Telco Churn Prediction using ANN

In [1]:

```
#importing required library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential #builds neural networks
from tensorflow.keras.layers import Dense,Flatten,Dropout
```

Reading the data

In [2]:

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

Out[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl
0	7590-VHVEG	Female	0	Yes	No	1	No	Nc
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	Nc
4	9237-HQITU	Female	0	No	No	2	Yes	
...	...	...	...	...	...	...	...	
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	Nc
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	
7042	3186-AJIEK	Male	0	No	No	66	Yes	

7043 rows × 21 columns

Understanding the data

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   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 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Descriptive Statistics

In [4]:

```
df.describe(include="all").T
```

Out[4]:

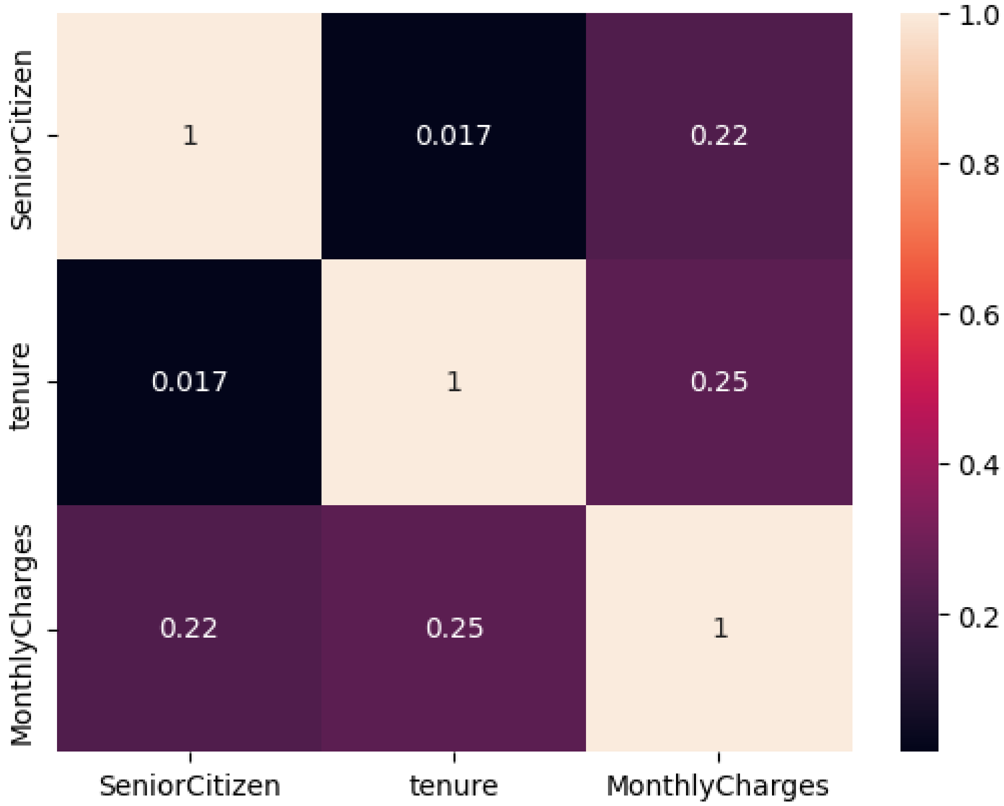
	count	unique	top	freq	mean	std	min	25%	50%
customerID	7043	7043	7590-VHVEG	1	NaN	NaN	NaN	NaN	NaN
gender	7043	2	Male	3555	NaN	NaN	NaN	NaN	NaN
SeniorCitizen	7043.0	NaN	NaN	NaN	0.162147	0.368612	0.0	0.0	0.0
Partner	7043	2	No	3641	NaN	NaN	NaN	NaN	NaN
Dependents	7043	2	No	4933	NaN	NaN	NaN	NaN	NaN
tenure	7043.0	NaN	NaN	NaN	32.371149	24.559481	0.0	9.0	29.0
PhoneService	7043	2	Yes	6361	NaN	NaN	NaN	NaN	NaN
MultipleLines	7043	3	No	3390	NaN	NaN	NaN	NaN	NaN
InternetService	7043	3	Fiber optic	3096	NaN	NaN	NaN	NaN	NaN
OnlineSecurity	7043	3	No	3498	NaN	NaN	NaN	NaN	NaN
OnlineBackup	7043	3	No	3088	NaN	NaN	NaN	NaN	NaN
DeviceProtection	7043	3	No	3095	NaN	NaN	NaN	NaN	NaN
TechSupport	7043	3	No	3473	NaN	NaN	NaN	NaN	NaN
StreamingTV	7043	3	No	2810	NaN	NaN	NaN	NaN	NaN
StreamingMovies	7043	3	No	2785	NaN	NaN	NaN	NaN	NaN
Contract	7043	3	Month-to-month	3875	NaN	NaN	NaN	NaN	NaN
PaperlessBilling	7043	2	Yes	4171	NaN	NaN	NaN	NaN	NaN
PaymentMethod	7043	4	Electronic check	2365	NaN	NaN	NaN	NaN	NaN
MonthlyCharges	7043.0	NaN	NaN	NaN	64.761692	30.090047	18.25	35.5	70.35
TotalCharges	7043	6531		11	NaN	NaN	NaN	NaN	NaN
Churn	7043	2	No	5174	NaN	NaN	NaN	NaN	NaN

In [5]:

```
sns.heatmap(df.corr(),annot=True)
```

Out[5]:

```
<Axes: >
```



Converting to correct data type to check for any missing value

In [6]:

