(new_labels)
    plt.show()


def test_scores(model, model_name, n_classes, proba=True):
    pred = model.predict(x_test)
    print('****** For Testing on', model_name, 'Model ******\n')

    # Print confusion matrix
    print('The Confusion Matrix:\n', confusion_matrix(y_test, pred))

    # Print accuracy score
    acc_score = accuracy_score(y_test, pred)
    print('\n The Accuray Score:', acc_score)

    # Print recall score
    recall = recall_score(y_test==2, pred==2)
    print('\n The Recall Score:', recall)

    # Print precision score
    precision = precision_score(y_test==2, pred==2)
    print('\n The Precision Score:', precision)

    # Print F1 score
    f1 = f1_score(y_test==2, pred==2)
    print('\n The F1 Score:', f1)

    # Compute and print ROC AUC score for multiclass classification
    y_test_binarized = label_binarize(y_test, classes=range(n_classes))
    y_pred_binarized = label_binarize(pred, classes=range(n_classes))
    roc_auc = roc_auc_score(y_test_binarized, y_pred_binarized, multi_class='ovr')
    print('\n The ROC AUC Score:', roc_auc)
    print('\n')
    print("Class 0 Corresponds to LOW SALARY RANGE")
    print("Class 1 Corresponds to AVERAGE SALARY RANGE")
    print("Class 2 Corresponds to HIGH SALARY RANGE")
    print('\n')

    if(proba==False):
        return
    y_pred_prob=model.predict_proba(x_test)

    fpr = {}
    tpr = {}
    thresholds = {}
    roc_auc = {}
    for i in range(y_pred_prob.shape[1]):
        fpr[i], tpr[i], thresholds[i] = roc_curve(y_test, y_pred_prob[:, i], pos_label=i)
        roc_auc[i] = auc(fpr[i], tpr[i])

    # plot ROC curve for each class
    plt.figure()
    for i in range(y_pred_prob.shape[1]):
        plt.plot(fpr[i], tpr[i], label='Class {} (AUC = {:0.2f})'.format(i, roc_auc[i]))

    # plot the random guessing line
    plt.plot([0, 1], [0, 1], 'k--')

    # format the plot
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    new_labels = ['LOW SALARY RANGE', 'AVERAGE SALARY RANGE', 'HIGH SALARY RANGE']
    plt.legend(new_labels)
    plt.show()
```

Logistic Regression Classifier

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(x_train, y_train)
# y_pred_lr = model.predict(x_test)
train_scores(model,'Logistic Regression',3)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
****** For Training on  Logistic Regression Model ******

The Confusion Matrix:
 [[ 12 213  31]
 [  3 979 182]
 [  0 269 422]]

 The Accuray Score: 0.6693510184746566

 The Recall Score: 0.6107091172214182

 The Precision Score: 0.6645669291338583

 The F1 Score: 0.636500754147813

 The ROC AUC Score: 0.6396760743110989


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```




