churn-prediction-using-ann

January 31, 2024

[2]:
```python
#imports necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

[3]:
```python
df = pd.read_csv('/kaggle/input/churndata/Churn_Modelling.csv')
df.head()
```

[3]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

[4]:
```python
df.shape
```

[4]:
```
(10000, 14)
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

[6]:
```
df.describe()
```

[6]:
```
         RowNumber    CustomerId   CreditScore           Age        Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000  10000.000000
mean    5000.50000  1.569094e+07    650.528800     38.921800      5.012800
std     2886.89568  7.193619e+04     96.653299     10.487806      2.892174
min        1.00000  1.556570e+07    350.000000     18.000000      0.000000
25%     2500.75000  1.562853e+07    584.000000     32.000000      3.000000
50%     5000.50000  1.569074e+07    652.000000     37.000000      5.000000
75%     7500.25000  1.575323e+07    718.000000     44.000000      7.000000
max    10000.00000  1.581569e+07    850.000000     92.000000     10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.530200      0.70550        0.515100
std     62397.405202       0.581654      0.45584        0.499797
min         0.000000       1.000000      0.00000        0.000000
25%         0.000000       1.000000      0.00000        0.000000
50%     97198.540000       1.000000      1.00000        1.000000
75%    127644.240000       2.000000      1.00000        1.000000
max    250898.090000       4.000000      1.00000        1.000000

       EstimatedSalary        Exited
```

```
count     10000.000000  10000.000000
mean     100090.239881      0.203700
std       57510.492818      0.402769
min          11.580000      0.000000
25%       51002.110000      0.000000
50%      100193.915000      0.000000
75%      149388.247500      0.000000
max      199992.480000      1.000000
```

[7]:
```
df.isnull().sum()
```

[7]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

[8]:
```
df.isnull().any().any()
```

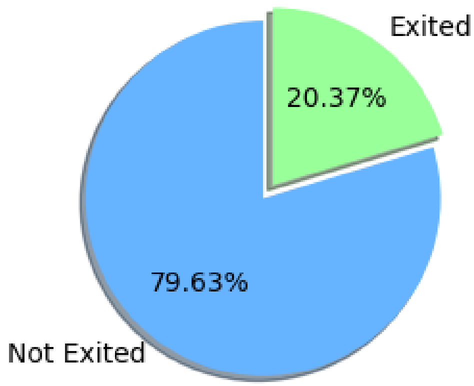
[8]:
```
False
```

[9]:
```
df.columns
```

[9]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

[10]:
```
values = df['Exited'].value_counts()
labels = ['Not Exited', 'Exited']
colors = ['#66b3ff', '#99ff99']

fig, ax = plt.subplots(figsize=(4, 3), dpi=100)
ax.pie(values, labels=labels, autopct='%1.2f%%', startangle=90, explode=(0, 0.
 ↪09), colors=colors, shadow=True)
plt.show()
```



20% of the customers have churned and 80% haven't.

[11]:
```
# visualizing categorical variables
fig, ax = plt.subplots(3, 2, figsize=(18, 15))
colors = ['#66b3ff', '#99ff99']

sns.countplot(x='Geography', hue='Exited', data=df, ax=ax[0][0], palette=colors)
sns.countplot(x='Gender', hue='Exited', data=df, ax=ax[0][1], palette=colors)
sns.countplot(x='Tenure', hue='Exited', data=df, ax=ax[1][0], palette=colors)
sns.countplot(x='NumOfProducts', hue='Exited', data=df, ax=ax[1][1],␣
 ↪palette=colors)
sns.countplot(x='HasCrCard', hue='Exited', data=df, ax=ax[2][0], palette=colors)
sns.countplot(x='IsActiveMember', hue='Exited', data=df, ax=ax[2][1],␣
 ↪palette=colors)

plt.tight_layout()
plt.show()
```

0.0.1 Based on the plots above, we can determine that:-

The bulk of the clients are from France, but the majority of those that have left are from Germany, possibly as a result of resource shortages brought on by the small client base.

In addition, a higher percentage of female customers are leaving than male customers.

The majority of clients have tenures ranging from 1 to 9, and the rate of attrition is high in between.

The majority of customers own one or two products, and the majority of those that have churned have only one product—possibly because they were dissatisfied and wanted something else.