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

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

Imputing missing values

In [8]:

```
from sklearn.impute import SimpleImputer
si=SimpleImputer(missing_values=np.nan,strategy="mean")
df[["TotalCharges"]]=si.fit_transform(df[["TotalCharges"]])
```

In [9]:

```
df.isna().sum()
```

Out[9]:

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [10]:

```
df.describe(include="all").T
```

Out[10]:

	count	unique	top	freq	mean	std	min	25%
customerID	7043	7043	7590-VHVEG	1	NaN	NaN	NaN	NaN
gender	7043	2	Male	3555	NaN	NaN	NaN	NaN
SeniorCitizen	7043.0	NaN	NaN	NaN	0.162147	0.368612	0.0	0.0
Partner	7043	2	No	3641	NaN	NaN	NaN	NaN
Dependents	7043	2	No	4933	NaN	NaN	NaN	NaN
tenure	7043.0	NaN	NaN	NaN	32.371149	24.559481	0.0	9.0
PhoneService	7043	2	Yes	6361	NaN	NaN	NaN	NaN
MultipleLines	7043	3	No	3390	NaN	NaN	NaN	NaN
InternetService	7043	3	Fiber optic	3096	NaN	NaN	NaN	NaN
OnlineSecurity	7043	3	No	3498	NaN	NaN	NaN	NaN
OnlineBackup	7043	3	No	3088	NaN	NaN	NaN	NaN
DeviceProtection	7043	3	No	3095	NaN	NaN	NaN	NaN
TechSupport	7043	3	No	3473	NaN	NaN	NaN	NaN
StreamingTV	7043	3	No	2810	NaN	NaN	NaN	NaN
StreamingMovies	7043	3	No	2785	NaN	NaN	NaN	NaN
Contract	7043	3	Month-to-month	3875	NaN	NaN	NaN	NaN
PaperlessBilling	7043	2	Yes	4171	NaN	NaN	NaN	NaN
PaymentMethod	7043	4	Electronic check	2365	NaN	NaN	NaN	NaN
MonthlyCharges	7043.0	NaN	NaN	NaN	64.761692	30.090047	18.25	35.5
TotalCharges	7043.0	NaN	NaN	NaN	2283.300441	2265.000258	18.8	402.225
Churn	7043	2	No	5174	NaN	NaN	NaN	NaN

In [11]:

```
df=df.iloc[:,1:]        #removing customer id
```

DATA CLEANING

In [12]:

```
for i in df.select_dtypes(object).columns:
  print(f"{i} : {df[i].unique()}")
```

```
gender : ['Female' 'Male']
Partner : ['Yes' 'No']
Dependents : ['No' 'Yes']
PhoneService : ['No' 'Yes']
MultipleLines : ['No phone service' 'No' 'Yes']
InternetService : ['DSL' 'Fiber optic' 'No']
OnlineSecurity : ['No' 'Yes' 'No internet service']
OnlineBackup : ['Yes' 'No' 'No internet service']
DeviceProtection : ['No' 'Yes' 'No internet service']
TechSupport : ['No' 'Yes' 'No internet service']
StreamingTV : ['No' 'Yes' 'No internet service']
StreamingMovies : ['No' 'Yes' 'No internet service']
Contract : ['Month-to-month' 'One year' 'Two year']
PaperlessBilling : ['Yes' 'No']
PaymentMethod : ['Electronic check' 'Mailed check' 'Bank transfer (automat
ic)'
 'Credit card (automatic)']
Churn : ['No' 'Yes']
```

Some of the columns have no service and no separately which can be classified in a single category no

In [13]:

```
df.replace("No internet service","No",inplace=True)
df.replace("No phone service","No",inplace=True)
```

In [14]:

```
for i in df.select_dtypes(object).columns:
  print(f"{i} : {df[i].unique()}")
```

