

Project 2: Binary Classification on 'Customer_Churn' using Keras

```
import pandas as pd
df= pd.read_csv("customer_churn.csv")
```

```
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure
0	7590-VHVEG	Female	0	Yes	No	1
1	5575-GNVDE	Male	0	No	No	34
2	3668-QPYBK	Male	0	No	No	2
3	7795-CF0CW	Male	0	No	No	45
4	9237-HQITU	Female	0	No	No	2

	MultipleLines	InternetService	OnlineSecurity	...
0	No phone service	DSL	No	...
1	No	DSL	Yes	...
2	No	DSL	Yes	...
3	No phone service	DSL	Yes	...
4	No	Fiber optic	No	...

	TechSupport	StreamingTV	StreamingMovies	Contract
0	No	No	No	Month-to-month
1	No	No	No	One year
2	No	No	No	Month-to-month
3	Yes	No	No	One year
4	No	No	No	Month-to-month

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Electronic check	29.85	29.85	No

1	Mailed check	56.95	1889.5	No
2	Mailed check	53.85	108.15	Yes
3	Bank transfer (automatic)	42.30	1840.75	No
4	Electronic check	70.70	151.65	Yes

[5 rows x 21 columns]

A) Data Manipulation:

a. Find the total number of male customers

b. Find the total number of customers whose Internet Service is 'DSL'

c. Extract all the Female senior citizens whose Payment Method is Mailed check & store the

result in 'new_customer'

d. Extract all those customers whose tenure is less than 10 months or their Total charges is less

than 500\$ & store the result in 'new_customer'

```
total_male_customers = df[df['gender'] == 'Male'].shape[0]
```

```
print("Total number of male customers:", total_male_customers)
```

Total number of male customers: 3555

b. Find the total number of customers whose Internet Service is 'DSL'

```
total_dsl_customers = df[df['InternetService'] == 'DSL'].shape[0]
```

```
print("Total number of customers with DSL internet service:",  
total_dsl_customers)
```

Total number of customers with DSL internet service: 2421

c. Extract all the Female senior citizens whose Payment Method is Mailed check & store the result in 'new_customer'

```
new_customer = df[(df['gender'] == 'Female') & (df['SeniorCitizen'] ==  
1) & (df['PaymentMethod'] == 'Mailed check')]
```

