In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
import io
%cd "C:\Users\deepe\OneDrive\Desktop\Python Datasets\Telecom"
```

C:\Users\deepe\OneDrive\Desktop\Python Datasets\Telecom

In [3]:

```
telust=pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn (2).csv")
```

In [4]:

```
telust.info()
```

object

object

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
#
    Column
                       Non-Null Count Dtype
     -----
                       -----
                                       ----
                       7043 non-null
0
     customerID
                                       object
1
    gender
                       7043 non-null
                                       object
2
    SeniorCitizen
                       7043 non-null
                                       int64
3
    Partner
                       7043 non-null
                                       object
4
                       7043 non-null
    Dependents
                                       object
5
    tenure
                       7043 non-null
                                       int64
6
    PhoneService
                       7043 non-null
                                       object
7
    MultipleLines
                       7043 non-null
                                       object
8
    InternetService
                       7043 non-null
                                       object
9
    OnlineSecurity
                       7043 non-null
                                       object
10
    OnlineBackup
                       7043 non-null
                                       object
11
    DeviceProtection
                       7043 non-null
                                       object
12
    TechSupport
                       7043 non-null
                                       object
13
    StreamingTV
                       7043 non-null
                                       object
14 StreamingMovies
                       7043 non-null
                                       object
 15
    Contract
                       7043 non-null
                                       object
16
    PaperlessBilling 7043 non-null
                                       object
```

18 MonthlyCharges 7043 non-null float64
19 TotalCharges 7043 non-null object

7043 non-null

7043 non-null

dtypes: float64(1), int64(2), object(18)

memory usage: 1.1+ MB

PaymentMethod

17

20 Churn

In [5]:

telust.head()

Out[5]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLir
0	7590- VHVEG	Female	0	Yes	No	1	No	No pho ser\
1	5575- GNVDE	Male	0	No	No	34	Yes	
2	3668- QPYBK	Male	0	No	No	2	Yes	
3	7795- CFOCW	Male	0	No	No	45	No	No pho ser\
4	9237- HQITU	Female	0	No	No	2	Yes	
5 rows × 21 columns								

In [6]:

telust.tail()

Out[6]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl			
7038	6840- RESVB	Male	0	Yes	Yes	24	Yes				
7039	2234- XADUH	Female	0	Yes	Yes	72	Yes				
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No			
7041	8361- LTMKD	Male	1	Yes	No	4	Yes				
7042	3186-AJIEK	Male	0	No	No	66	Yes				
5 rows	5 rows × 21 columns										

In [7]:

```
telust.columns
```

Out[7]:

In [8]:

In [9]:

```
objcols.head()
```

Out[9]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService
0	Female	0	Yes	No	No	No phone service	DSL
1	Male	0	No	No	Yes	No	DSL
2	Male	0	No	No	Yes	No	DSL
3	Male	0	No	No	No	No phone service	DSL
4	Female	0	No	No	Yes	No	Fiber optic
4							>

In [10]:

```
numcols=telust[['tenure','MonthlyCharges', 'TotalCharges']]
```

In [11]:

```
numcols['TotalCharges']=pd.to_numeric(numcols.TotalCharges,errors='coerce')
```

C:\Users\deepe\AppData\Local\Temp\ipykernel_15636\2108254401.py:1: Setting
WithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

numcols['TotalCharges']=pd.to_numeric(numcols.TotalCharges,errors='coerc
e')

In [12]:

```
numcols.isnull().sum().sort_values(ascending=False)/numcols.shape[0]
```

Out[12]:

TotalCharges 0.001562 tenure 0.000000 MonthlyCharges 0.000000

dtype: float64

In [13]:

```
# fill the missing values useing median maximum we use median
for col in numcols.columns:
    numcols[col]=numcols[col].fillna(numcols[col].median())
```

C:\Users\deepe\AppData\Local\Temp\ipykernel_15636\1347123924.py:3: Setting
WithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

numcols[col]=numcols[col].fillna(numcols[col].median())

In [14]:

numcols.head()

Out[14]:

	tenure	MonthlyCharges	TotalCharges
0	1	29.85	29.85
1	34	56.95	1889.50
2	2	53.85	108.15
3	45	42.30	1840.75
4	2	70.70	151.65

In [15]:

```
numcols.describe()
```

Out[15]:

	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000
mean	32.371149	64.761692	2281.916928
std	24.559481	30.090047	2265.270398
min	0.000000	18.250000	18.800000
25%	9.000000	35.500000	402.225000
50%	29.000000	70.350000	1397.475000
75%	55.000000	89.850000	3786.600000
max	72.000000	118.750000	8684.800000