```
test_scores(model,'Logistic Regression',3)
```

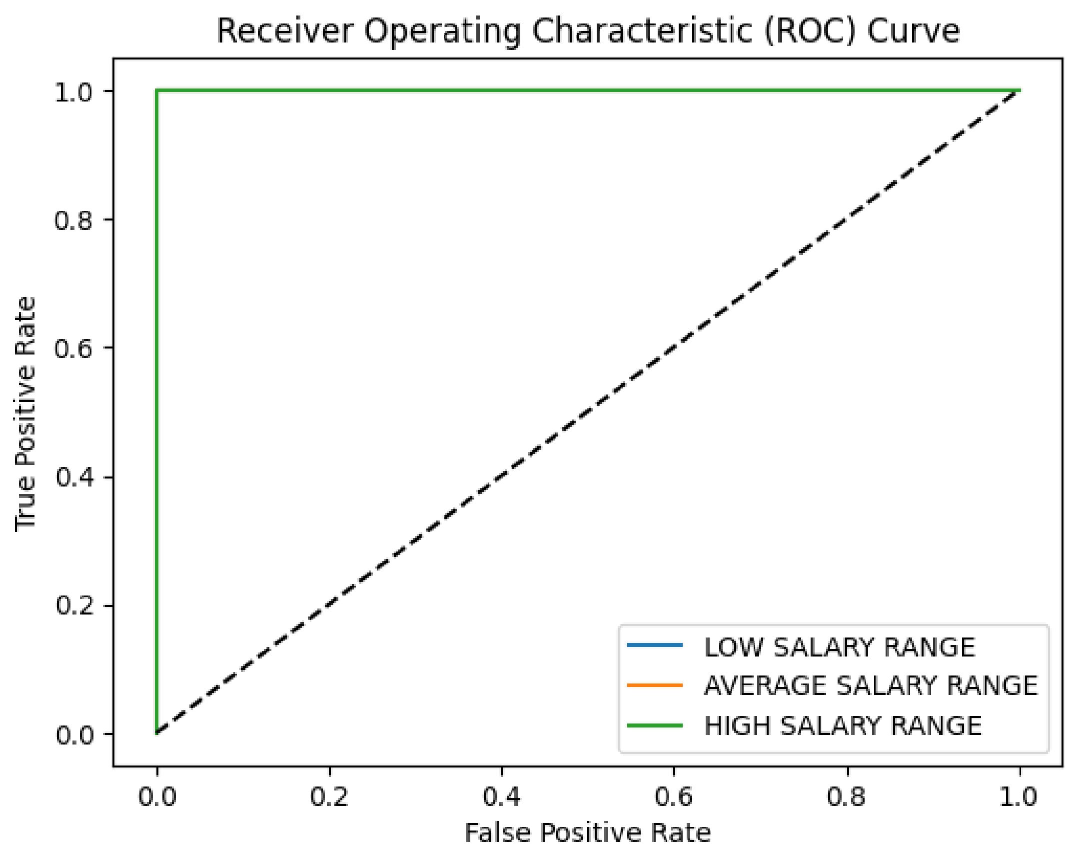
```
****** For Testing on Logistic Regression Model ******

The Confusion Matrix:
 [[  2  66   7]
 [  6 286  68]
 [  0 103  93]]