```
print("Female senior citizens with Payment Method as Mailed check:")
```

```
print(new_customer)
```

Female senior citizens with Payment Method as Mailed check:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
139	0390-DCFDQ	Female	1	Yes	No	1	
176	2656-FMOKZ	Female	1	No	No	15	
267	3197-ARFOY	Female	1	No	No	19	
451	5760-WRAHC	Female	1	No	No	22	
470	4933-IKULF	Female	1	No	No	17	
694	2682-KEVRP	Female	1	No	No	22	
747	3966-HRMZA	Female	1	No	No	3	
947	9904-EHEVJ	Female	1	Yes	Yes	32	
1029	4184-TJFAN	Female	1	Yes	Yes	3	
1112	2176-LVPNX	Female	1	No	No	71	
1513	0661-XEYAN	Female	1	No	No	1	

1811	2070-XYMFH	Female	1	No	No	23
1831	3402-XRIUO	Female	1	Yes	No	22
1864	7105-MXJLL	Female	1	Yes	No	26
1891	4193-ORFCL	Female	1	No	No	1
2037	8309-IEYJD	Female	1	No	No	1
2344	9796-MVYXX	Female	1	No	No	14
2441	9050-IKDZA	Female	1	No	No	2
2674	1855-CFULU	Female	1	No	No	4
3005	0516-QREYC	Female	1	No	No	24
3185	9907-SWKKF	Female	1	No	No	1
3341	1125-SNVCK	Female	1	No	No	49
3373	2516-VQRRV	Female	1	No	No	2
3374	7580-UGXNC	Female	1	No	No	2
3454	6773-LQTVT	Female	1	Yes	Yes	29
3893	5816-SCGFC	Female	1	No	No	7
4258	9360-AHGNI	Female	1	Yes	No	43
4382	2277-VWCNI	Female	1	No	No	4
4541	9058-CBREO	Female	1	No	No	1
4542	9029-FEGVJ	Female	1	Yes	No	32
4673	6402-ZFPPI	Female	1	No	No	25
5183	8988-ECPJR	Female	1	Yes	Yes	34
5251	8485-GJCDN	Female	1	No	No	5
5319	9866-OCCKE	Female	1	Yes	No	72
5341	2982-IHMFT	Female	1	No	No	1
5437	7000-WCEVQ	Female	1	No	No	20
5476	6060-DRTNL	Female	1	No	No	5
5569	0013-EXCHZ	Female	1	Yes	No	3
5680	6982-UQZLY	Female	1	Yes	No	1
5743	2384-0VPSA	Female	1	No	No	38
5757	5539-HIVAK	Female	1	Yes	No	28
5792	3500-RMZLT	Female	1	No	No	15
6031	0282-NVSJS	Female	1	Yes	Yes	12
6042	4750-UKWJK	Female	1	Yes	No	37
6147	6383-ZTSIW	Female	1	Yes	No	39
6178	3719-TDVQB	Female	1	Yes	No	54
6219	1496-GGSUK	Female	1	No	No	1
6231	3296-SILRA	Female	1	Yes	No	1
6534	5195-KPUNQ	Female	1	No	No	53
6581	2453-SAFNS	Female	1	No	No	54

	PhoneService	MultipleLines	InternetService
OnlineSecurity ... \			
139	Yes	No	Fiber optic
No ...			
176	Yes	Yes	Fiber optic
No ...			
267	Yes	No	Fiber optic
Yes ...			
451	Yes	No	DSL

Yes ...				
470	Yes	No	No	No internet
service ...				
694	Yes	No	No	No internet
service ...				
747	Yes	No	Fiber optic	
No ...				
947	Yes	Yes	Fiber optic	
No ...				
1029	Yes	No	Fiber optic	
Yes ...				
1112	Yes	Yes	DSL	
Yes ...				
1513	No	No phone service	DSL	
No ...				
1811	Yes	Yes	Fiber optic	
No ...				
1831	Yes	Yes	DSL	
Yes ...				
1864	Yes	No	DSL	
No ...				
1891	Yes	No	DSL	
No ...				
2037	Yes	No	Fiber optic	
No ...				
2344	No	No phone service	DSL	
Yes ...				
2441	Yes	No	Fiber optic	
No ...				
2674	Yes	No	No	No internet
service ...				
3005	Yes	No	No	No internet
service ...				
3185	No	No phone service	DSL	
No ...				
3341	Yes	No	DSL	
No ...				
3373	Yes	Yes	Fiber optic	
No ...				
3374	Yes	No	DSL	
Yes ...				
3454	No	No phone service	DSL	
No ...				
3893	Yes	No	DSL	
No ...				
4258	Yes	Yes	Fiber optic	
Yes ...				
4382	Yes	Yes	DSL	
No ...				

4541	Yes	Yes	DSL	
No ...				
4542	Yes	Yes	Fiber optic	
No ...				
4673	Yes	Yes	Fiber optic	
Yes ...				
5183	Yes	Yes	Fiber optic	
No ...				
5251	Yes	No	Fiber optic	
No ...				
5319	Yes	Yes	Fiber optic	
Yes ...				
5341	Yes	Yes	Fiber optic	
No ...				
5437	Yes	Yes	DSL	
No ...				
5476	Yes	No	Fiber optic	
No ...				
5569	Yes	No	Fiber optic	
No ...				
5680	Yes	No	No	No internet
service ...				
5743	Yes	No	No	No internet
service ...				
5757	Yes	Yes	No	No internet
service ...				
5792	Yes	No	Fiber optic	
Yes ...				
6031	No	No phone service	DSL	
No ...				
6042	Yes	No	No	No internet
service ...				
6147	Yes	No	Fiber optic	
Yes ...				
6178	Yes	No	No	No internet
service ...				
6219	No	No phone service	DSL	
No ...				
6231	Yes	No	Fiber optic	
No ...				
6534	Yes	No	Fiber optic	
Yes ...				
6581	Yes	Yes	DSL	
No ...				

	DeviceProtection	TechSupport	StreamingTV \
139	No	No	No
176	No	No	No
267	No	Yes	Yes

451		Yes		Yes		No
470	No internet service		No internet service		No internet service	
694	No internet service		No internet service		No internet service	
747		Yes		No		No
947		Yes		No		Yes
1029		No		Yes		Yes
1112		Yes		Yes		Yes
1513		No		No		No
1811		Yes		No		No
1831		No		Yes		No
1864		Yes		No		No
1891		No		No		No
2037		No		No		No
2344		Yes		Yes		No
2441		No		No		Yes
2674	No internet service		No internet service		No internet service	
3005	No internet service		No internet service		No internet service	