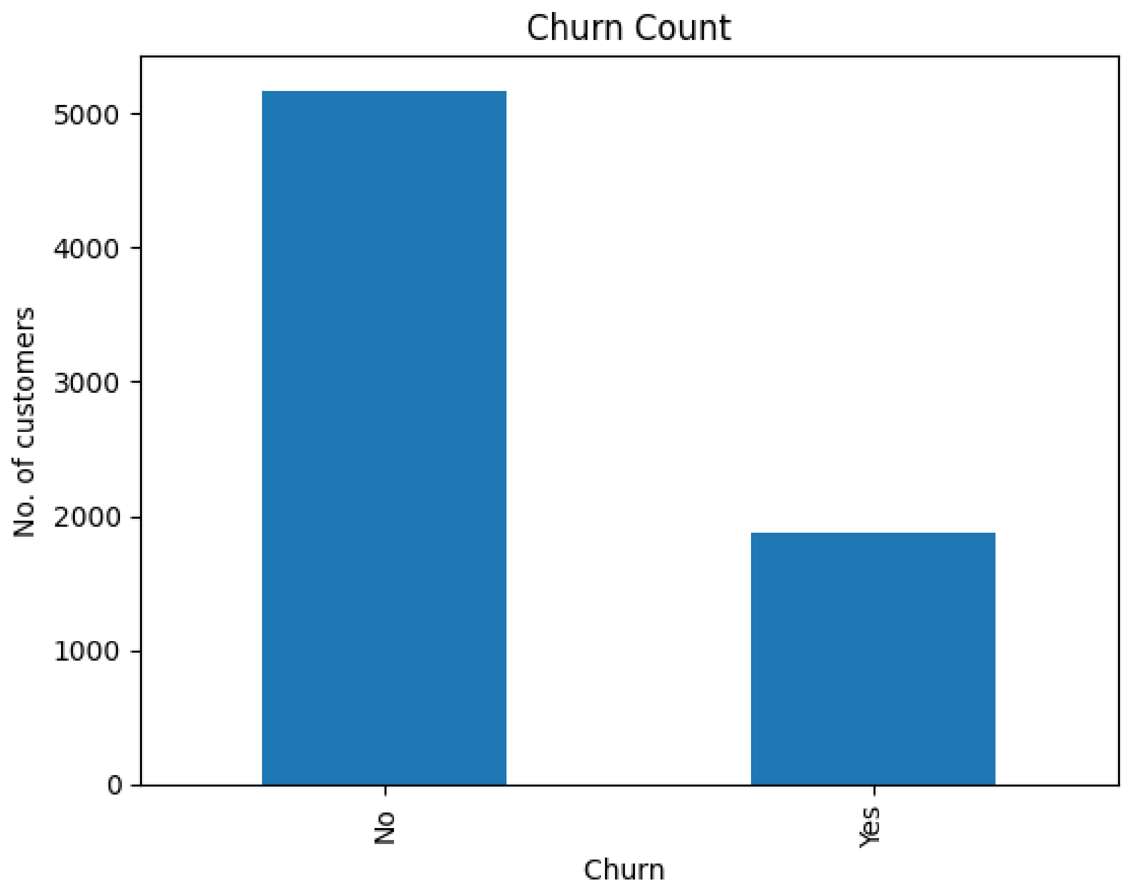
```
gender : ['Female' 'Male']
Partner : ['Yes' 'No']
Dependents : ['No' 'Yes']
PhoneService : ['No' 'Yes']
MultipleLines : ['No' 'Yes']
InternetService : ['DSL' 'Fiber optic' 'No']
OnlineSecurity : ['No' 'Yes']
OnlineBackup : ['Yes' 'No']
DeviceProtection : ['No' 'Yes']
TechSupport : ['No' 'Yes']
StreamingTV : ['No' 'Yes']
StreamingMovies : ['No' 'Yes']
Contract : ['Month-to-month' 'One year' 'Two year']
PaperlessBilling : ['Yes' 'No']
PaymentMethod : ['Electronic check' 'Mailed check' 'Bank transfer (automat
ic)'
 'Credit card (automatic)']
Churn : ['No' 'Yes']
```

Exploratory Data Analysis

Churn Ratio

In [15]:

```
(df["Churn"].value_counts()).plot(kind="bar")
plt.title("Churn Count")
plt.xlabel("Churn ")
plt.ylabel("No. of customers")
plt.show()
```



Gender Distribution

In [16]:

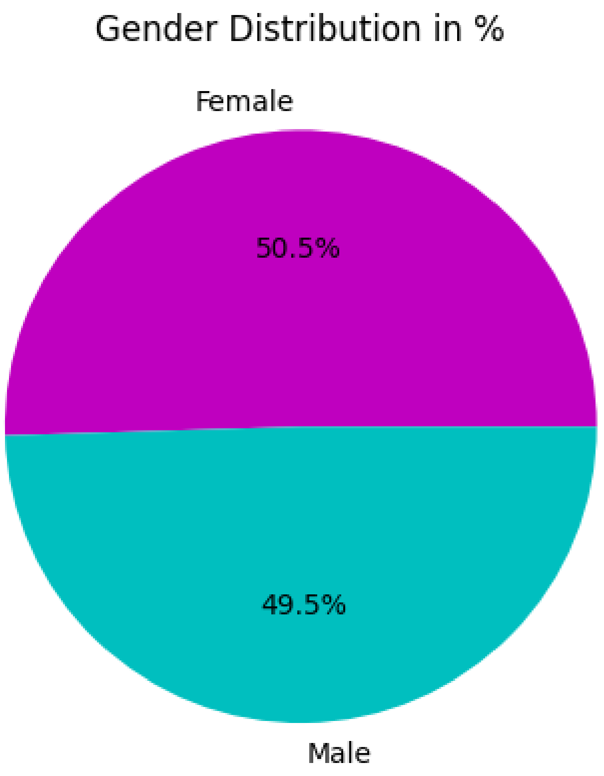
```
df["gender"].value_counts()/df.shape[0]*100
```

Out[16]:

```
Male      50.47565
Female    49.52435
Name: gender, dtype: float64
```

In [17]:

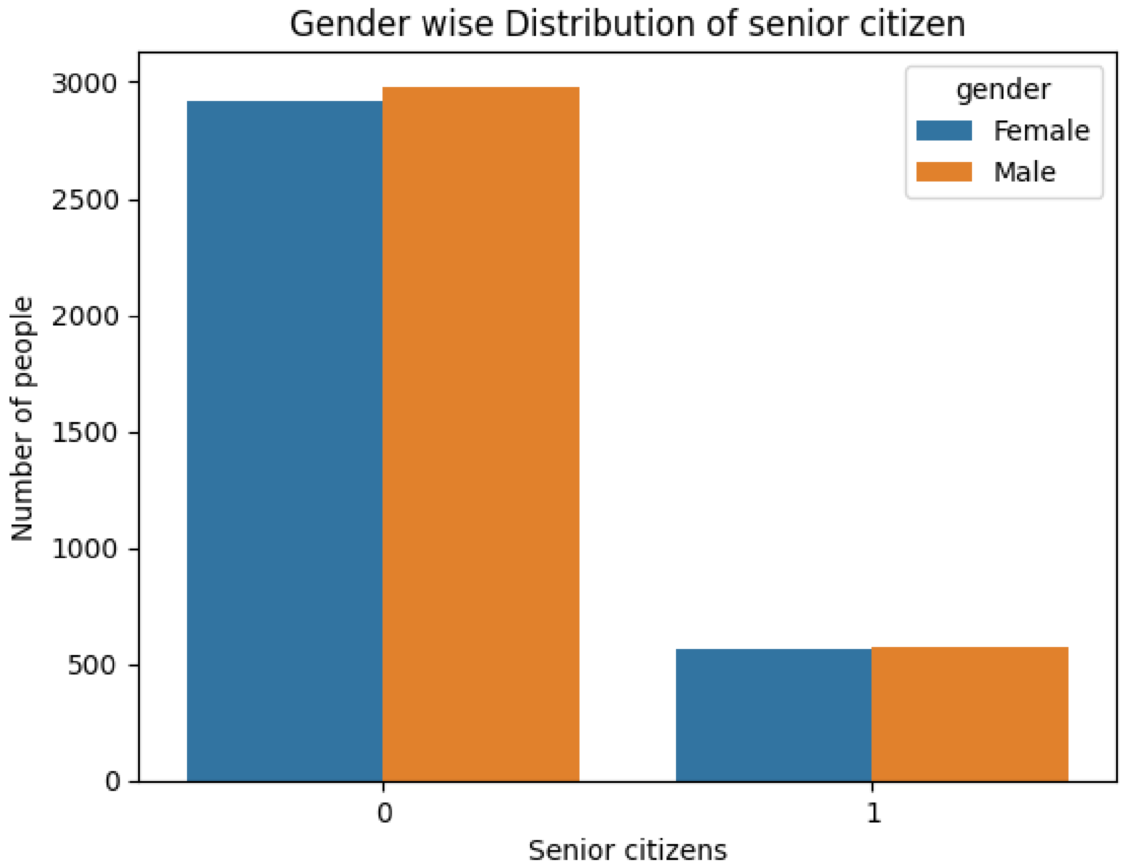
```
plt.pie(df["gender"].value_counts()*100/df.shape[0],labels=df["gender"].unique(),colors=
plt.title("Gender Distribution in %")
plt.show()
```



Gender wise Distribution of senior citizen

In [18]:

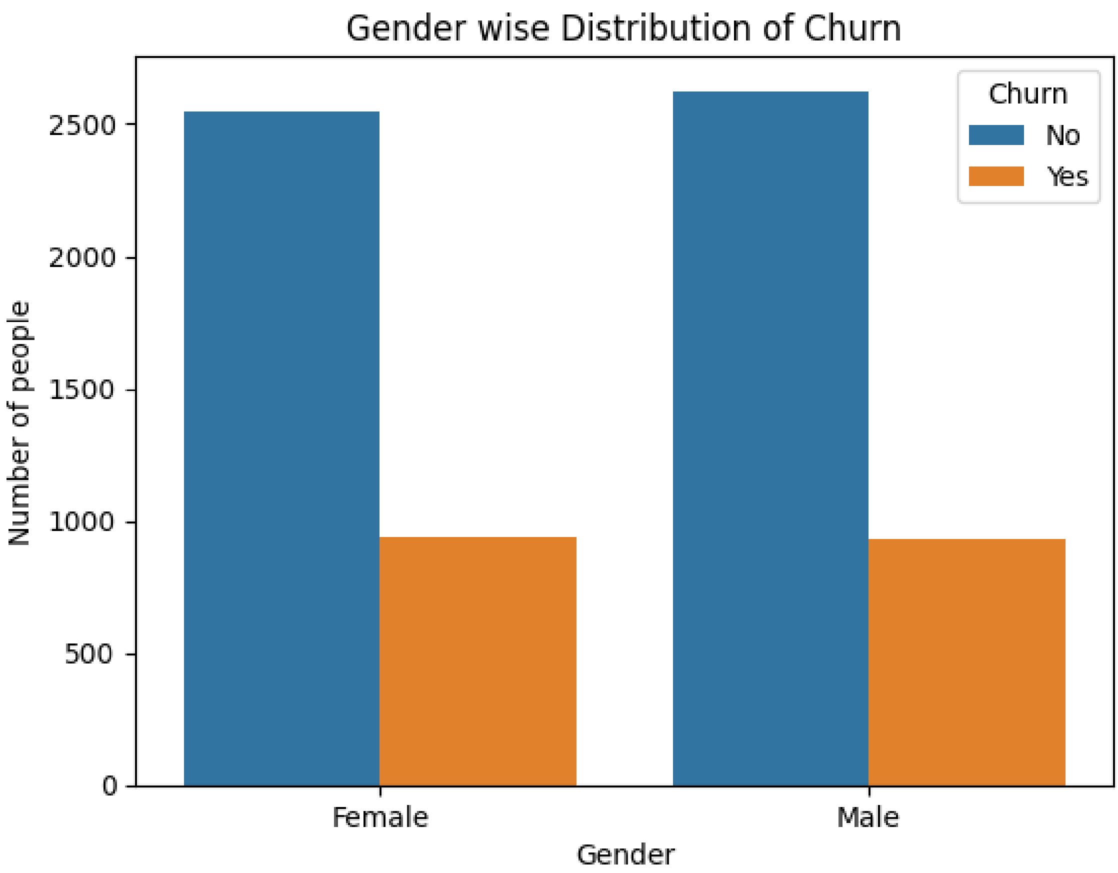
```
sns.countplot(x=df["SeniorCitizen"],hue=df["gender"])
plt.title("Gender wise Distribution of senior citizen")
plt.xlabel("Senior citizens")
plt.ylabel("Number of people")
plt.show()
```



Gender wise churn

In [19]:

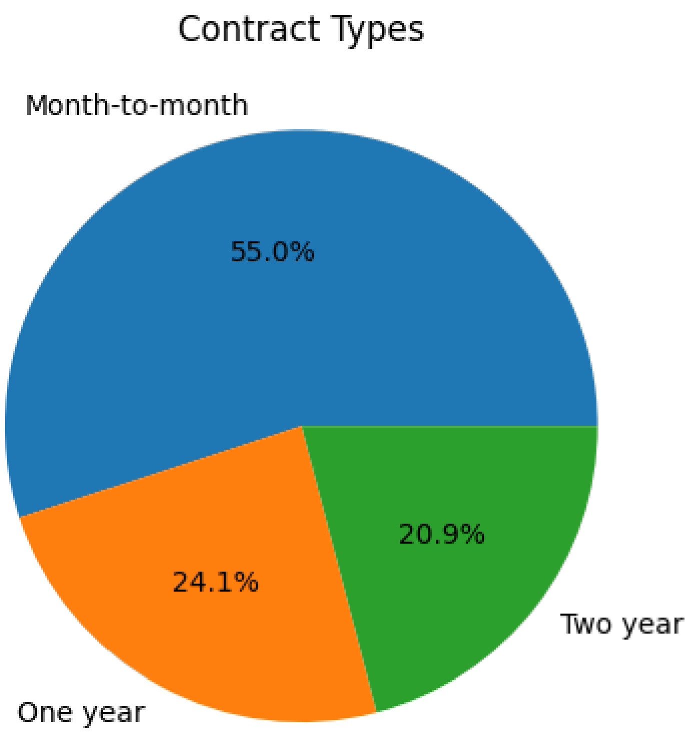
```
sns.countplot(x=df["gender"],hue=df["Churn"])

plt.title("Gender wise Distribution of Churn")
plt.xlabel("Gender")
plt.ylabel("Number of people")
plt.show()
```



Distribution of contract type

In [20]:

```
plt.pie(df["Contract"].value_counts(),labels=df["Contract"].unique(),autopct="%1.1f%%",e
plt.title("Contract Types")
plt.show()
```



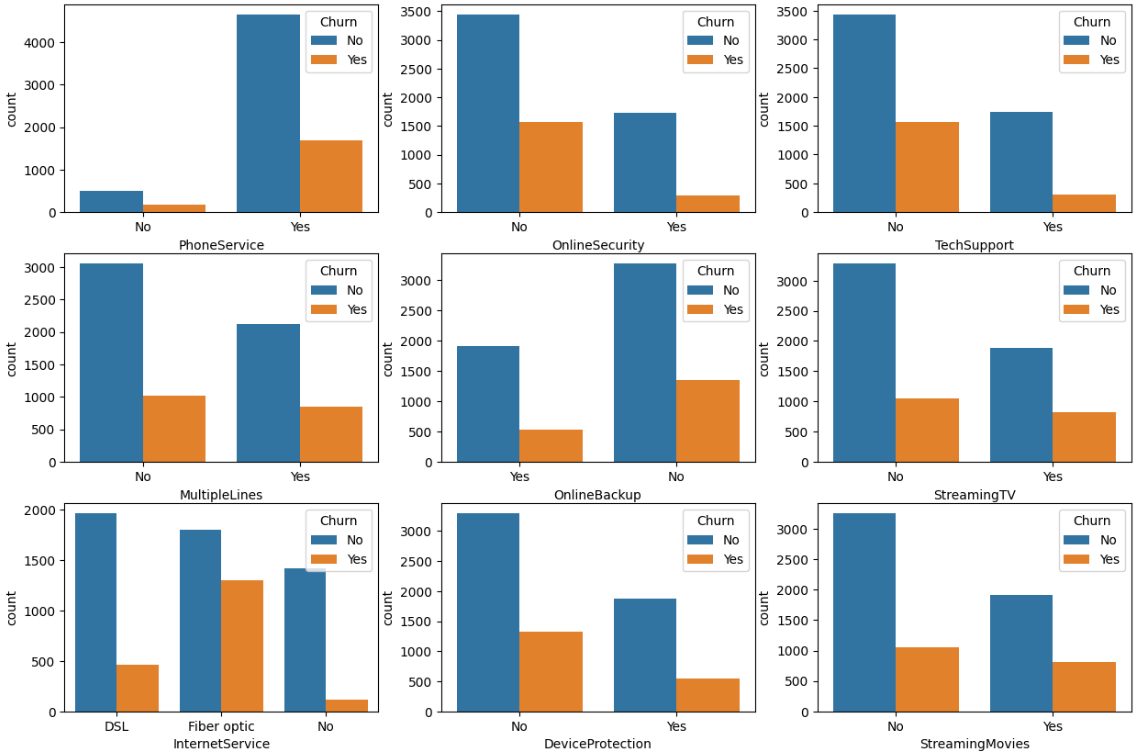
Churn distribution of customer in various sectors

In [21]:

```
service=df.select_dtypes(object).columns[3:-4]
```

In [22]:

```
fig,axes=plt.subplots(nrows=3,ncols=3,figsize=(15,10))

for i,j in enumerate(service):
  if i<3:
    sns.countplot(x=df[j],hue=df["Churn"],ax=axes[i,0])
  elif i>=3 and i<6:
    sns.countplot(x=df[j],hue=df["Churn"],ax=axes[i-3,1])
  elif i<9:
    sns.countplot(x=df[j],hue=df["Churn"],ax=axes[i-6,2])
```