In [16]:

```
telustdf=pd.concat([objcols,numcols],axis=1)
```

<class 'pandas.core.frame.DataFrame'>

In [17]:

```
telustdf.info()
```

```
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #
     Column
                       Non-Null Count
                                       Dtype
     ----
                       -----
                       7043 non-null
                                       object
 0
     gender
 1
     SeniorCitizen
                       7043 non-null
                                       int64
 2
     Partner
                       7043 non-null
                                       object
 3
     Dependents
                       7043 non-null
                                       object
 4
     PhoneService
                       7043 non-null
                                       object
 5
     MultipleLines
                       7043 non-null
                                       object
 6
     InternetService
                       7043 non-null
                                       object
 7
     OnlineSecurity
                       7043 non-null
                                       object
 8
     OnlineBackup
                       7043 non-null
                                       object
 9
     DeviceProtection
                       7043 non-null
                                       object
 10
    TechSupport
                       7043 non-null
                                       object
 11
     StreamingTV
                       7043 non-null
                                       object
    StreamingMovies
                       7043 non-null
 12
                                       object
                       7043 non-null
 13
    Contract
                                       object
 14
     PaperlessBilling
                       7043 non-null
                                       object
 15
     PaymentMethod
                       7043 non-null
                                       object
 16
     Churn
                       7043 non-null
                                       object
                       7043 non-null
 17
     tenure
                                       int64
 18
     MonthlyCharges
                       7043 non-null
                                       float64
     TotalCharges
                       7043 non-null
                                       float64
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

In [18]:

telustdf.head()

Out[18]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService
0	Female	0	Yes	No	No	No phone service	DSL
1	Male	0	No	No	Yes	No	DSL
2	Male	0	No	No	Yes	No	DSL
3	Male	0	No	No	No	No phone service	DSL
4	Female	0	No	No	Yes	No	Fiber optic
4							>

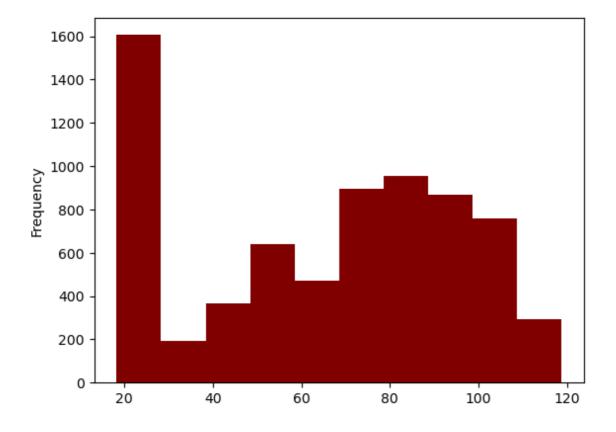
EDA

In [19]:

telustdf.MonthlyCharges.plot(kind="hist",color="maroon")

Out[19]:

<Axes: ylabel='Frequency'>

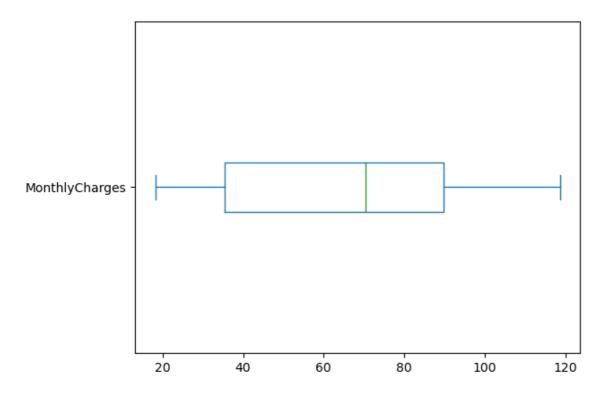


In [20]:

telustdf.MonthlyCharges.plot(kind="box",vert=False)

Out[20]:

<Axes: >

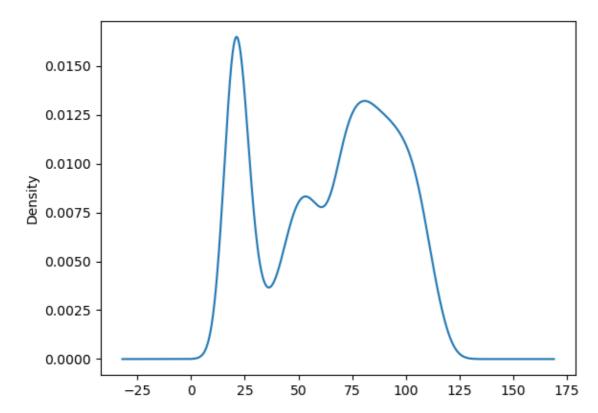


In [21]:

```
telustdf.MonthlyCharges.plot(kind="density")
```

Out[21]:

<Axes: ylabel='Density'>

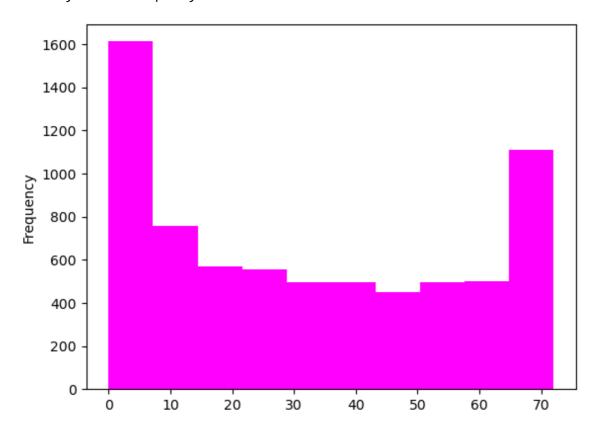


In [22]:

```
telustdf.tenure.plot(kind="hist",color="magenta")
```

Out[22]:

<Axes: ylabel='Frequency'>

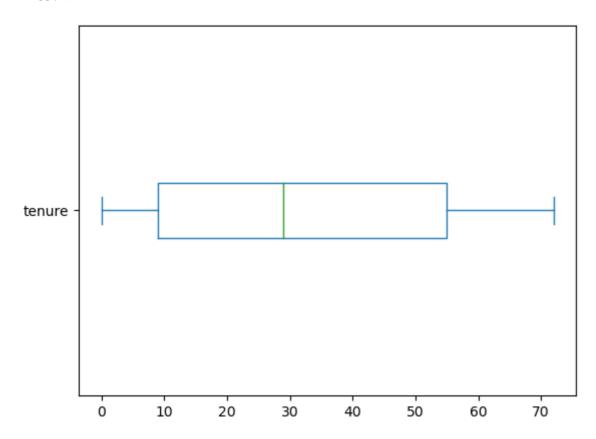


In [23]:

telustdf.tenure.plot(kind="box",vert=False)

Out[23]:

<Axes: >

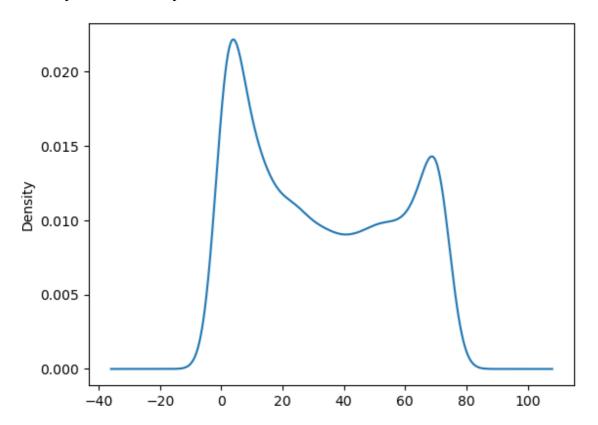


```
In [24]:
```

```
telustdf.tenure.plot(kind="density")
```

Out[24]:

<Axes: ylabel='Density'>



Frequency Counts

In [25]:

telustdf.Churn.value_counts()

Out[25]:

No 5174 Yes 1869

Name: Churn, dtype: int64

In [26]:

telustdf.gender.value_counts()

Out[26]:

Male 3555 Female 3488

Name: gender, dtype: int64

```
In [27]:
```

```
telustdf.SeniorCitizen.value_counts()
```

Out[27]:

0 59011 1142

Name: SeniorCitizen, dtype: int64

In [28]:

```
telustdf.PaymentMethod.value_counts()
```

Out[28]:

Electronic check 2365
Mailed check 1612
Bank transfer (automatic) 1544
Credit card (automatic) 1522
Name: PaymentMethod, dtype: int64

Cross Tabulation And Visualisation

In [29]:

```
# Cross tabulation of Churn & gender
pd.crosstab(telustdf.Churn,telustdf.gender)
```

Out[29]:

gender	Female	Male	
Churn			
No	2549	2625	
Yes	939	930	

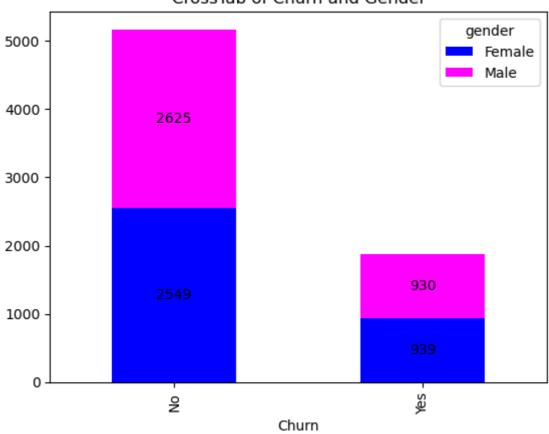
In [30]:

Visualisation

df=pd.crosstab(telustdf.Churn,telustdf.gender)
ax=df.plot.bar(stacked=True,color=["blue","magenta"],title="CrossTab of Churn and Gender
for i in ax.containers:

ax.bar_label(i,fontsize=10,label_type="center")

CrossTab of Churn and Gender



In [31]:

Cross tabulation Churn & InternetService

pd.crosstab(telustdf.Churn,telustdf.InternetService)

Out[31]:

InternetService	DSL	Fiber optic	No
Churn			
No	1962	1799	1413
Voe	459	1297	113

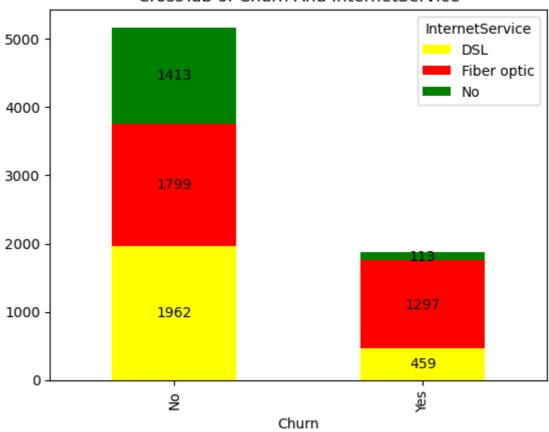
In [32]:

Visualisation

df=pd.crosstab(telustdf.Churn,telustdf.InternetService)
ax=df.plot.bar(stacked=True,color=["yellow","red","green"],title="CrossTab of Churn And
for i in ax.containers:

ax.bar_label(i,fontsize=10,label_type="center")

CrossTab of Churn And InternetService



In [33]:

Cross tabulation gender & PaymentMethod
pd.crosstab(telustdf.gender,telustdf.PaymentMethod)

Out[33]:

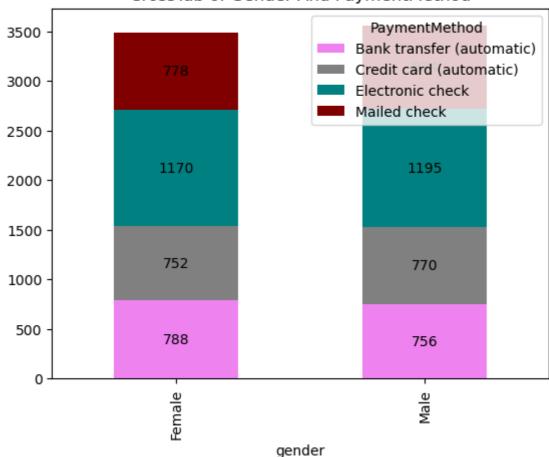
PaymentMethod	Bank transfer (automatic)	Credit card (automatic)	Electronic check	Mailed check	
gender					
Female	788	752	1170	778	
Male	756	770	1195	834	

In [34]:

```
# Visualisation

df=pd.crosstab(telustdf.gender,telustdf.PaymentMethod)
ax=df.plot.bar(stacked=True,color=["violet","grey","teal","maroon"],title="CrossTab of G
for i in ax.containers:
    ax.bar_label(i,fontsize=10,label_type="center")
```





groupby() and Visualisation

In [35]:

```
# Average MonthlyCharges by gender
telustdf.MonthlyCharges.groupby(telustdf.gender).mean()
```

Out[35]:

gender

Female 65.204243 Male 64.327482

Name: MonthlyCharges, dtype: float64

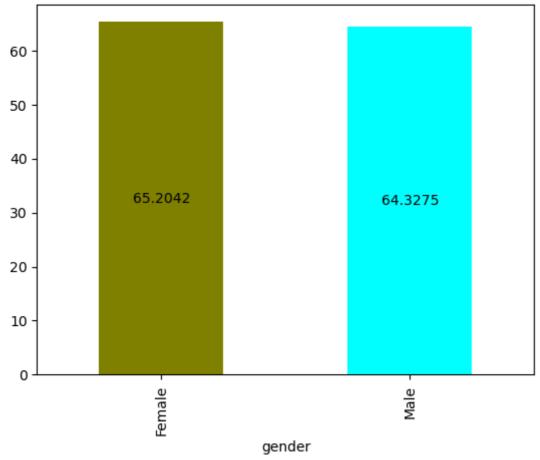
In [36]:

Visualisation

for i in ax.containers:

ax.bar_label(i,fontsize=10,label_type="center")

Average MonthlyCharges by gender

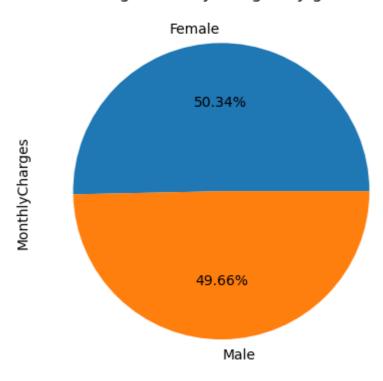


In [37]:

Out[37]:

<Axes: title={'center': 'Average MonthlyCharges by gender'}, ylabel='Month
lyCharges'>

Average MonthlyCharges by gender



In [38]:

Average tenure by SeniorCitizen

telustdf.tenure.groupby(telustdf.SeniorCitizen).mean()

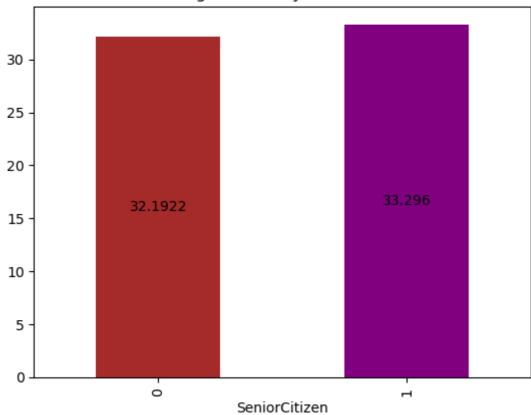
Out[38]:

SeniorCitizen
0 32.192171
1 33.295972

Name: tenure, dtype: float64

In [39]:

Average tenure by SeniorCitizen



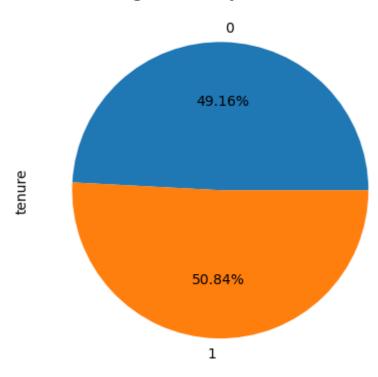
In [40]:

telustdf.tenure.groupby(telustdf.SeniorCitizen).mean().plot(kind="pie",autopct="%.2f%%",

Out[40]:

<Axes: title={'center': 'Average tenure by SeniorCitizen'}, ylabel='tenur
e'>

Average tenure by SeniorCitizen



In [41]:

Average tenure by PaymentMethod

telustdf.tenure.groupby(telustdf.PaymentMethod).mean()

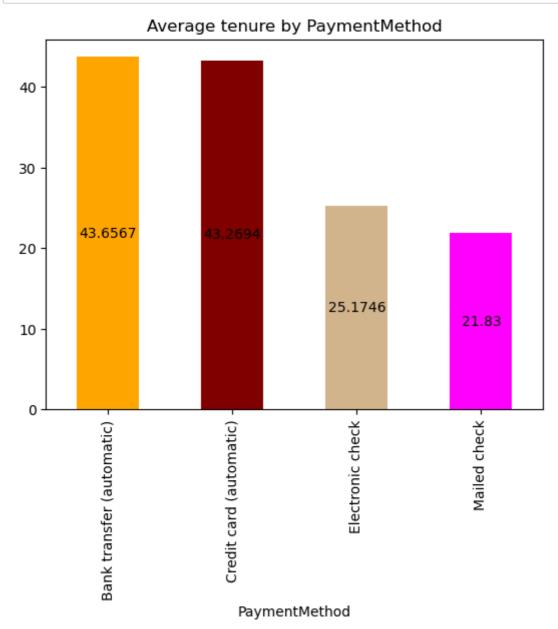
Out[41]:

PaymentMethod

Bank transfer (automatic) 43.656736 Credit card (automatic) 43.269382 Electronic check 25.174630 Mailed check 21.830025

Name: tenure, dtype: float64

In [42]:



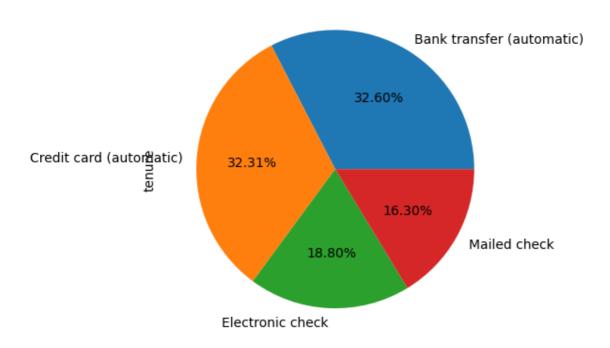
In [43]:

telustdf.tenure.groupby(telustdf.PaymentMethod).mean().plot(kind="pie",autopct="%.2f%%",

Out[43]:

<Axes: title={'center': 'Average tenure by PaymentMethod'}, ylabel='tenur
e'>

Average tenure by PaymentMethod



In [44]:

Average tenure by InternetService

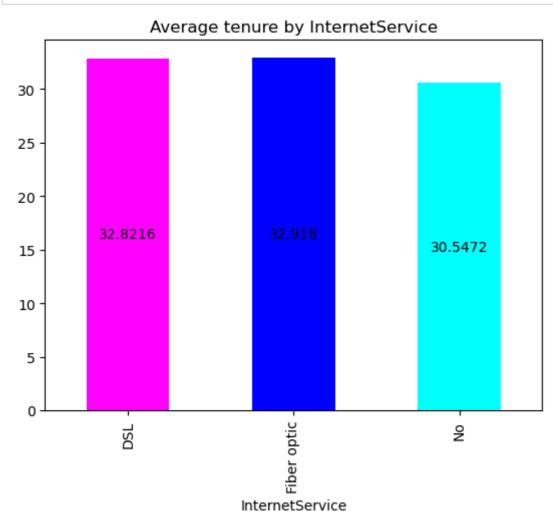
telustdf.tenure.groupby(telustdf.InternetService).mean()

Out[44]:

InternetService

DSL 32.821561 Fiber optic 32.917959 No 30.547182 Name: tenure, dtype: float64

In [45]:



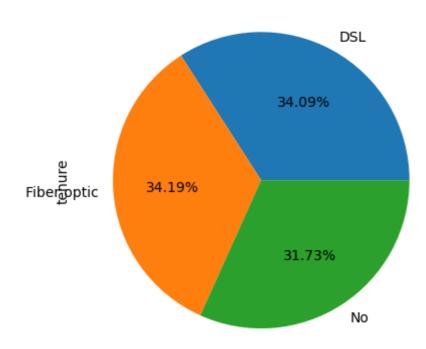
In [46]:

telustdf.tenure.groupby(telustdf.InternetService).mean().plot(kind="pie",autopct="%.2f%%")

Out[46]:

<Axes: title={'center': 'Average tenure by InternetService'}, ylabel='tenu
re'>

Average tenure by InternetService



In [47]:

Average Monthly Charges by StreamingMovies

telustdf.MonthlyCharges.groupby(telustdf.StreamingMovies).mean()

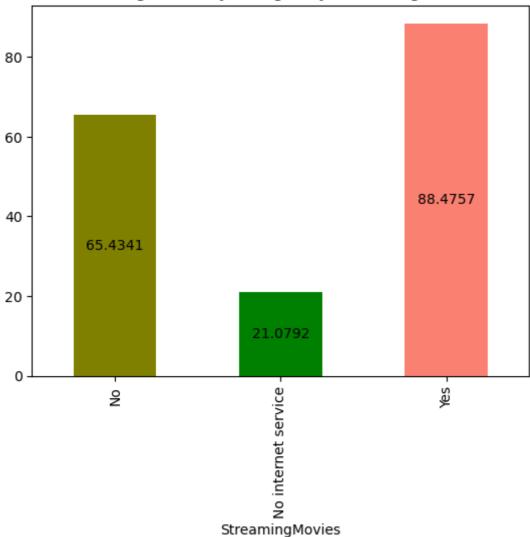
Out[47]:

StreamingMovies

No 65.434147 No internet service 21.079194 Yes 88.475714 Name: MonthlyCharges, dtype: float64

In [48]:

Average Monthly Charges by StreamingMovies



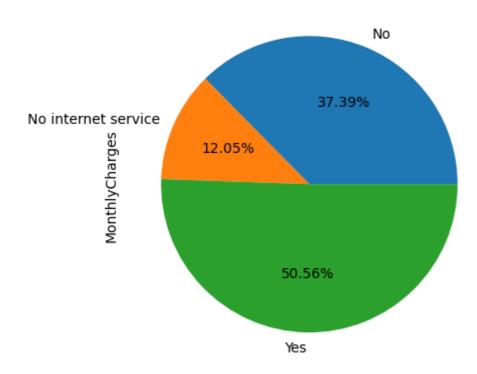
In [49]:

```
telustdf.MonthlyCharges.groupby(telustdf.StreamingMovies).mean().plot(kind="pie",autopct
```

Out[49]:

<Axes: title={'center': ' Average Monthly Charges by StreamingMovies'}, yl
abel='MonthlyCharges'>

Average Monthly Charges by StreamingMovies



Hypothesis Testing

In [50]:

from scipy.stats import ttest_ind

In [51]:

Test Null Average MonthlyCharges Churn Yes/No Equal

telustdf.MonthlyCharges.groupby(telustdf.Churn).mean()

Out[51]:

Churn

No 61.265124 Yes 74.441332

Name: MonthlyCharges, dtype: float64

```
In [52]:
churnno=telustdf[telustdf.Churn=='No']
churnyes=telustdf[telustdf.Churn=='Yes']

In [53]:
ttest_ind(churnyes.MonthlyCharges,churnno.MonthlyCharges,equal_var=False)
```

Out[53]:

Ttest_indResult(statistic=18.407526676414673, pvalue=8.59244933154705e-73)

In [54]:

```
# Test Null Average tenure of Churn Yes/No Equal
telustdf.tenure.groupby(telustdf.Churn).mean()
```

Out[54]:

Churn

No 37.569965 Yes 17.979133

Name: tenure, dtype: float64

In [55]:

```
ChurnNo=telustdf[telustdf.Churn=='No']
ChurnYes=telustdf[telustdf.Churn=='Yes']
```

In [56]:

```
ttest_ind(ChurnNo.tenure,ChurnYes.tenure,equal_var=False)
```

Out[56]:

Ttest_indResult(statistic=34.823818696312976, pvalue=1.1954945472607151e-2 32)

In [57]:

```
# Test Null Average Monthly Charges of different PaymentMethod Equal telustdf.MonthlyCharges.groupby(telustdf.PaymentMethod).mean()
```

Out[57]:

PaymentMethod

Bank transfer (automatic) 67.192649
Credit card (automatic) 66.512385
Electronic check 76.255814
Mailed check 43.917060
Name: MonthlyCharges, dtype: float64

In [58]:

```
from scipy.stats import f_oneway
```

In [59]:

```
# split data

PaymentMethodBT=telustdf[telustdf.PaymentMethod=="Bank transfer (automatic)"]
PaymentMethodCC=telustdf[telustdf.PaymentMethod=="Credit card (automatic)"]
PaymentMethodEC=telustdf[telustdf.PaymentMethod=="Electronic check"]
PaymentMethodMC=telustdf[telustdf.PaymentMethod=="Mailed check"]
```

In [60]:

 $\label{lem:coneway} f_oneway(PaymentMethodBT.MonthlyCharges,PaymentMethodCC.MonthlyCharges,PaymentMethodEC.MonthlyCharges)\\ PaymentMethodMC.MonthlyCharges)$

Out[60]:

F_onewayResult(statistic=450.3189918892516, pvalue=1.1802197193575694e-26 7)

In [61]:

```
# Test Null Average tenure of different PaymentMethod Equal
telustdf.tenure.groupby(telustdf.PaymentMethod).mean()
```

Out[61]:

PaymentMethod

Bank transfer (automatic) 43.656736 Credit card (automatic) 43.269382 Electronic check 25.174630 Mailed check 21.830025

Name: tenure, dtype: float64

In [62]:

```
PaymentMethodBT=telustdf[telustdf.PaymentMethod=="Bank transfer (automatic)"]
PaymentMethodCC=telustdf[telustdf.PaymentMethod=="Credit card (automatic)"]
PaymentMethodEC=telustdf[telustdf.PaymentMethod=="Electronic check"]
PaymentMethodMC=telustdf[telustdf.PaymentMethod=="Mailed check"]
```

In [63]:

 $\verb|f_oneway(PaymentMethodBT.tenure, PaymentMethodCC.tenure, PaymentMethodEC.tenure, PaymentMethodEC.t$

Out[63]:

F_onewayResult(statistic=446.4668862479716, pvalue=1.503848361277172e-265)

```
In [64]:
```

```
#Test Null No Asssociation between gender & Churn
pd.crosstab(telustdf.gender,telustdf.Churn)
```

Out[64]:

Churn No Yes

gender

Female 2549 939

Male 2625 930

In [65]:

```
from scipy.stats import chi2_contingency
```

In [66]:

```
chi2_contingency(pd.crosstab(telustdf.gender,telustdf.Churn))
```

Out[66]:

```
Chi2ContingencyResult(statistic=0.4840828822091383, pvalue=0.4865787360561 8596, dof=1, expected_freq=array([[2562.38989067, 925.61010933], [2611.61010933, 943.38989067]]))
```

In [67]:

```
# Test Null No Association between SeniorCitizen & Churn
pd.crosstab(telustdf.SeniorCitizen,telustdf.Churn)
```

Out[67]:

Churn No Yes

SeniorCitizen

- **0** 4508 1393
- **1** 666 476

In [68]:

```
chi2_contingency(pd.crosstab(telustdf.SeniorCitizen,telustdf.Churn))
```

Out[68]:

```
Chi2ContingencyResult(statistic=159.42630036838742, pvalue=1.5100668050923 78e-36, dof=1, expected_freq=array([[4335.05239245, 1565.94760755], [838.94760755, 303.05239245]]))
```

LabelEncode data

In [69]:

objcols.head()

Out[69]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService
0	Female	0	Yes	No	No	No phone service	DSL
1	Male	0	No	No	Yes	No	DSL
2	Male	0	No	No	Yes	No	DSL
3	Male	0	No	No	No	No phone service	DSL
4	Female	0	No	No	Yes	No	Fiber optic
4							•

In [70]:

from sklearn.preprocessing import LabelEncoder

In [71]:

le=LabelEncoder()

In [72]:

objcols_labelencoder=objcols.apply(le.fit_transform)

In [73]:

objcols_labelencoder.head()

Out[73]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService
0	0	0	1	0	0	1	0
1	1	0	0	0	1	0	0
2	1	0	0	0	1	0	0
3	1	0	0	0	0	1	0
4	0	0	0	0	1	0	1
4							>

```
In [74]:
```

```
objcols_labelencoder.describe()
```

Out[74]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	ln
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	
mean	0.504756	0.162147	0.483033	0.299588	0.903166	0.940508	
std	0.500013	0.368612	0.499748	0.458110	0.295752	0.948554	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	1.000000	1.000000	
75%	1.000000	0.000000	1.000000	1.000000	1.000000	2.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	2.000000	
4							•

In [75]:

objcols_labelencoder.shape

Out[75]:

(7043, 17)

Get Dummies

In [76]:

objcols_dummies=pd.get_dummies(objcols)

In [77]:

objcols_dummies.head()

Out[77]:

	SeniorCitizen	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	De
0	0	1	0	0	1	1	
1	0	0	1	1	0	1	
2	0	0	1	1	0	1	
3	0	0	1	1	0	1	
4	0	1	0	1	0	1	

5 rows × 44 columns

→