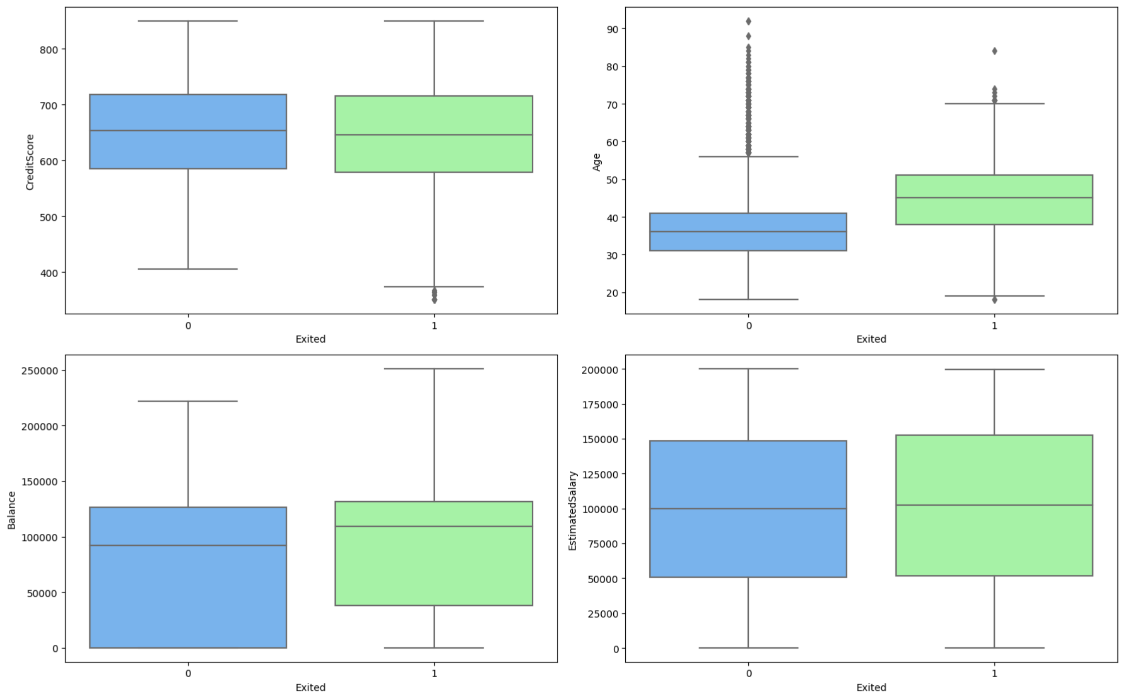
It's interesting to note that most of the customers who churned had credit cards, though this could just be a coincidence given that most customers do.

It should come as no surprise that there is a higher turnover rate among inactive members, with a relatively high percentage overall.

[12]:
```
fig, ax = plt.subplots(2, 2, figsize=(16, 10))
colors = ['#66b3ff', '#99ff99']
```

```
sns.boxplot(x='Exited', y='CreditScore', data=df, ax=ax[0][0], palette=colors)
sns.boxplot(x='Exited', y='Age', data=df, ax=ax[0][1], palette=colors)
sns.boxplot(x='Exited', y='Balance', data=df, ax=ax[1][0], palette=colors)
sns.boxplot(x='Exited', y='EstimatedSalary', data=df, ax=ax[1][1],␣
↪palette=colors)

plt.tight_layout()
plt.show()
```



0.0.2 Based on the plots above, we can determine that:

The distribution of credit scores does not significantly differ between customers who experience churning and those who do not.

More elderly clients are leaving than new ones.

The bank is losing clients who have sizable balances.