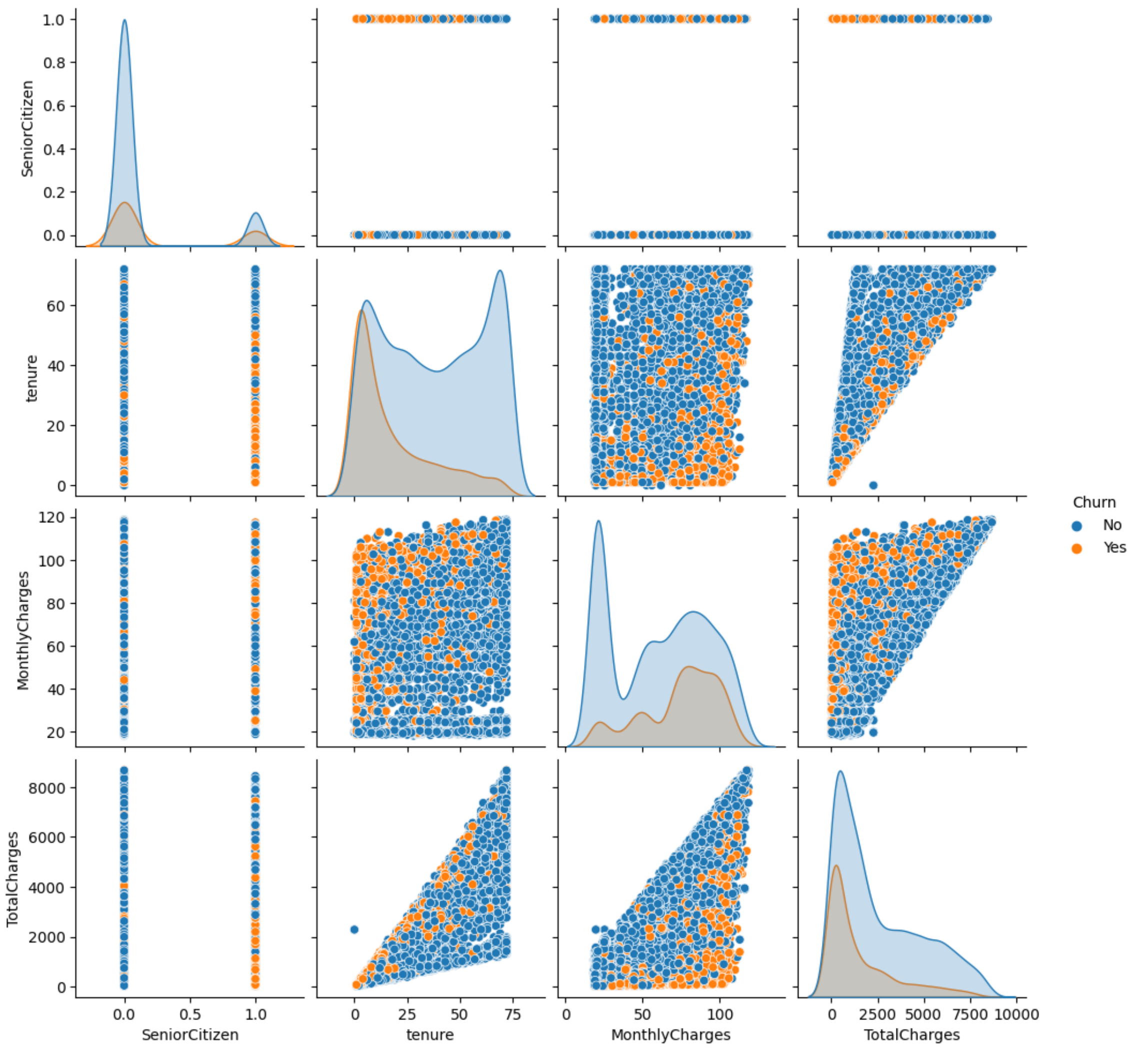
Relation between features and target

In [23]:

```
sns.pairplot(df,hue="Churn")
```

Out[23]:

<seaborn.axisgrid.PairGrid at 0x7fd99ce29d00>



Data Encoding

In [24]:

```
from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder()
catcol=df.select_dtypes(object).columns
df[catcol]=oe.fit_transform(df[catcol])
df.info()
```

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

In [25]:

```
df["Churn"]=df["Churn"].astype(int)
```

Splitting the features and target

In [26]:

```
x=df.iloc[:,:-1]
x
```

Out[26]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Interı
0	0.0	0	1.0	0.0	1	0.0	0.0	
1	1.0	0	0.0	0.0	34	1.0	0.0	
2	1.0	0	0.0	0.0	2	1.0	0.0	
3	1.0	0	0.0	0.0	45	0.0	0.0	
4	0.0	0	0.0	0.0	2	1.0	0.0	
...	...	...	...	...	...	...	...	
7038	1.0	0	1.0	1.0	24	1.0	1.0	
7039	0.0	0	1.0	1.0	72	1.0	1.0	
7040	0.0	0	1.0	1.0	11	0.0	0.0	
7041	1.0	1	1.0	0.0	4	1.0	1.0	
7042	1.0	0	0.0	0.0	66	1.0	0.0	

7043 rows × 19 columns

In [27]:

```
y=df.iloc[:,-1].values
y
```

Out[27]:

```
array([0, 0, 1, ..., 0, 1, 0])
```

Splitting training and testing data

In [28]:

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=1)
```

Checking if the data is balanced

In [29]:

```
df["Churn"].value_counts()/df.shape[0]*100
```

Out[29]:

```
0    73.463013
1    26.536987
Name: Churn, dtype: float64
```

This is an IMBALANCED DATA so performing SMOTE Technique

In [30]:

```
from imblearn.over_sampling import SMOTE
```

In [31]:

```
#Applying smote to training data
st=SMOTE(random_state=1)
xtrain_new,ytrain_new=st.fit_resample(xtrain,ytrain)
```

Feature Scaling

In [32]:

```
from sklearn.preprocessing import MinMaxScaler
mn=MinMaxScaler()

xtrain_new=mn.fit_transform(xtrain_new)
xtest=mn.transform(xtest)
```

Early stopping for overcoming Overfitting issue

In [33]:

```
from tensorflow.keras.callbacks import EarlyStopping
```

In [34]:

```
early_stop=EarlyStopping(monitor="val_loss",mode="min",verbose=1,min_delta=1,patience=25
```

Building Neural Network

In [43]:

```
#Step 1: Initialize the model
ann=Sequential()
#Step 2: Add Layers into the model
# 1st Hidden Layer
ann.add(Dense(units=128,activation="relu"))
# Drop out Layer for 1st hidden layer
ann.add(Dropout(rate=0.2))
# 2nd hidden Layer
ann.add(Dense(units=128,activation="relu"))
# Drop out Layer for 2nd hidden layer
ann.add(Dropout(rate=0.1))

#Output Layer
ann.add(Dense(units=1,activation="sigmoid"))        #since its binary classification

#Step 3: Establish connection between layers
ann.compile(optimizer="adam",loss="binary_crossentropy",metrics="accuracy")

#Step 4:Train the model
ann.fit(xtrain_new,ytrain_new,validation_data=(xtest,ytest),epochs=800,verbose=1,callbac
```

```
Epoch 1/800
258/258 [==============================] - 1s 3ms/step - loss: 0.5076 - ac
curacy: 0.7552 - val_loss: 0.4916 - val_accuracy: 0.7445
Epoch 2/800
258/258 [==============================] - 1s 2ms/step - loss: 0.4688 - ac
curacy: 0.7784 - val_loss: 0.4387 - val_accuracy: 0.7729
Epoch 3/800
258/258 [==============================] - 1s 2ms/step - loss: 0.4548 - ac
curacy: 0.7818 - val_loss: 0.4832 - val_accuracy: 0.7530
Epoch 4/800
258/258 [==============================] - 1s 2ms/step - loss: 0.4439 - ac
curacy: 0.7905 - val_loss: 0.4524 - val_accuracy: 0.7693
Epoch 5/800
258/258 [==============================] - 1s 2ms/step - loss: 0.4364 - ac
curacy: 0.7941 - val_loss: 0.4966 - val_accuracy: 0.7381
Epoch 6/800
258/258 [==============================] - 1s 3ms/step - loss: 0.4282 - ac
curacy: 0.8044 - val_loss: 0.4520 - val_accuracy: 0.7679
Epoch 7/800
258/258 [==============================] - 1s 3ms/step - loss: 0.4185 - ac
curacy: 0.8057 - val_loss: 0.4402 - val_accuracy: 0.7850
Epoch 8/800
258/258 [==============================] - 1s 3ms/step - loss: 0.4161 - ac
curacy: 0.8023 - val_loss: 0.4637 - val_accuracy: 0.7722
Epoch 9/800
258/258 [==============================] - 1s 2ms/step - loss: 0.4080 - ac
curacy: 0.8147 - val_loss: 0.4355 - val_accuracy: 0.7928
Epoch 10/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3991 - ac
curacy: 0.8151 - val_loss: 0.4464 - val_accuracy: 0.7828
Epoch 11/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3975 - ac
curacy: 0.8175 - val_loss: 0.4610 - val_accuracy: 0.7672
Epoch 12/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3914 - ac
curacy: 0.8221 - val_loss: 0.4922 - val_accuracy: 0.7566
Epoch 13/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3828 - ac
curacy: 0.8280 - val_loss: 0.4787 - val_accuracy: 0.7729
Epoch 14/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3792 - ac
curacy: 0.8274 - val_loss: 0.4482 - val_accuracy: 0.7906
Epoch 15/800
258/258 [==============================] - 1s 3ms/step - loss: 0.3763 - ac
curacy: 0.8292 - val_loss: 0.4947 - val_accuracy: 0.7594
Epoch 16/800
258/258 [==============================] - 1s 4ms/step - loss: 0.3690 - ac
curacy: 0.8355 - val_loss: 0.4377 - val_accuracy: 0.7942
Epoch 17/800
258/258 [==============================] - 1s 4ms/step - loss: 0.3646 - ac
curacy: 0.8388 - val_loss: 0.4379 - val_accuracy: 0.7949
Epoch 18/800
258/258 [==============================] - 1s 3ms/step - loss: 0.3628 - ac
curacy: 0.8392 - val_loss: 0.4377 - val_accuracy: 0.7970
Epoch 19/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3626 - ac
curacy: 0.8366 - val_loss: 0.4713 - val_accuracy: 0.7736
Epoch 20/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3499 - ac
curacy: 0.8438 - val_loss: 0.4657 - val_accuracy: 0.7850
Epoch 21/800
```