3185		No		No		No
3341		No		No		No
3373		No		No		No
3374		No		No		No
3454		Yes		No		No
3893		No		No		No
4258		Yes		Yes		Yes
4382		No		No		No
4541		No		No		No
4542		Yes		No		No
4673		No		No		Yes
5183		No		No		No
5251		No		No		No
5319		Yes		Yes		Yes
5341		No		No		No
5437		No		No		No
5476		Yes		No		Yes
5569		No		Yes		Yes
5680	No internet service		No internet service		No internet service	
5743	No internet service		No internet service		No internet service	
5757	No internet service		No internet service		No internet service	
5792		Yes		Yes		No
6031		No		Yes		No
6042	No internet service		No internet service		No internet service	
6147		No		No		Yes
6178	No internet service		No internet service		No internet service	
6219		No		No		No
6231		No		No		No
6534		No		Yes		No
6581		No		Yes		Yes
StreamingMovies			Contract PaperlessBilling			

PaymentMethod \					
139	No	Month-to-month	Yes	Mailed	
check					
176	No	Month-to-month	Yes	Mailed	
check					
267	Yes	Month-to-month	Yes	Mailed	
check					
451	Yes	Month-to-month	Yes	Mailed	
check					
470	No internet service	One year	No	Mailed	
check					
694	No internet service	One year	Yes	Mailed	
check					
747	No	Month-to-month	No	Mailed	
check					
947	No	Month-to-month	Yes	Mailed	
check					
1029	No	Month-to-month	Yes	Mailed	
check					
1112	Yes	Two year	No	Mailed	
check					
1513	No	Month-to-month	Yes	Mailed	
check					
1811	No	Month-to-month	Yes	Mailed	
check					
1831	No	Month-to-month	Yes	Mailed	
check					
1864	Yes	One year	No	Mailed	
check					
1891	No	Month-to-month	No	Mailed	
check					
2037	No	Month-to-month	Yes	Mailed	
check					
2344	No	Two year	No	Mailed	
check					
2441	No	Month-to-month	No	Mailed	
check					
2674	No internet service	Month-to-month	No	Mailed	
check					
3005	No internet service	Month-to-month	Yes	Mailed	
check					
3185	No	Month-to-month	No	Mailed	
check					
3341	No	Month-to-month	No	Mailed	
check					
3373	No	Month-to-month	Yes	Mailed	
check					
3374	No	Month-to-month	No	Mailed	
check					

3454		No	Month-to-month	Yes	Mailed
check					
3893		No	Month-to-month	Yes	Mailed
check					
4258		Yes	One year	Yes	Mailed
check					
4382		No	Month-to-month	No	Mailed
check					
4541		No	Month-to-month	No	Mailed
check					
4542		No	Month-to-month	No	Mailed
check					
4673		Yes	Month-to-month	Yes	Mailed
check					
5183		No	Month-to-month	Yes	Mailed
check					
5251		No	Month-to-month	Yes	Mailed
check					
5319		Yes	Two year	Yes	Mailed
check					
5341		No	Month-to-month	Yes	Mailed
check					
5437		Yes	Month-to-month	Yes	Mailed
check					
5476		No	Month-to-month	Yes	Mailed
check					
5569		No	Month-to-month	Yes	Mailed
check					
5680	No internet service		Month-to-month	Yes	Mailed
check					
5743	No internet service		Two year	No	Mailed
check					
5757	No internet service		Month-to-month	No	Mailed
check					
5792		Yes	Month-to-month	Yes	Mailed
check					
6031		No	Month-to-month	Yes	Mailed
check					
6042	No internet service		One year	No	Mailed
check					
6147		Yes	One year	No	Mailed
check					
6178	No internet service		Two year	Yes	Mailed
check					
6219		No	Month-to-month	Yes	Mailed
check					
6231		No	Month-to-month	Yes	Mailed
check					
6534		Yes	One year	Yes	Mailed

check			
6581	No	One year	No Mailed
check			

	MonthlyCharges	TotalCharges	Churn
139	70.45	70.45	Yes
176	74.45	1145.7	Yes
267	105.00	2007.25	No
451	69.75	1545.4	No
470	20.65	330.6	No
694	20.05	417	No
747	75.05	202.9	No
947	91.35	2896.55	No
1029	88.30	273.75	Yes
1112	89.85	6293.45	No
1513	25.80	25.8	Yes
1811	79.35	1835.3	No
1831	63.55	1381.8	No
1864	60.70	1597.4	No
1891	45.10	45.1	Yes
2037	70.60	70.6	No
2344	39.70	692.35	No
2441	81.50	162.55	No
2674	20.05	91.45	No
3005	20.30	459.95	No
3185	25.05	25.05	Yes
3341	43.80	2106.05	No
3373	75.45	158.4	Yes
3374	54.85	104.2	Yes
3454	35.65	1025.15	No
3893	51.30	419.35	No
4258	109.55	4830.25	Yes
4382	48.75	179.85	No
4541	50.55	50.55	Yes
4542	79.30	2570	No
4673	102.80	2660.2	Yes
5183	79.60	2718.3	Yes
5251	69.05	318.5	Yes
5319	109.75	8075.35	No
5341	74.45	74.45	Yes
5437	61.60	1174.35	Yes
5476	84.85	415.55	Yes
5569	83.90	267.4	Yes
5680	20.85	20.85	Yes
5743	20.20	735.9	No
5757	25.70	734.6	No
5792	96.30	1426.75	Yes
6031	29.30	355.9	No
6042	19.60	727.8	No

6147	99.10	3877.95	No
6178	18.95	1031.1	No
6219	25.70	25.7	Yes
6231	76.40	76.4	Yes
6534	96.75	5206.55	No
6581	72.10	3886.05	No

[50 rows x 21 columns]

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