 The Accuray Score: 0.6038034865293186

 The Recall Score: 0.4744897959183674

 The Precision Score: 0.5535714285714286

 The F1 Score: 0.5109890109890111

 The ROC AUC Score: 0.5814632518095323
```

Decision Tree Classifier

```
Class 2 Corresponds to HIGH SALARY RANGE
```

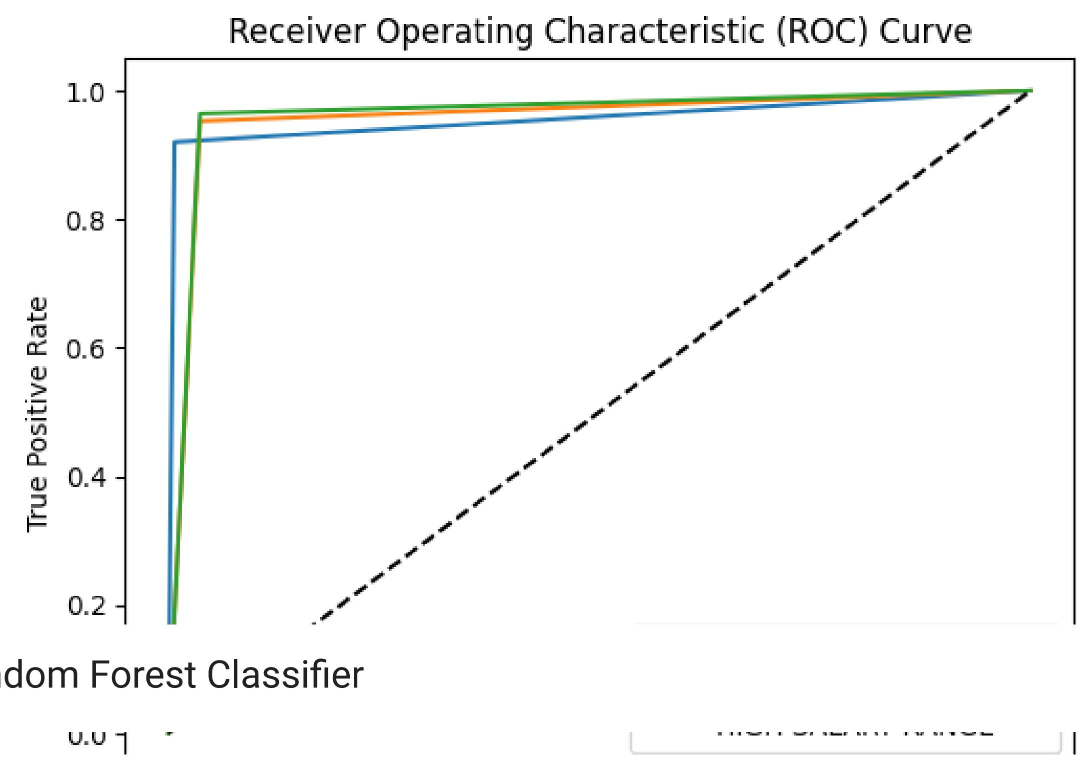
```
from sklearn.tree import DecisionTreeClassifier
model1 = DecisionTreeClassifier()
model1.fit(x_train, y_train)
#y_pred_dt = model1.predict(x_test)
train_scores(model1,'Decision Tree Classifier',3)
```

```
****** For Training on  Decision Tree Classifier Model ******

The Confusion Matrix:
 [[ 256    0    0]
 [    0 1164    0]
 [    0    0  691]]