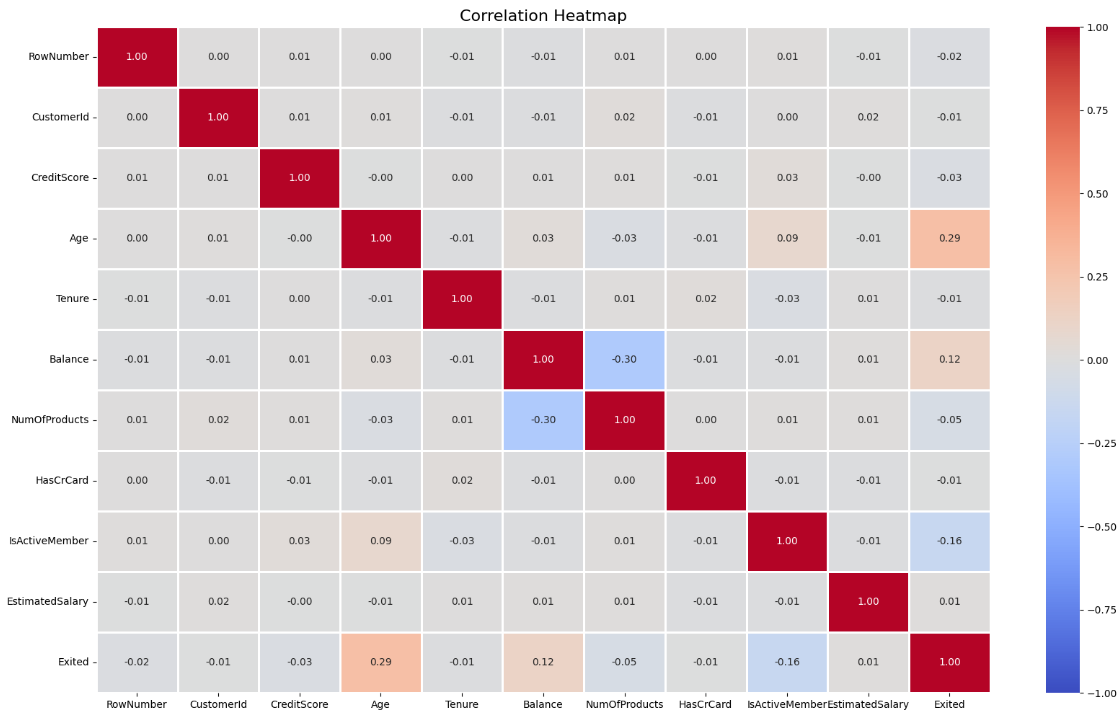
The chance of churn is not significantly impacted by estimated salary.

It's interesting to note that most of the customers who churned had credit cards, though this could just be a coincidence given that most customers do.

It should come as no surprise that there is a higher turnover rate among inactive members, with a relatively high percentage overall.

[13]:
```python
#Heatmap
numeric_df = df.select_dtypes(include=['float64', 'int64'])
plt.figure(figsize=(20, 12))
corr = numeric_df.corr()
sns.heatmap(corr, linewidths=1, annot=True, fmt=".2f", cmap='coolwarm',␣
 ↪vmin=-1, vmax=1)

plt.title('Correlation Heatmap', fontsize=16)
plt.show()
```



[14]:
```python
# dropping useless columns
df.drop(columns = ['RowNumber', 'CustomerId', 'Surname'], axis = 1, inplace =␣
 ↪True)
df.head()
```

[14]:
```
   CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0          619    France  Female   42       2       0.00              1
1          608     Spain  Female   41       1   83807.86              1
2          502    France  Female   42       8  159660.80              3
3          699    France  Female   39       1       0.00              2
4          850     Spain  Female   43       2  125510.82              1

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          1               1        101348.88       1
```

```
1          0              1        112542.58       0
2          1              0        113931.57       1
3          0              0         93826.63       0
4          1              1         79084.10       0
```

[15]:
```
df.Geography.value_counts()
```

[15]:
```
Geography
France     5014
Germany    2509
Spain      2477
Name: count, dtype: int64
```

[16]:
```
# Encoding categorical variables

df['Geography'] = df['Geography'].map({'France' : 0, 'Germany' : 1, 'Spain' :
 ↪2})
df['Gender'] = df['Gender'].map({'Male' : 0, 'Female' : 1})
```

[17]:
```
df.head()
```

[17]:
```
   CreditScore  Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0          619          0       1   42       2       0.00              1
1          608          2       1   41       1   83807.86              1
2          502          0       1   42       8  159660.80              3
3          699          0       1   39       1       0.00              2
4          850          2       1   43       2  125510.82              1

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          1               1        101348.88       1
1          0               1        112542.58       0
2          1               0        113931.57       1
3          0               0         93826.63       0
4          1               1         79084.10       0
```

[18]:
```
# creating features and label
from tensorflow.keras.utils import to_categorical

X = df.drop('Exited', axis = 1)
y = to_categorical(df.Exited)
```

```
2024-01-31 14:54:56.471769: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-01-31 14:54:56.471908: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register
```

```
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-01-31 14:54:56.667096: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
```