```
new_customer = df[(df['tenure'] < 10) | (df['TotalCharges'] < 500)]
print("Customers with tenure less than 10 months or Total charges less
than $500:")
print(new_customer)
```

Customers with tenure less than 10 months or Total charges less than \$500:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
0	7590-VHVEG	Female	0	Yes	No	1	
2	3668-QPYBK	Male	0	No	No	2	
4	9237-HQITU	Female	0	No	No	2	
5	9305-CDSKC	Female	0	No	No	8	
7	6713-OKOMC	Female	0	No	No	10	
...	
7029	2235-DWLJU	Female	1	No	No	6	
7030	0871-OPBXW	Female	0	No	No	2	
7032	6894-LFHLY	Male	1	No	No	1	
7040	4801-JZAZL	Female	0	Yes	Yes	11	
7041	8361-LTMKD	Male	1	Yes	No	4	

	PhoneService	MultipleLines	InternetService
OnlineSecurity	...	\	
0	No	No phone service	DSL
No	...		
2	Yes	No	DSL
Yes	...		
4	Yes	No	Fiber optic
No	...		
5	Yes	Yes	Fiber optic
No	...		
7	No	No phone service	DSL
Yes	...		
...
...	...		
7029	No	No phone service	DSL
No	...		
7030	Yes	No	No No internet service
service	...		

7032	Yes	Yes	Fiber optic
No ...			
7040	No	No phone service	DSL
Yes ...			
7041	Yes	Yes	Fiber optic
No ...			

	DeviceProtection	TechSupport	StreamingTV \
0	No	No	No
2	No	No	No
4	No	No	No
5	Yes	No	Yes
7	No	No	No
...
7029	No	No	Yes
7030	No internet service	No internet service	No internet service
7032	No	No	No
7040	No	No	No
7041	No	No	No

	StreamingMovies	Contract	PaperlessBilling
PaymentMethod \			
0	No	Month-to-month	Yes Electronic
check			
2	No	Month-to-month	Yes Mailed
check			
4	No	Month-to-month	Yes Electronic
check			
5	Yes	Month-to-month	Yes Electronic
check			
7	No	Month-to-month	No Mailed
check			
...
...			
7029	Yes	Month-to-month	Yes Electronic
check			
7030	No internet service	Month-to-month	Yes Mailed
check			
7032	No	Month-to-month	Yes Electronic
check			
7040	No	Month-to-month	Yes Electronic
check			
7041	No	Month-to-month	Yes Mailed
check			

	MonthlyCharges	TotalCharges	Churn
0	29.85	29.85	No
2	53.85	108.15	Yes
4	70.70	151.65	Yes
5	99.65	820.50	Yes

7	29.75	301.90	No
...
7029	44.40	263.05	No
7030	20.05	39.25	No
7032	75.75	75.75	Yes
7040	29.60	346.45	No
7041	74.40	306.60	Yes

[2233 rows x 21 columns]

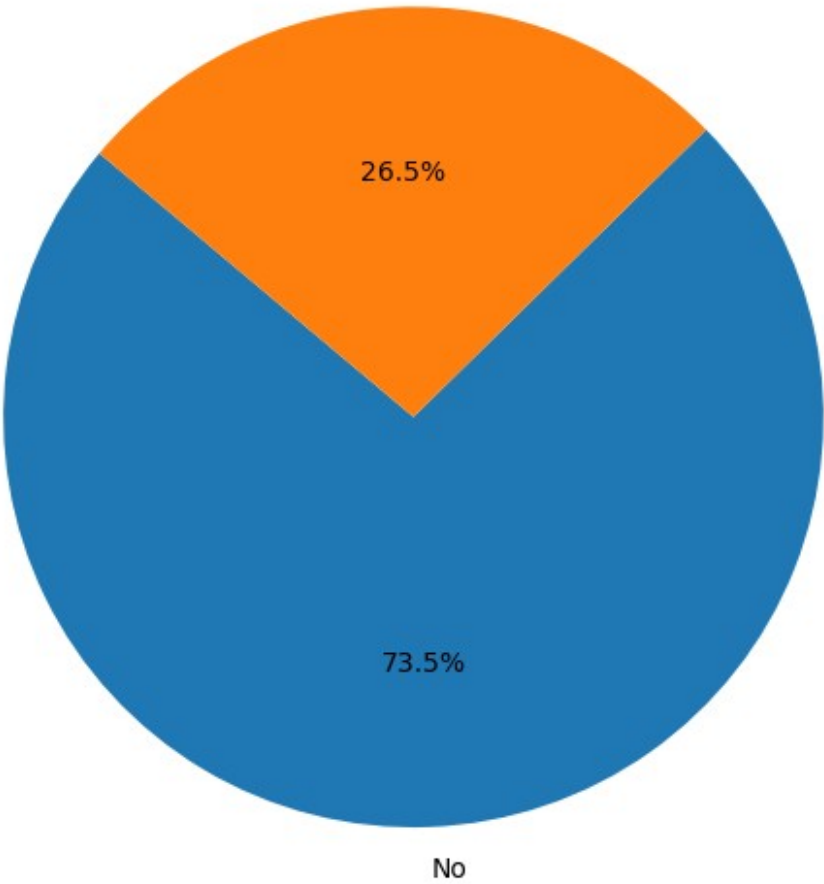
B) Data Visualization:

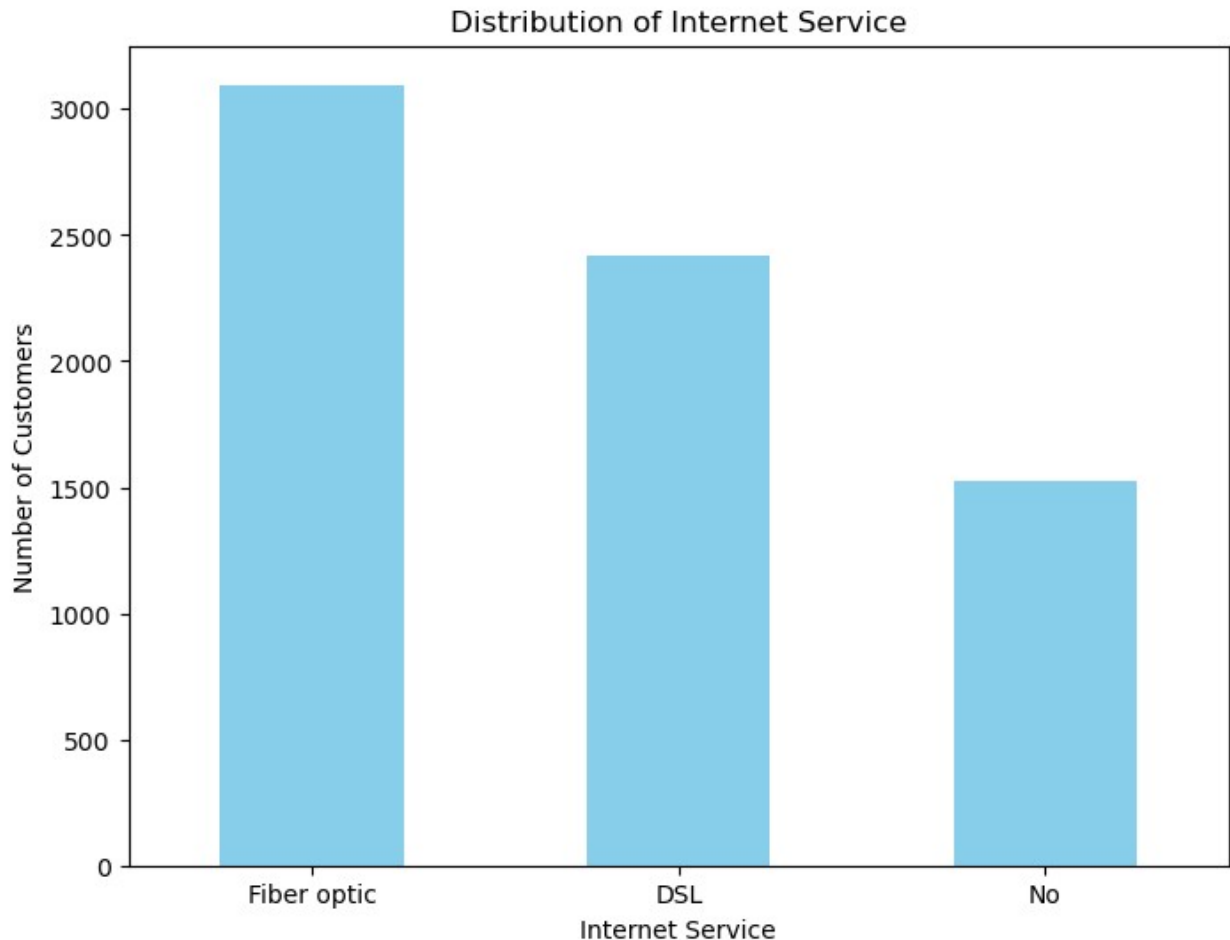
- Build a pie-chart to show the distribution of customers would be churning out
- Build a bar-plot to show the distribution of 'Internet Service'