```
In [78]:
```

objcols_dummies.describe()

Out[78]:

	SeniorCitizen	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	0.495244	0.504756	0.516967	0.483033	0.700412
std	0.368612	0.500013	0.500013	0.499748	0.499748	0.45811(
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000
75%	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 44 columns

In [79]:

objcols_dummies.shape

Out[79]:

(7043, 44)

Scaleing

In [80]:

numcols.head()

Out[80]:

	tenure	MonthlyCharges	TotalCharges
0	1	29.85	29.85
1	34	56.95	1889.50
2	2	53.85	108.15
3	45	42.30	1840.75
4	2	70.70	151.65

In [81]:

from sklearn.preprocessing import StandardScaler

In [82]:

ss=StandardScaler()

In [83]:

numcols_std_scale=ss.fit_transform(numcols)

In [84]:

numcols_std_scale=pd.DataFrame(numcols_std_scale,columns=numcols.columns)

In [85]:

numcols_std_scale.head()

Out[85]:

	tenure	MonthlyCharges	TotalCharges
0	-1.277445	-1.160323	-0.994242
1	0.066327	-0.259629	-0.173244
2	-1.236724	-0.362660	-0.959674
3	0.514251	-0.746535	-0.194766
4	-1.236724	0.197365	-0.940470

In [86]:

combindf=pd.concat([numcols_std_scale,objcols_labelencoder],axis=1)

In [87]:

combindf.head()

Out[87]:

	tenure	MonthlyCharges	TotalCharges	gender	SeniorCitizen	Partner	Dependents	Ph
0	-1.277445	-1.160323	-0.994242	0	0	1	0	
1	0.066327	-0.259629	-0.173244	1	0	0	0	
2	-1.236724	-0.362660	-0.959674	1	0	0	0	
3	0.514251	-0.746535	-0.194766	1	0	0	0	
4	-1.236724	0.197365	-0.940470	0	0	0	0	
4								•

```
In [88]:
```

```
# Spliting Data into Dependent and Independent variables

X=combindf.drop("Churn",axis=1)
y=combindf.Churn
```

In [89]:

```
from sklearn.linear_model import LogisticRegression
```

In [90]:

```
lg=LogisticRegression()
```

In [91]:

```
lgmodel=lg.fit(X,y)
```

In [92]:

```
lgmodel.score(X,y)
```

Out[92]:

0.8044867244072128

In [93]:

```
lgpred=lgmodel.predict(X)
```

In [94]:

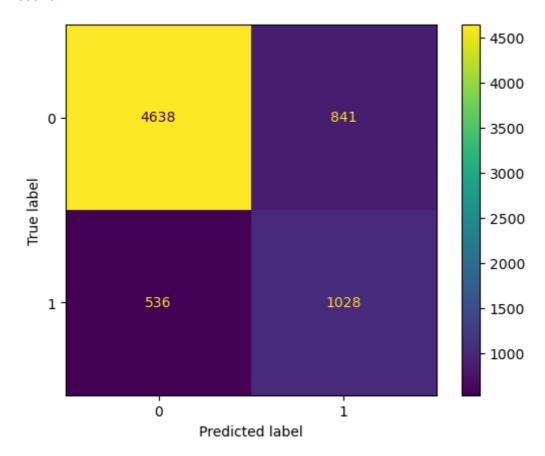
 $\textbf{from} \ \ \textbf{sklearn.metrics} \ \ \textbf{import} \ \ \textbf{ConfusionMatrixDisplay,} \\ \textbf{RocCurveDisplay,} \textbf{classification_report} \\ \textbf{confusionMatrixDisplay,} \\ \textbf{RocCurveDisplay,} \ \ \textbf{classification_report} \\ \textbf{confusionMatrixDisplay,} \\ \textbf{classification_report} \\ \textbf{confusionMatrixDisplay,} \\ \textbf{conf$