[19]:
```python
# splitting data into training set and test set

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

[20]:
```python
# Scaling data

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

[21]:
```python
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras.layers import BatchNormalization

# initializing ann
model = Sequential()

# adding the first input layer and the first hidden layer
model.add(Dense(10, kernel_initializer = 'normal', activation = 'relu',␣
 ↪input_shape = (10, )))

# adding batch normalization and dropout layer
model.add(Dropout(rate = 0.1))
model.add(BatchNormalization())

# adding the third hidden layer
model.add(Dense(7, kernel_initializer = 'normal', activation = 'relu'))

# adding batch normalization and dropout layer
model.add(Dropout(rate = 0.1))
model.add(BatchNormalization())

# adding the output layer
model.add(Dense(2, kernel_initializer = 'normal', activation = 'sigmoid'))

# compiling the model
```

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

# fitting the model to the training set

model_history = model.fit(X_train, y_train, validation_split = 0.20,
    validation_data = (X_test, y_test), epochs = 50)
```

```
Epoch 1/50
250/250 [==============================] - 3s 4ms/step - loss: 0.6020 -
accuracy: 0.7237 - val_loss: 0.5272 - val_accuracy: 0.7990
Epoch 2/50
250/250 [==============================] - 1s 3ms/step - loss: 0.4278 -
accuracy: 0.8234 - val_loss: 0.3874 - val_accuracy: 0.8460
Epoch 3/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3868 -
accuracy: 0.8389 - val_loss: 0.3609 - val_accuracy: 0.8515
Epoch 4/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3805 -
accuracy: 0.8421 - val_loss: 0.3608 - val_accuracy: 0.8500
Epoch 5/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3764 -
accuracy: 0.8438 - val_loss: 0.3593 - val_accuracy: 0.8520
Epoch 6/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3804 -
accuracy: 0.8380 - val_loss: 0.3596 - val_accuracy: 0.8495
Epoch 7/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3713 -
accuracy: 0.8476 - val_loss: 0.3620 - val_accuracy: 0.8490
Epoch 8/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3726 -
accuracy: 0.8469 - val_loss: 0.3636 - val_accuracy: 0.8510
Epoch 9/50
250/250 [==============================] - 1s 4ms/step - loss: 0.3722 -
accuracy: 0.8434 - val_loss: 0.3598 - val_accuracy: 0.8485
Epoch 10/50
250/250 [==============================] - 1s 4ms/step - loss: 0.3744 -
accuracy: 0.8487 - val_loss: 0.3607 - val_accuracy: 0.8500
Epoch 11/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3724 -
accuracy: 0.8464 - val_loss: 0.3586 - val_accuracy: 0.8490
Epoch 12/50
250/250 [==============================] - 1s 4ms/step - loss: 0.3667 -
accuracy: 0.8489 - val_loss: 0.3619 - val_accuracy: 0.8490
Epoch 13/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3683 -
accuracy: 0.8457 - val_loss: 0.3577 - val_accuracy: 0.8450
```

```
Epoch 14/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3678 -
accuracy: 0.8503 - val_loss: 0.3598 - val_accuracy: 0.8490
Epoch 15/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3705 -
accuracy: 0.8455 - val_loss: 0.3615 - val_accuracy: 0.8495
Epoch 16/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3725 -
accuracy: 0.8474 - val_loss: 0.3628 - val_accuracy: 0.8495
Epoch 17/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3673 -
accuracy: 0.8496 - val_loss: 0.3615 - val_accuracy: 0.8435
Epoch 18/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3679 -
accuracy: 0.8465 - val_loss: 0.3572 - val_accuracy: 0.8470
Epoch 19/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3714 -
accuracy: 0.8465 - val_loss: 0.3597 - val_accuracy: 0.8480
Epoch 20/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3689 -
accuracy: 0.8499 - val_loss: 0.3568 - val_accuracy: 0.8475
Epoch 21/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3663 -
accuracy: 0.8511 - val_loss: 0.3560 - val_accuracy: 0.8475
Epoch 22/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3693 -
accuracy: 0.8497 - val_loss: 0.3556 - val_accuracy: 0.8500
Epoch 23/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3662 -
accuracy: 0.8504 - val_loss: 0.3559 - val_accuracy: 0.8515
Epoch 24/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3680 -
accuracy: 0.8453 - val_loss: 0.3592 - val_accuracy: 0.8480
Epoch 25/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3680 -
accuracy: 0.8505 - val_loss: 0.3559 - val_accuracy: 0.8470
Epoch 26/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3642 -
accuracy: 0.8503 - val_loss: 0.3571 - val_accuracy: 0.8500
Epoch 27/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3645 -
accuracy: 0.8480 - val_loss: 0.3593 - val_accuracy: 0.8470
Epoch 28/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3673 -
accuracy: 0.8509 - val_loss: 0.3565 - val_accuracy: 0.8465
Epoch 29/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3689 -
accuracy: 0.8454 - val_loss: 0.3601 - val_accuracy: 0.8495
```