```
import matplotlib.pyplot as plt
churn_distribution = df['Churn'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(churn_distribution, labels=churn_distribution.index,
autopct='%1.1f%%', startangle=140)
plt.title('Distribution of Customers Churning Out')
plt.axis('equal') # Equal aspect ratio ensures that pie is drawn as a
circle
plt.show()
```

```
# b. Build a bar-plot to show the distribution of 'Internet Service'
internet_service_distribution = df['InternetService'].value_counts()
plt.figure(figsize=(8, 6))
internet_service_distribution.plot(kind='bar', color='skyblue')
plt.title('Distribution of Internet Service')
plt.xlabel('Internet Service')
plt.ylabel('Number of Customers')
plt.xticks(rotation=0) # Rotate x-labels to avoid overlap
plt.show()
```

Distribution of Customers Churning Out





C) Model Building:

- a. Build a sequential model using Keras, to find out if the customer would churn or not, using 'tenure' as the feature and 'Churn' as the dependent/target column:
 - i. The visible/input layer should have 12 nodes with 'Relu' as activation function.
 - ii. This model would have 1 hidden layer with 8 nodes and 'Relu' as activation function
 - iii. Use 'Adam' as the optimization algorithm
 - iv. Fit the model on the train set, with number of epochs to be 150
 - v. Predict the values on the test set and build a confusion matrix
 - vi. Plot the 'Accuracy vs Epochs' graph

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense
from sklearn.metrics import confusion_matrix

X = df[['tenure']]
y = df['Churn'].map({'No': 0, 'Yes': 1}) # Map 'No' to 0 and 'Yes' to 1
```

1 for binary classification

Train-test split

```
X_train, X_test, y_train, y_test = train_test_split(X, y,  
test_size=0.2, random_state=42)
```

Feature scaling

```
scaler = StandardScaler()  
X_train_scaled = scaler.fit_transform(X_train)  
X_test_scaled = scaler.transform(X_test)
```

Build the sequential model

```
model = Sequential()  
model.add(Dense(12, input_dim=1, activation='relu')) # Input layer  
with 12 nodes and 'relu' activation function  
model.add(Dense(8, activation='relu')) # Hidden layer with 8 nodes  
and 'relu' activation function  
model.add(Dense(1, activation='sigmoid')) # Output layer with sigmoid  
activation function for binary classification
```

Compile the model

```
model.compile(loss='binary_crossentropy', optimizer='adam',  
metrics=['accuracy'])
```

Fit the model on the train set

```
history = model.fit(X_train_scaled, y_train, epochs=150,  
batch_size=10, verbose=1)  
y_pred = model.predict_classes(X_test_scaled)
```

Build a confusion matrix

```
conf_matrix = confusion_matrix(y_test, y_pred)  
print("Confusion Matrix:")  
print(conf_matrix)
```

Plot the 'Accuracy vs Epochs' graph

```
plt.plot(history.history['accuracy'])  
plt.title('Accuracy vs Epochs')  
plt.xlabel('Epochs')  
plt.ylabel('Accuracy')  
plt.show()
```

Epoch 1/150

```
564/564 [=====] - 0s 313us/step - loss:  
0.5556 - accuracy: 0.7345
```

Epoch 2/150

```
564/564 [=====] - 0s 301us/step - loss:  
0.5204 - accuracy: 0.7345
```