In [95]:

ConfusionMatrixDisplay.from_predictions(lgpred,y)

Out[95]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4e99
bbaf0>

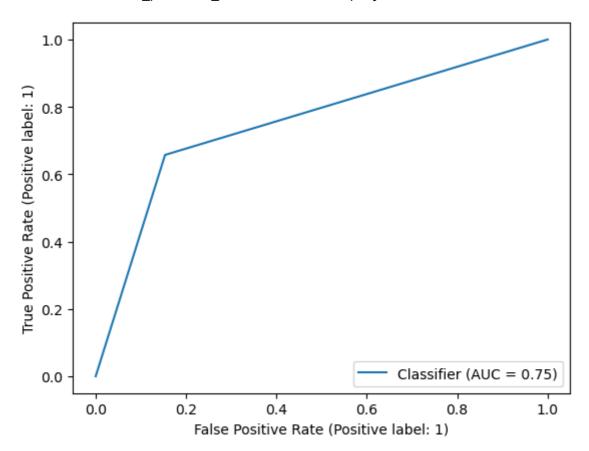


In [96]:

RocCurveDisplay.from_predictions(lgpred,y)

Out[96]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4e9a58f10>



In [97]:

print(classification_report(lgpred,y))

	precision	recall	f1-score	support
0	0.90	0.85	0.87	5479
1	0.55	0.66	0.60	1564
accuracy			0.80	7043
macro avg	0.72	0.75	0.73	7043
weighted avg	0.82	0.80	0.81	7043

In [98]:

from sklearn.tree import DecisionTreeClassifier

In [99]:

tree=DecisionTreeClassifier(max_depth=8)

In [100]:

treemodel=tree.fit(X,y)

In [101]:

treemodel.score(X,y)

Out[101]:

0.8313218798807327

In [102]:

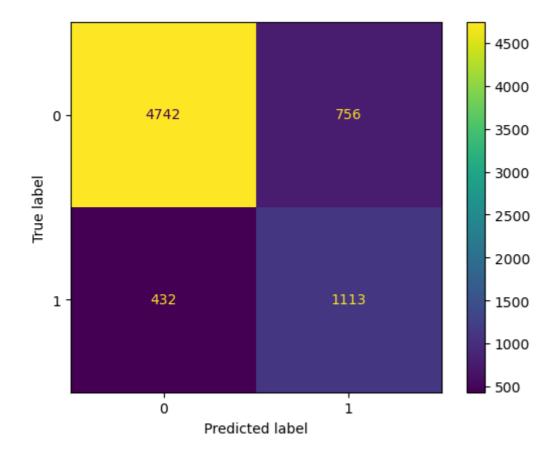
treepred=treemodel.predict(X)

In [103]:

ConfusionMatrixDisplay.from_predictions(treepred,y)

Out[103]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4e99
e4040>

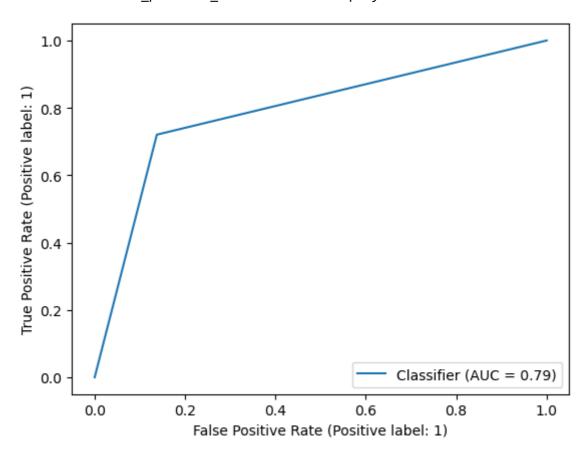


In [104]:

RocCurveDisplay.from_predictions(treepred,y)

Out[104]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4e9d16e80>



In [105]:

print(classification_report(treepred,y))

	precision	recall	f1-score	support
0	0.92	0.86	0.89	5498
1	0.60	0.72	0.65	1545
accuracy			0.83	7043
macro avg	0.76	0.79	0.77	7043
weighted avg	0.85	0.83	0.84	7043

In [106]:

from sklearn.ensemble import RandomForestClassifier

In [107]:

rfc=RandomForestClassifier(n_estimators=2000, max_depth=12)

In [108]:

rfcmodel=rfc.fit(X,y)

In [109]:

rfcmodel.score(X,y)

Out[109]:

0.941644185716314

In [110]:

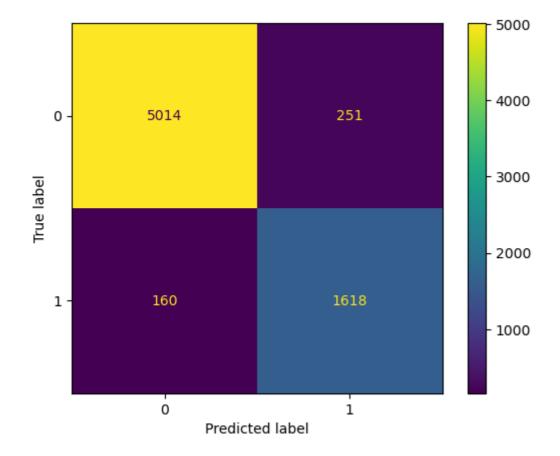
rfcpred=rfcmodel.predict(X)

In [111]:

ConfusionMatrixDisplay.from_predictions(rfcpred,y)

Out[111]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4e0d
d2070>

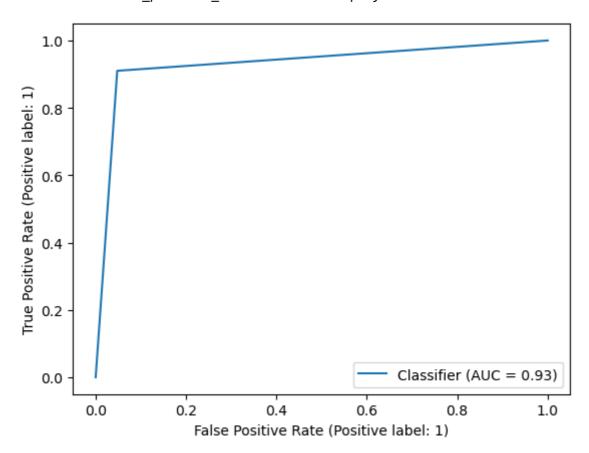


In [112]:

RocCurveDisplay.from_predictions(rfcpred,y)

Out[112]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4e0de40a0>



In [113]:

print(classification_report(rfcpred,y))

	precision	recall	f1-score	support
0 1	0.97 0.87	0.95 0.91	0.96 0.89	5265 1778
accuracy			0.94	7043
macro avg	0.92	0.93	0.92	7043
weighted avg	0.94	0.94	0.94	7043

In [114]:

from sklearn.ensemble import GradientBoostingClassifier

In [115]:

gbc=GradientBoostingClassifier()

In [116]:

```
gbcmodel=gbc.fit(X,y)
```

In [117]:

```
gbcmodel.score(X,y)
```

Out[117]:

0.8253585119977283

In [118]:

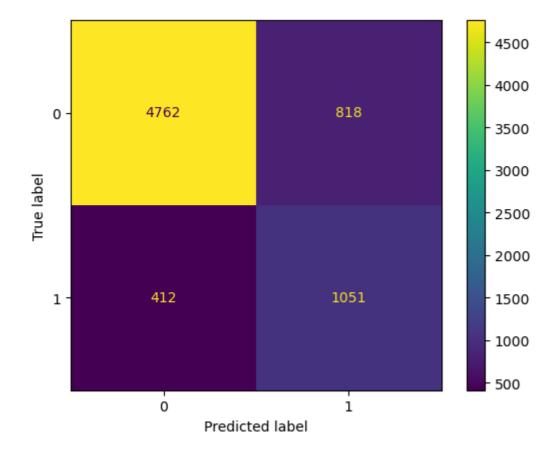
```
gbcpred=gbcmodel.predict(X)
```

In [119]:

```
ConfusionMatrixDisplay.from_predictions(gbcpred,y)
```

Out[119]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4e9e
55790>

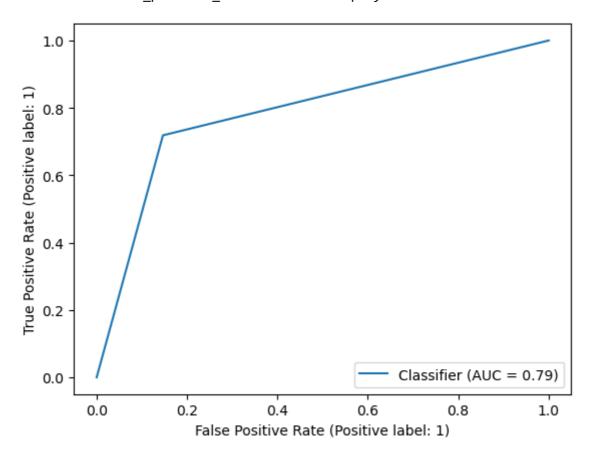


In [120]:

RocCurveDisplay.from_predictions(gbcpred,y)

Out[120]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4f912b580>



In [121]:

print(classification_report(gbcpred,y))

	precision	recall	f1-score	support
0	0.92	0.85	0.89	5580
1	0.56	0.72	0.63	1463
accuracy			0.83	7043
macro avg	0.74	0.79	0.76	7043
weighted avg	0.85	0.83	0.83	7043

In [122]:

GausssianNB

from sklearn.naive_bayes import GaussianNB

In [123]:

Gnb=GaussianNB()

In [124]:

gnbmodel=Gnb.fit(X,y)

In [125]:

gnbmodel.score(X,y)

Out[125]:

0.7526622178049127

In [126]:

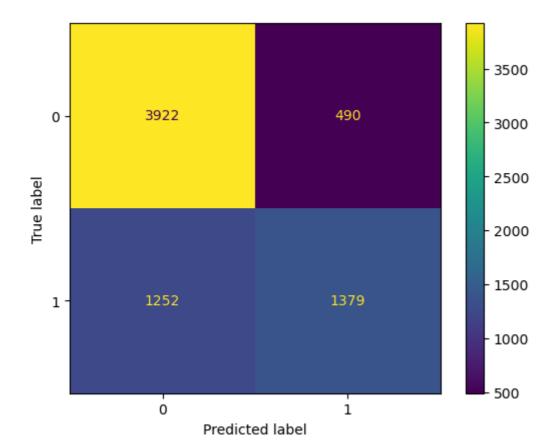
gnbpred=gnbmodel.predict(X)

In [127]:

ConfusionMatrixDisplay.from_predictions(gnbpred,y)

Out[127]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4e9e
774c0>

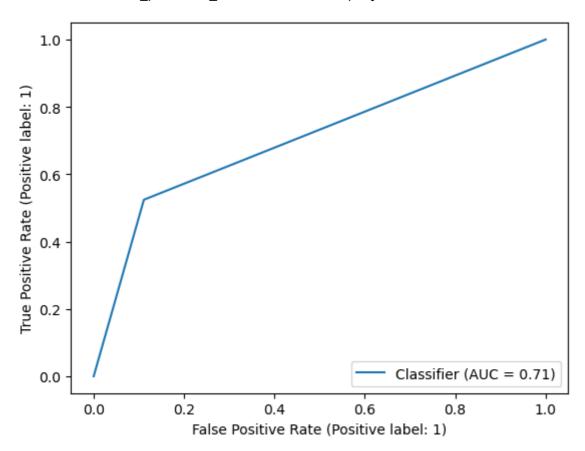


In [128]:

RocCurveDisplay.from_predictions(gnbpred,y)

Out[128]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4f921b280>



In [129]:

print(classification_report(gnbpred,y))

	precision	recall	f1-score	support
0 1	0.76 0.74	0.89 0.52	0.82 0.61	4412 2631
accuracy macro avg weighted avg	0.75 0.75	0.71 0.75	0.75 0.72 0.74	7043 7043 7043

In [130]:

KNeighbors Classifier

from sklearn.neighbors import KNeighborsClassifier

In [131]:

knc=KNeighborsClassifier()

In [132]:

kncmodel=knc.fit(X,y)

In [133]:

kncmodel.score(X,y)

Out[133]:

0.8385631123100952

In [134]:

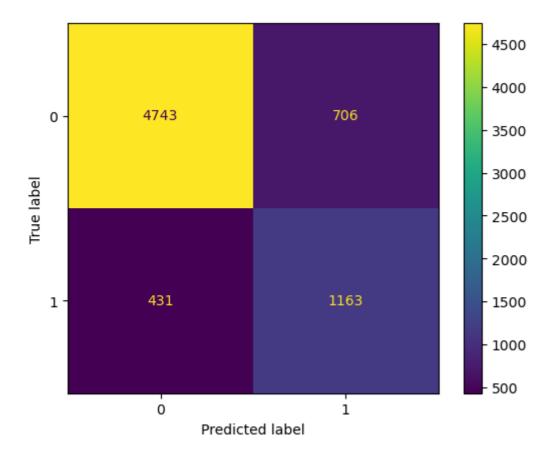
kncpred=kncmodel.predict(X)

In [135]:

ConfusionMatrixDisplay.from_predictions(kncpred,y)

Out[135]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4f92
83e80>

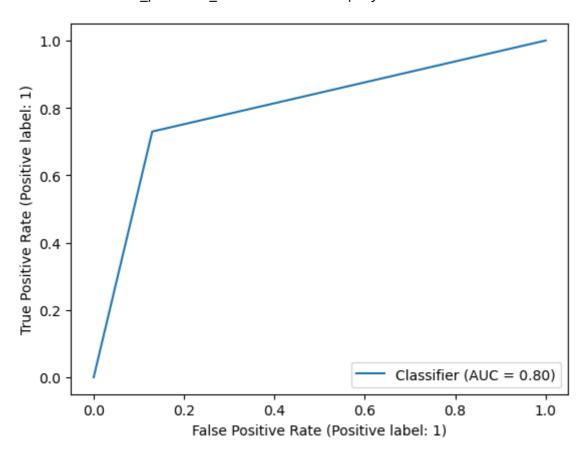


In [136]:

RocCurveDisplay.from_predictions(kncpred,y)

Out[136]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4fa470760>



In [137]:

print(classification_report(kncpred,y))

	precision	recall	f1-score	support
0 1	0.92 0.62	0.87 0.73	0.89 0.67	5449 1594
accuracy macro avg weighted avg	0.77 0.85	0.80 0.84	0.84 0.78 0.84	7043 7043 7043

In [138]:

Support Vector Classifier

from sklearn.svm import SVC

```
In [139]:
```

```
svc=SVC()
```

In [140]:

```
svcmodel=svc.fit(X,y)
```

In [141]:

```
svcmodel.score(X,y)
```

Out[141]:

0.81158597188698

In [142]:

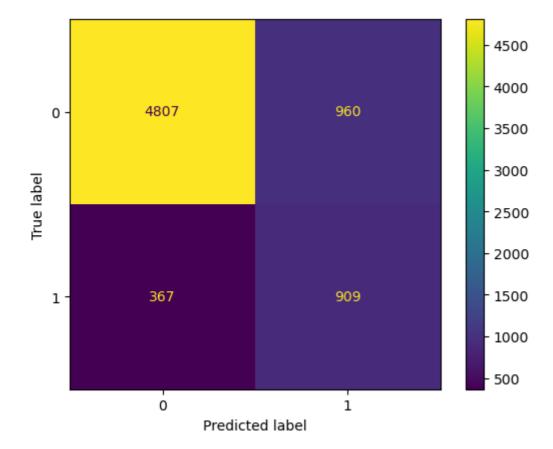
```
svcpred=svcmodel.predict(X)
```

In [143]:

```
ConfusionMatrixDisplay.from_predictions(svcpred,y)
```

Out[143]:

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f4fa6
270d0>

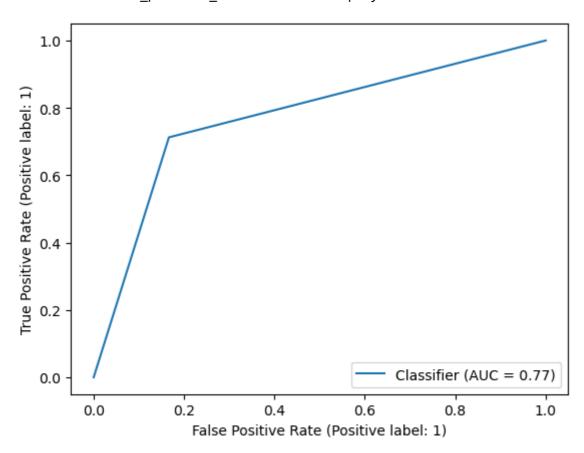


In [144]:

RocCurveDisplay.from_predictions(svcpred,y)

Out[144]:

<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1f4fcb17280>



In [145]:

print(classification_report(svcpred,y))

	precision	recall	f1-score	support
0 1	0.93 0.49	0.83 0.71	0.88 0.58	5767 1276
accuracy macro avg weighted avg	0.71 0.85	0.77 0.81	0.81 0.73 0.82	7043 7043 7043