```
Epoch 30/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3616 -
accuracy: 0.8551 - val_loss: 0.3567 - val_accuracy: 0.8510
Epoch 31/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3639 -
accuracy: 0.8497 - val_loss: 0.3592 - val_accuracy: 0.8470
Epoch 32/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3645 -
accuracy: 0.8485 - val_loss: 0.3570 - val_accuracy: 0.8485
Epoch 33/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3647 -
accuracy: 0.8509 - val_loss: 0.3594 - val_accuracy: 0.8500
Epoch 34/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3622 -
accuracy: 0.8514 - val_loss: 0.3570 - val_accuracy: 0.8505
Epoch 35/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3683 -
accuracy: 0.8497 - val_loss: 0.3559 - val_accuracy: 0.8495
Epoch 36/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3634 -
accuracy: 0.8503 - val_loss: 0.3651 - val_accuracy: 0.8465
Epoch 37/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3637 -
accuracy: 0.8551 - val_loss: 0.3661 - val_accuracy: 0.8475
Epoch 38/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3660 -
accuracy: 0.8511 - val_loss: 0.3582 - val_accuracy: 0.8480
Epoch 39/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3637 -
accuracy: 0.8526 - val_loss: 0.3566 - val_accuracy: 0.8510
Epoch 40/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3642 -
accuracy: 0.8536 - val_loss: 0.3575 - val_accuracy: 0.8485
Epoch 41/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3614 -
accuracy: 0.8514 - val_loss: 0.3594 - val_accuracy: 0.8455
Epoch 42/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3646 -
accuracy: 0.8489 - val_loss: 0.3573 - val_accuracy: 0.8465
Epoch 43/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3596 -
accuracy: 0.8533 - val_loss: 0.3546 - val_accuracy: 0.8460
Epoch 44/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3676 -
accuracy: 0.8495 - val_loss: 0.3562 - val_accuracy: 0.8460
Epoch 45/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3626 -
accuracy: 0.8512 - val_loss: 0.3549 - val_accuracy: 0.8485
```