Epoch 3/150

```
564/564 [=====] - 0s 298us/step - loss:  
0.5163 - accuracy: 0.7345
```

```
Epoch 4/150
564/564 [=====] - 0s 297us/step - loss:
0.5146 - accuracy: 0.7345
Epoch 5/150
564/564 [=====] - 0s 297us/step - loss:
0.5140 - accuracy: 0.7345
Epoch 6/150
564/564 [=====] - 0s 296us/step - loss:
0.5132 - accuracy: 0.7345
Epoch 7/150
564/564 [=====] - 0s 297us/step - loss:
0.5130 - accuracy: 0.7345
Epoch 8/150
564/564 [=====] - 0s 296us/step - loss:
0.5127 - accuracy: 0.7352
Epoch 9/150
564/564 [=====] - 0s 297us/step - loss:
0.5123 - accuracy: 0.7467
Epoch 10/150
564/564 [=====] - 0s 296us/step - loss:
0.5121 - accuracy: 0.7457
Epoch 11/150
564/564 [=====] - 0s 296us/step - loss:
0.5122 - accuracy: 0.7492
Epoch 12/150
564/564 [=====] - 0s 295us/step - loss:
0.5113 - accuracy: 0.7512
Epoch 13/150
564/564 [=====] - 0s 296us/step - loss:
0.5111 - accuracy: 0.7533
Epoch 14/150
564/564 [=====] - 0s 297us/step - loss:
0.5108 - accuracy: 0.7512
Epoch 15/150
564/564 [=====] - 0s 297us/step - loss:
0.5111 - accuracy: 0.7503
Epoch 16/150
564/564 [=====] - 0s 296us/step - loss:
0.5108 - accuracy: 0.7528
Epoch 17/150
564/564 [=====] - 0s 297us/step - loss:
0.5111 - accuracy: 0.7538
Epoch 18/150
564/564 [=====] - 0s 296us/step - loss:
0.5108 - accuracy: 0.7522
Epoch 19/150
564/564 [=====] - 0s 297us/step - loss:
0.5106 - accuracy: 0.7513
Epoch 20/150
```



```
564/564 [=====] - 0s 297us/step - loss:
0.5104 - accuracy: 0.7501
Epoch 21/150
564/564 [=====] - 0s 296us/step - loss:
0.5106 - accuracy: 0.7512
Epoch 22/150
564/564 [=====] - 0s 297us/step - loss:
0.5105 - accuracy: 0.7528
Epoch 23/150
564/564 [=====] - 0s 304us/step - loss:
0.5106 - accuracy: 0.7517
Epoch 24/150
564/564 [=====] - 0s 304us/step - loss:
0.5104 - accuracy: 0.7531
Epoch 25/150
564/564 [=====] - 0s 299us/step - loss:
0.5101 - accuracy: 0.7551
Epoch 26/150
564/564 [=====] - 0s 295us/step - loss:
0.5101 - accuracy: 0.7506
Epoch 27/150
564/564 [=====] - 0s 296us/step - loss:
0.5102 - accuracy: 0.7531
Epoch 28/150
564/564 [=====] - 0s 295us/step - loss:
0.5102 - accuracy: 0.7512
Epoch 29/150
564/564 [=====] - 0s 296us/step - loss:
0.5101 - accuracy: 0.7496
Epoch 30/150
564/564 [=====] - 0s 301us/step - loss:
0.5099 - accuracy: 0.7535
Epoch 31/150
564/564 [=====] - 0s 294us/step - loss:
0.5102 - accuracy: 0.7513
Epoch 32/150
564/564 [=====] - 0s 299us/step - loss:
0.5099 - accuracy: 0.7524
Epoch 33/150
564/564 [=====] - 0s 302us/step - loss:
0.5097 - accuracy: 0.7512
Epoch 34/150
564/564 [=====] - 0s 303us/step - loss:
0.5100 - accuracy: 0.7519
Epoch 35/150
564/564 [=====] - 0s 297us/step - loss:
0.5095 - accuracy: 0.7519
Epoch 36/150
564/564 [=====] - 0s 296us/step - loss:
```

```
0.5106 - accuracy: 0.7506
Epoch 37/150
564/564 [=====] - 0s 295us/step - loss:
0.5093 - accuracy: 0.7519
Epoch 38/150
564/564 [=====] - 0s 296us/step - loss:
0.5100 - accuracy: 0.7522
Epoch 39/150
564/564 [=====] - 0s 295us/step - loss:
0.5094 - accuracy: 0.7540
Epoch 40/150
564/564 [=====] - 0s 303us/step - loss:
0.5097 - accuracy: 0.7531
Epoch 41/150
564/564 [=====] - 0s 296us/step - loss:
0.5100 - accuracy: 0.7526
Epoch 42/150
564/564 [=====] - 0s 296us/step - loss:
0.5093 - accuracy: 0.7524
Epoch 43/150
564/564 [=====] - 0s 296us/step - loss:
0.5096 - accuracy: 0.7506
Epoch 44/150
564/564 [=====] - 0s 295us/step - loss:
0.5094 - accuracy: 0.7540
Epoch 45/150
564/564 [=====] - 0s 298us/step - loss:
0.5092 - accuracy: 0.7515
Epoch 46/150
564/564 [=====] - 0s 297us/step - loss:
0.5098 - accuracy: 0.7522
Epoch 47/150
564/564 [=====] - 0s 296us/step - loss:
0.5095 - accuracy: 0.7506
Epoch 48/150
564/564 [=====] - 0s 296us/step - loss:
0.5097 - accuracy: 0.7526
Epoch 49/150
564/564 [=====] - 0s 296us/step - loss:
0.5095 - accuracy: 0.7524
Epoch 50/150
564/564 [=====] - 0s 296us/step - loss:
0.5093 - accuracy: 0.7520
Epoch 51/150
564/564 [=====] - 0s 295us/step - loss:
0.5095 - accuracy: 0.7526
Epoch 52/150
564/564 [=====] - 0s 310us/step - loss:
0.5091 - accuracy: 0.7538
```

```
Epoch 53/150
564/564 [=====] - 0s 297us/step - loss:
0.5093 - accuracy: 0.7545
Epoch 54/150
564/564 [=====] - 0s 296us/step - loss:
0.5093 - accuracy: 0.7499
Epoch 55/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7517
Epoch 56/150
564/564 [=====] - 0s 296us/step - loss:
0.5094 - accuracy: 0.7520
Epoch 57/150
564/564 [=====] - 0s 295us/step - loss:
0.5091 - accuracy: 0.7533
Epoch 58/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7519
Epoch 59/150
564/564 [=====] - 0s 296us/step - loss:
0.5092 - accuracy: 0.7542
Epoch 60/150
564/564 [=====] - 0s 296us/step - loss:
0.5091 - accuracy: 0.7513
Epoch 61/150
564/564 [=====] - 0s 296us/step - loss:
0.5092 - accuracy: 0.7506
Epoch 62/150
564/564 [=====] - 0s 295us/step - loss:
0.5092 - accuracy: 0.7512
Epoch 63/150
564/564 [=====] - 0s 295us/step - loss:
0.5090 - accuracy: 0.7515
Epoch 64/150
564/564 [=====] - 0s 307us/step - loss:
0.5090 - accuracy: 0.7547
Epoch 65/150
564/564 [=====] - 0s 297us/step - loss:
0.5088 - accuracy: 0.7528
Epoch 66/150
564/564 [=====] - 0s 297us/step - loss:
0.5092 - accuracy: 0.7526
Epoch 67/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7551
Epoch 68/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7529
Epoch 69/150
```

```
564/564 [=====] - 0s 296us/step - loss:
0.5091 - accuracy: 0.7526
Epoch 70/150
564/564 [=====] - 0s 296us/step - loss:
0.5094 - accuracy: 0.7490
Epoch 71/150
564/564 [=====] - 0s 302us/step - loss:
0.5090 - accuracy: 0.7519
Epoch 72/150
564/564 [=====] - 0s 297us/step - loss:
0.5090 - accuracy: 0.7517
Epoch 73/150
564/564 [=====] - 0s 297us/step - loss:
0.5091 - accuracy: 0.7512
Epoch 74/150
564/564 [=====] - 0s 303us/step - loss:
0.5090 - accuracy: 0.7533
Epoch 75/150
564/564 [=====] - 0s 299us/step - loss:
0.5089 - accuracy: 0.7547
Epoch 76/150
564/564 [=====] - 0s 297us/step - loss:
0.5087 - accuracy: 0.7533
Epoch 77/150
564/564 [=====] - 0s 297us/step - loss:
0.5091 - accuracy: 0.7528
Epoch 78/150
564/564 [=====] - 0s 297us/step - loss:
0.5089 - accuracy: 0.7503
Epoch 79/150
564/564 [=====] - 0s 296us/step - loss:
0.5090 - accuracy: 0.7536
Epoch 80/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7535
Epoch 81/150
564/564 [=====] - 0s 296us/step - loss:
0.5090 - accuracy: 0.7526
Epoch 82/150
564/564 [=====] - 0s 296us/step - loss:
0.5089 - accuracy: 0.7526
Epoch 83/150
564/564 [=====] - 0s 296us/step - loss:
0.5088 - accuracy: 0.7545
Epoch 84/150
564/564 [=====] - 0s 296us/step - loss:
0.5094 - accuracy: 0.7524
Epoch 85/150
564/564 [=====] - 0s 297us/step - loss:
```

```
0.5085 - accuracy: 0.7522
Epoch 86/150
564/564 [=====] - 0s 295us/step - loss:
0.5087 - accuracy: 0.7536
Epoch 87/150
564/564 [=====] - 0s 296us/step - loss:
0.5085 - accuracy: 0.7552
Epoch 88/150
564/564 [=====] - 0s 296us/step - loss:
0.5086 - accuracy: 0.7535
Epoch 89/150
564/564 [=====] - 0s 298us/step - loss:
0.5089 - accuracy: 0.7499
Epoch 90/150
564/564 [=====] - 0s 297us/step - loss:
0.5089 - accuracy: 0.7528
Epoch 91/150
564/564 [=====] - 0s 297us/step - loss:
0.5091 - accuracy: 0.7517
Epoch 92/150
564/564 [=====] - 0s 297us/step - loss:
0.5086 - accuracy: 0.7517
Epoch 93/150
564/564 [=====] - 0s 296us/step - loss:
0.5088 - accuracy: 0.7528
Epoch 94/150
564/564 [=====] - 0s 297us/step - loss:
0.5088 - accuracy: 0.7545
Epoch 95/150
564/564 [=====] - 0s 297us/step - loss:
0.5089 - accuracy: 0.7515
Epoch 96/150
564/564 [=====] - 0s 297us/step - loss:
0.5089 - accuracy: 0.7535
Epoch 97/150
564/564 [=====] - 0s 297us/step - loss:
0.5093 - accuracy: 0.7531
Epoch 98/150
564/564 [=====] - 0s 298us/step - loss:
0.5089 - accuracy: 0.7524
Epoch 99/150
564/564 [=====] - 0s 300us/step - loss:
0.5089 - accuracy: 0.7504
Epoch 100/150
564/564 [=====] - 0s 297us/step - loss:
0.5089 - accuracy: 0.7528
Epoch 101/150
564/564 [=====] - 0s 299us/step - loss:
0.5088 - accuracy: 0.7533
```

```
Epoch 102/150
564/564 [=====] - 0s 298us/step - loss:
0.5087 - accuracy: 0.7529
Epoch 103/150
564/564 [=====] - 0s 297us/step - loss:
0.5090 - accuracy: 0.7519
Epoch 104/150
564/564 [=====] - 0s 299us/step - loss:
0.5091 - accuracy: 0.7526
Epoch 105/150
564/564 [=====] - 0s 299us/step - loss:
0.5087 - accuracy: 0.7552
Epoch 106/150
564/564 [=====] - 0s 298us/step - loss:
0.5088 - accuracy: 0.7519