 The Accuray Score: 1.0

 The Recall Score: 1.0

 The Precision Score: 1.0

 The F1 Score: 1.0

 The ROC AUC Score: 1.0


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```




```
test_scores(model1,'Decision Tree Classifier',3)
```

```
****** For Testing on Decision Tree Classifier Model ******

The Confusion Matrix:
 [[ 69   3   3]
 [  4 343  13]
 [  0   7 189]]

 The Accuray Score: 0.9524564183835182

 The Recall Score: 0.9642857142857143

 The Precision Score: 0.9219512195121952

 The F1 Score: 0.942643391521197

 The ROC AUC Score: 0.9593645448766805


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```



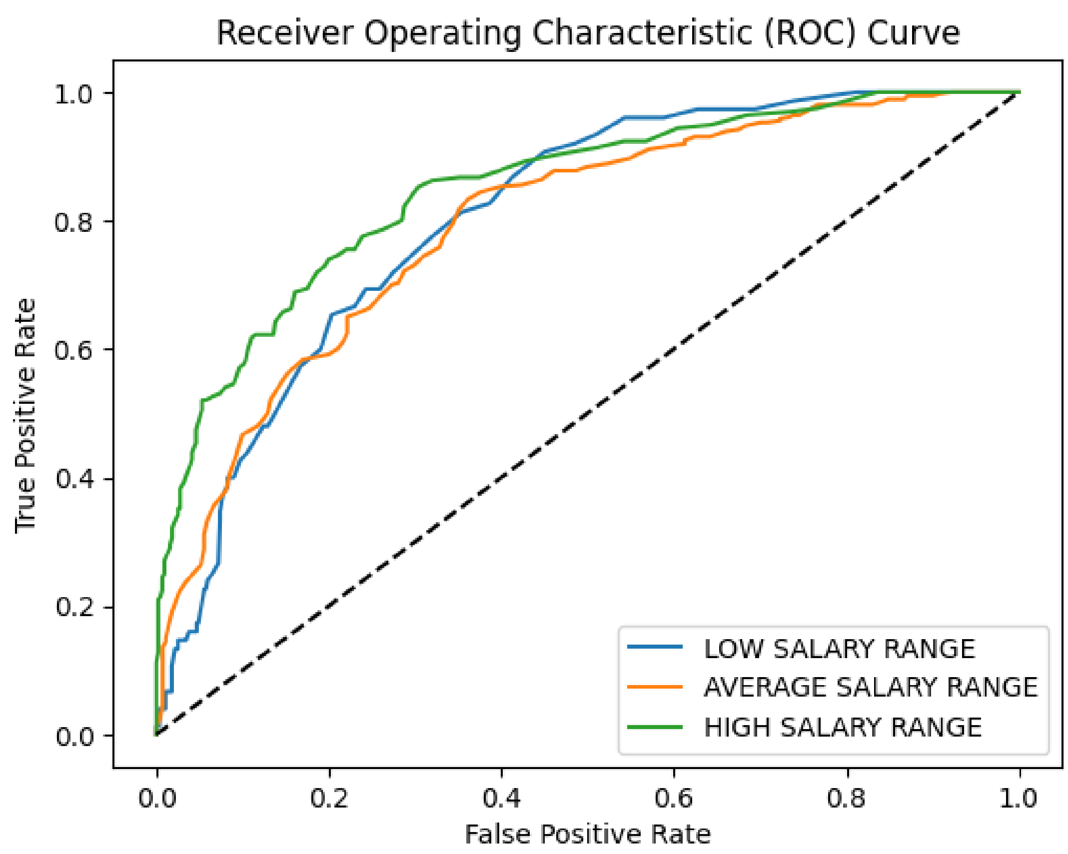
Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
model2 = RandomForestClassifier()
model2.fit(x_train, y_train)
#y_pred_knn = model2.predict(x_test)
train_scores(model2,'Random Forest Classifier',3)
```

```
****** For Training on  Random Forest Classifier Model ******

The Confusion Matrix:
 [[ 256    0    0]
 [   0 1164    0]
 [   0    0  691]]

 The Accuray Score: 1.0

 The Recall Score: 1.0

 The Precision Score: 1.0
```

```
test_scores(model2,'Random Forest Classifier',3)
```

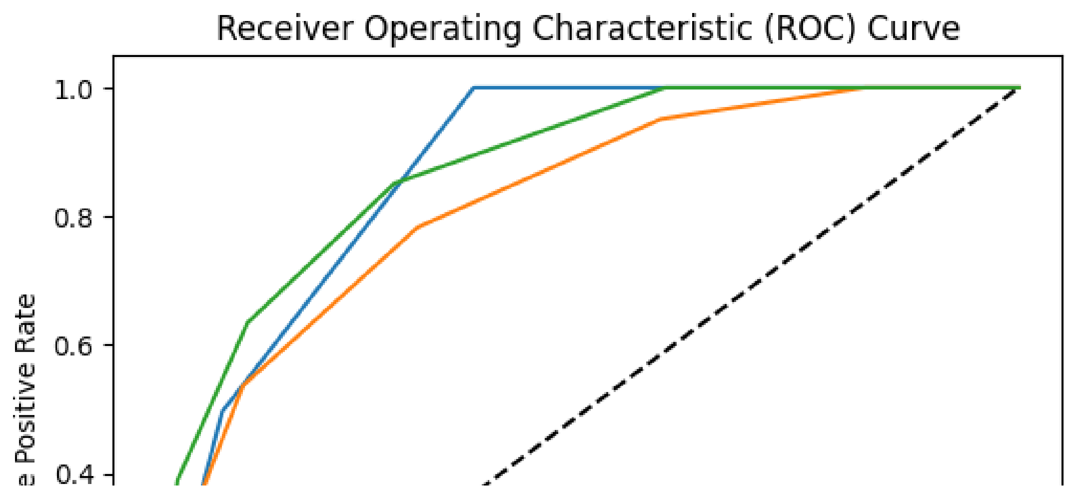
```
****** For Testing on Random Forest Classifier Model ******

The Confusion Matrix:
 [[ 13  57   5]
 [ 18 310  32]
 [  7  76 113]]

 The Accuray Score: 0.6909667194928685

 The Recall Score: 0.576530612244898

 The Precision Score: 0.7533333333333333

 The F1 Score: 0.6531791907514451

 The ROC AUC Score: 0.6650297748164865


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```



KNN Classifier