```
258/258 [==============================] - 1s 2ms/step - loss: 0.3531 - ac
curacy: 0.8395 - val_loss: 0.4618 - val_accuracy: 0.7821
Epoch 22/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3425 - ac
curacy: 0.8487 - val_loss: 0.4749 - val_accuracy: 0.7807
Epoch 23/800
258/258 [==============================] - 1s 2ms/step - loss: 0.3464 - ac
curacy: 0.8457 - val_loss: 0.4830 - val_accuracy: 0.7679
Epoch 24/800
258/258 [==============================] - 1s 3ms/step - loss: 0.3414 - ac
curacy: 0.8471 - val_loss: 0.4706 - val_accuracy: 0.7750
Epoch 25/800
258/258 [==============================] - 1s 3ms/step - loss: 0.3403 - ac
curacy: 0.8545 - val_loss: 0.4501 - val_accuracy: 0.7928
Epoch 26/800
258/258 [==============================] - 1s 3ms/step - loss: 0.3349 - ac
curacy: 0.8530 - val_loss: 0.4382 - val_accuracy: 0.7942
Epoch 26: early stopping
```

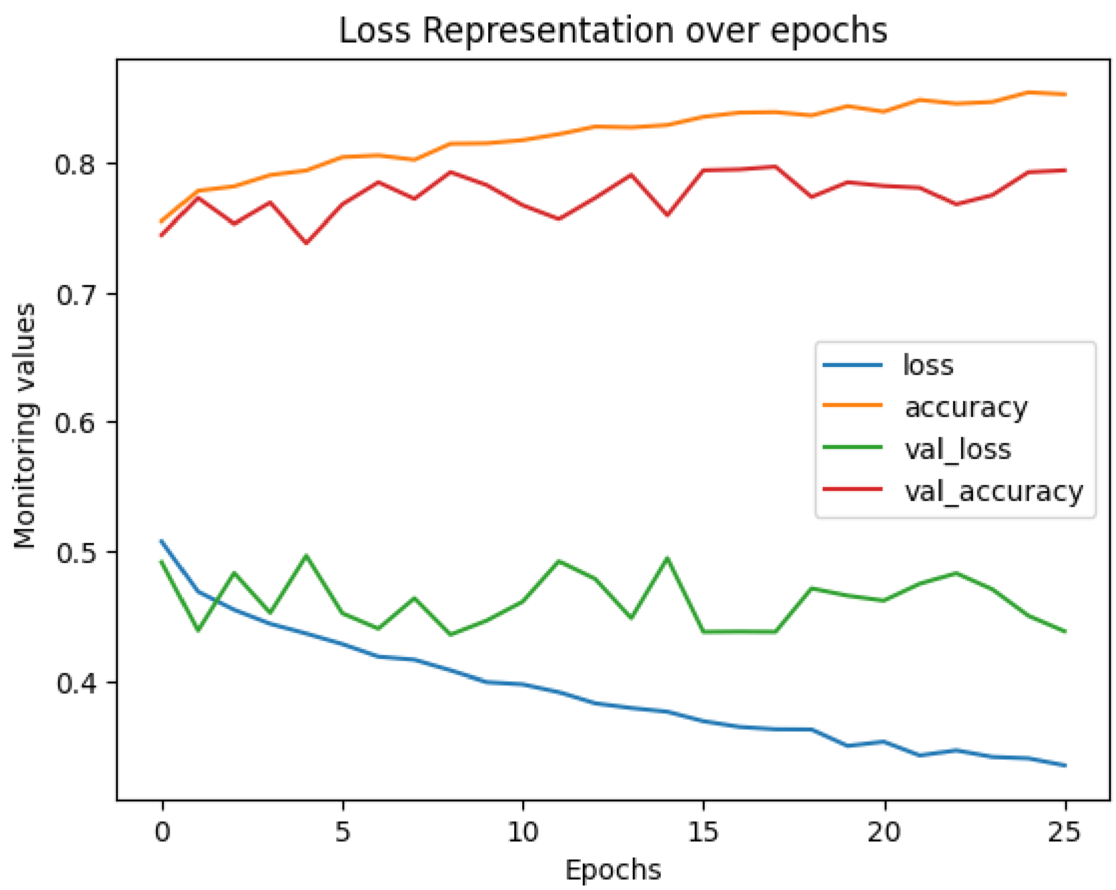
Out[43]:

```
<keras.callbacks.History at 0x7fd9906b63a0>
```

In [48]:

```
lossdata=pd.DataFrame(ann.history.history)
plt.figure(figsize=(2,2))
lossdata.plot()

plt.title("Loss Representation over epochs")
plt.xlabel("Epochs")
plt.ylabel(" Monitoring values")
plt.show()
```

<Figure size 200x200 with 0 Axes>



In [49]:

```
#Step 5 : Predicting
ypred=ann.predict(xtest)
ypred
```

```
45/45 [==============================] - 0s 941us/step
```

Out[49]:

```
array([[0.08973236],
       [0.0286712 ],
       [0.446712  ],
       ...,
       [0.00239313],
       [0.05342298],
       [0.5621679 ]], dtype=float32)
```

These are probablistic values so converting them in binary format by specifing the threshold value

In [50]:

```
ypred=np.where(ypred>0.5,1,0)
ypred
```

Out[50]:

```
array([[0],
       [0],
       [0],
       ...,
       [0],
       [0],
       [1]])
```

Actual VS predicted values

In [51]:

```
pd.DataFrame({"Actual Value":ytest,"Predicted Value":ypred.flatten()})
```

Out[51]:

	Actual Value	Predicted Value
0	0	0
1	0	0
2	0	0
3	1	0
4	0	0
...	...	...
1404	1	0
1405	0	0
1406	0	0
1407	0	0
1408	1	1

1409 rows × 2 columns

Evaluation of model

In [52]:

```
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
print(f"Accuracy:{accuracy_score(ytest,ypred)}\n{confusion_matrix(ytest,ypred)}\n{classi
```

```
Accuracy:0.794180269694819
[[927 134]
 [156 192]]
              precision    recall  f1-score   support

           0       0.86      0.87      0.86      1061
           1       0.59      0.55      0.57       348

    accuracy                           0.79      1409
   macro avg       0.72      0.71      0.72      1409
weighted avg       0.79      0.79      0.79      1409
```

In [ ]:

```
```