Epoch 107/150
564/564 [=====] - 0s 298us/step - loss:
0.5086 - accuracy: 0.7517
Epoch 108/150
564/564 [=====] - 0s 297us/step - loss:
0.5088 - accuracy: 0.7545
Epoch 109/150
564/564 [=====] - 0s 298us/step - loss:
0.5088 - accuracy: 0.7524
Epoch 110/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7494
Epoch 111/150
564/564 [=====] - 0s 299us/step - loss:
0.5086 - accuracy: 0.7528
Epoch 112/150
564/564 [=====] - 0s 298us/step - loss:
0.5089 - accuracy: 0.7529
Epoch 113/150
564/564 [=====] - 0s 299us/step - loss:
0.5090 - accuracy: 0.7522
Epoch 114/150
564/564 [=====] - 0s 298us/step - loss:
0.5090 - accuracy: 0.7531
Epoch 115/150
564/564 [=====] - 0s 299us/step - loss:
0.5091 - accuracy: 0.7520
Epoch 116/150
564/564 [=====] - 0s 299us/step - loss:
0.5091 - accuracy: 0.7504
Epoch 117/150
564/564 [=====] - 0s 299us/step - loss:
0.5087 - accuracy: 0.7503
Epoch 118/150
```

```
564/564 [=====] - 0s 299us/step - loss:
0.5086 - accuracy: 0.7519
Epoch 119/150
564/564 [=====] - 0s 300us/step - loss:
0.5091 - accuracy: 0.7529
Epoch 120/150
564/564 [=====] - 0s 308us/step - loss:
0.5088 - accuracy: 0.7538
Epoch 121/150
564/564 [=====] - 0s 299us/step - loss:
0.5088 - accuracy: 0.7536
Epoch 122/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7503
Epoch 123/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7528
Epoch 124/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7547
Epoch 125/150
564/564 [=====] - 0s 293us/step - loss:
0.5085 - accuracy: 0.7529
Epoch 126/150
564/564 [=====] - 0s 304us/step - loss:
0.5086 - accuracy: 0.7522
Epoch 127/150
564/564 [=====] - 0s 304us/step - loss:
0.5091 - accuracy: 0.7504
Epoch 128/150
564/564 [=====] - 0s 305us/step - loss:
0.5086 - accuracy: 0.7515
Epoch 129/150
564/564 [=====] - 0s 300us/step - loss:
0.5085 - accuracy: 0.7543
Epoch 130/150
564/564 [=====] - 0s 300us/step - loss:
0.5086 - accuracy: 0.7504
Epoch 131/150
564/564 [=====] - 0s 300us/step - loss:
0.5090 - accuracy: 0.7533
Epoch 132/150
564/564 [=====] - 0s 300us/step - loss:
0.5086 - accuracy: 0.7552
Epoch 133/150
564/564 [=====] - 0s 311us/step - loss:
0.5088 - accuracy: 0.7529
Epoch 134/150
564/564 [=====] - 0s 301us/step - loss:
```

```
0.5089 - accuracy: 0.7531
Epoch 135/150
564/564 [=====] - 0s 300us/step - loss:
0.5085 - accuracy: 0.7547
Epoch 136/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7529
Epoch 137/150
564/564 [=====] - 0s 299us/step - loss:
0.5093 - accuracy: 0.7512
Epoch 138/150
564/564 [=====] - 0s 300us/step - loss:
0.5087 - accuracy: 0.7517
Epoch 139/150
564/564 [=====] - 0s 300us/step - loss:
0.5090 - accuracy: 0.7538
Epoch 140/150
564/564 [=====] - 0s 300us/step - loss:
0.5090 - accuracy: 0.7540
Epoch 141/150
564/564 [=====] - 0s 300us/step - loss:
0.5084 - accuracy: 0.7547
Epoch 142/150
564/564 [=====] - 0s 299us/step - loss:
0.5088 - accuracy: 0.7517
Epoch 143/150
564/564 [=====] - 0s 299us/step - loss:
0.5086 - accuracy: 0.7520
Epoch 144/150
564/564 [=====] - 0s 311us/step - loss:
0.5084 - accuracy: 0.7549
Epoch 145/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7547
Epoch 146/150
564/564 [=====] - 0s 299us/step - loss:
0.5089 - accuracy: 0.7515
Epoch 147/150
564/564 [=====] - 0s 302us/step - loss:
0.5092 - accuracy: 0.7513
Epoch 148/150
564/564 [=====] - 0s 300us/step - loss:
0.5087 - accuracy: 0.7519
Epoch 149/150
564/564 [=====] - 0s 300us/step - loss:
0.5086 - accuracy: 0.7533
Epoch 150/150
564/564 [=====] - 0s 300us/step - loss:
0.5088 - accuracy: 0.7538
```



```
-----  
-----  
AttributeError                                Traceback (most recent call  
last)  
Cell In[16], line 23  
    21 # Fit the model on the train set  
    22 history = model.fit(X_train_scaled, y_train, epochs=150,  
batch_size=10, verbose=1)  
--> 23 y_pred = model.predict_classes(X_test_scaled)  
    25 # Build a confusion matrix  
    26 conf_matrix = confusion_matrix(y_test, y_pred)  
  
AttributeError: 'Sequential' object has no attribute 'predict_classes'  
  
plt.plot(history.history['accuracy'])  
plt.title('Accuracy vs Epochs')  
plt.xlabel('Epochs')  
plt.ylabel('Accuracy')  
plt.show()
```