```
from sklearn.neighbors import KNeighborsClassifier
model3 = KNeighborsClassifier(n_neighbors=5)
model3.fit(x_train, y_train)
#y_pred_knn = model3.predict(x_test)
train_scores(model3,'KNN Classifier',3)
```

```
****** For Training on  KNN Classifier Model ******

The Confusion Matrix:
 [[ 92 145  19]
 [ 67 966 131]
 [ 30 223 438]]

 The Accuray Score: 0.708668877309332

 The Recall Score: 0.6338639652677279

 The Precision Score: 0.7448979591836735

 The F1 Score: 0.684910086004691

 The ROC AUC Score: 0.712769233267351


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```



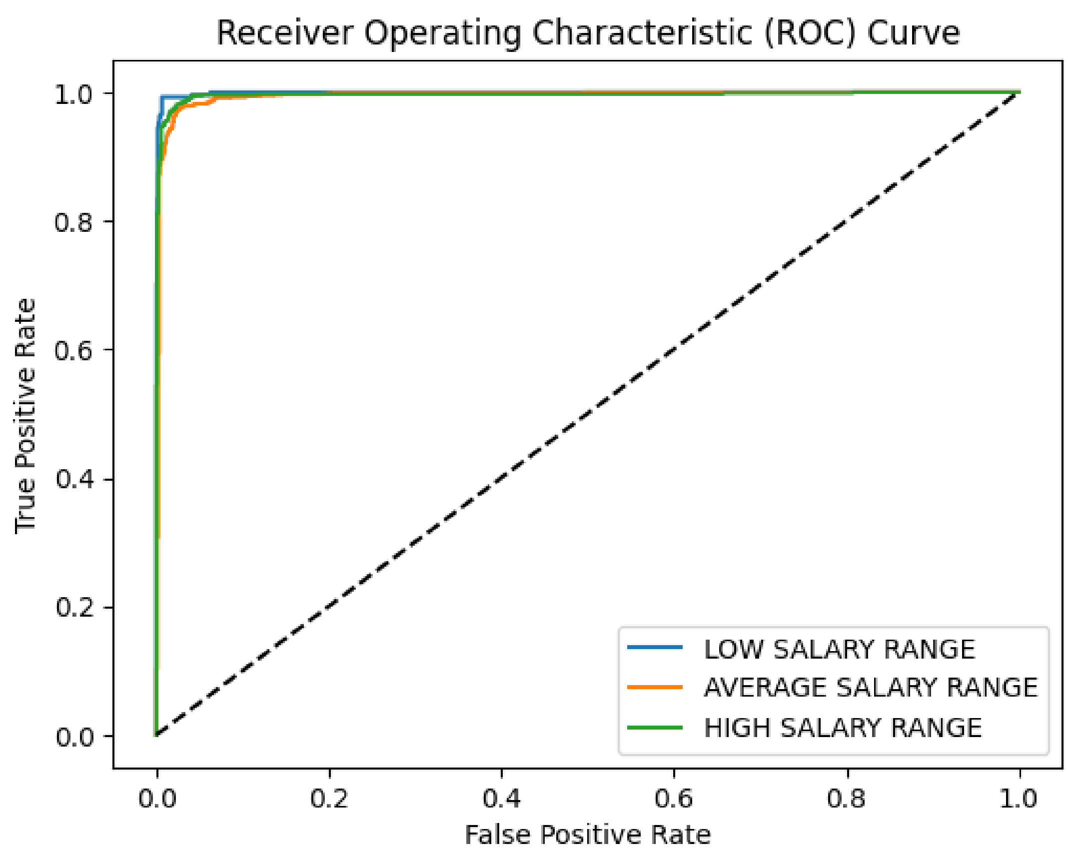

```
test_scores(model3,'KNN Classifier',3)
```

```
****** For Testing on KNN Classifier Model ******
```

Gradient Boosting Classifier

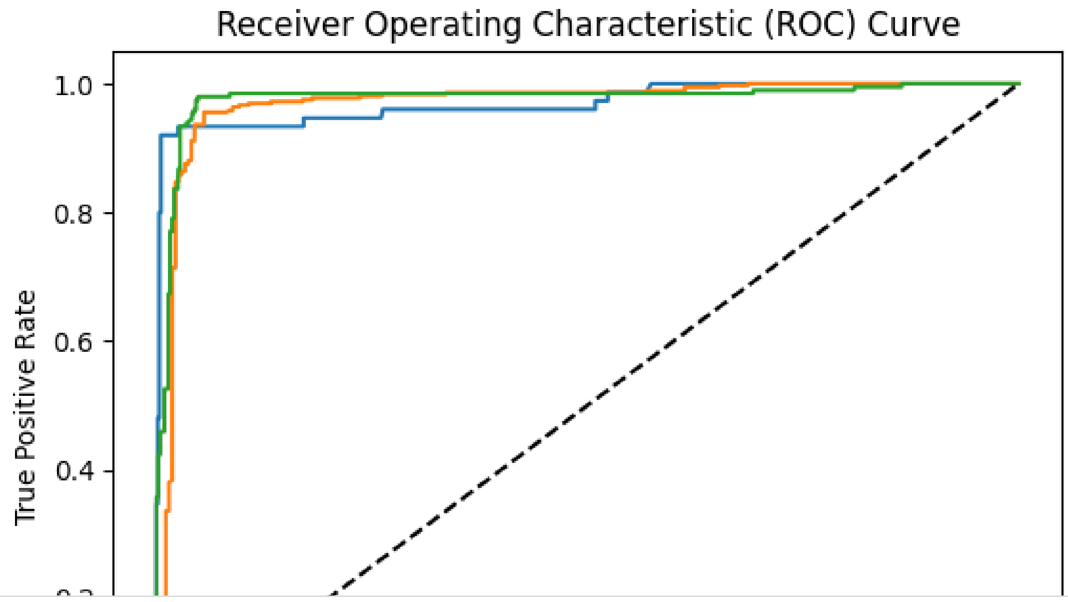
```
from sklearn.ensemble import GradientBoostingClassifier
model4 = GradientBoostingClassifier()
model4.fit(x_train, y_train)
train_scores(model4,'Gradient Boosting Classifier',3)
```

```
****** For Training on  Gradient Boosting Classifier Model ******

The Confusion Matrix:
 [[ 224   32    0]
 [    2 1154    8]
 [    1   46  644]]

 The Accuray Score: 0.9578398863098058

 The Recall Score: 0.9319826338639653

 The Precision Score: 0.9877300613496932

 The F1 Score: 0.9590469099032018

 The ROC AUC Score: 0.9514625251287953


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```




```
test_scores(model4,'Gradient Boosting Classifier',3)
```

```
****** For Testing on Gradient Boosting Classifier Model ******

The Confusion Matrix:
 [[ 58  14   3]
 [  2 349   9]
 [  0  20 176]]

 The Accuray Score: 0.9239302694136292

 The Recall Score: 0.8979591836734694

 The Precision Score: 0.9361702127659575

 The F1 Score: 0.9166666666666666

 The ROC AUC Score: 0.914015396273332


Class 0 Corresponds to LOW SALARY RANGE
Class 1 Corresponds to AVERAGE SALARY RANGE
Class 2 Corresponds to HIGH SALARY RANGE
```



✓ 0s completed at 7:28 PM