```
Epoch 46/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3630 -
accuracy: 0.8539 - val_loss: 0.3574 - val_accuracy: 0.8475
Epoch 47/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3623 -
accuracy: 0.8512 - val_loss: 0.3591 - val_accuracy: 0.8470
Epoch 48/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3608 -
accuracy: 0.8518 - val_loss: 0.3588 - val_accuracy: 0.8455
Epoch 49/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3661 -
accuracy: 0.8510 - val_loss: 0.3615 - val_accuracy: 0.8450
Epoch 50/50
250/250 [==============================] - 1s 3ms/step - loss: 0.3653 -
accuracy: 0.8533 - val_loss: 0.3586 - val_accuracy: 0.8480
```

[27]:

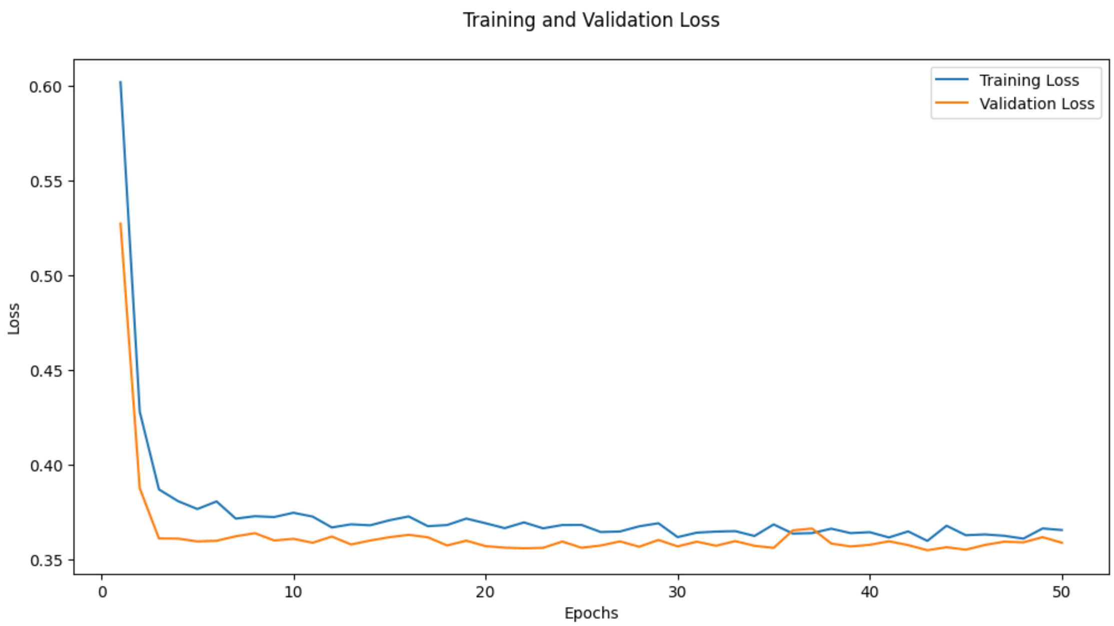
```
#Visualizing Training and Validation Loss

plt.figure(figsize=(12, 6))

train_loss = model_history.history['loss']
val_loss = model_history.history['val_loss']
epoch = range(1, 51)

sns.lineplot(x=epoch, y=train_loss, label='Training Loss')
sns.lineplot(x=epoch, y=val_loss, label='Validation Loss')

plt.title('Training and Validation Loss\n')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

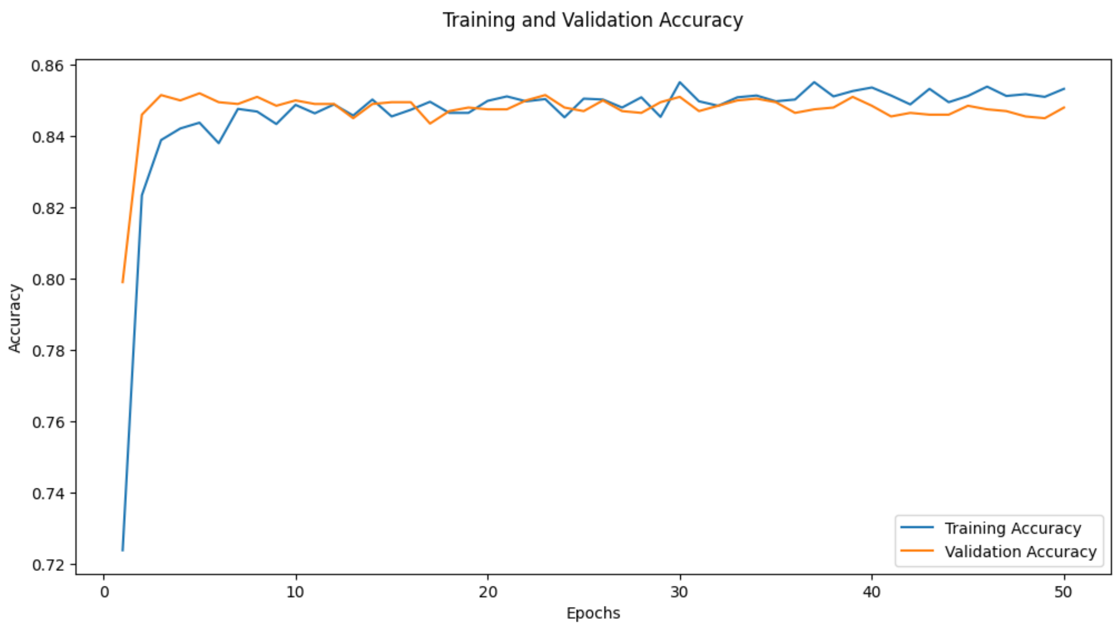


[30]:
```
# Visualizing Training and Validation accuracy
plt.figure(figsize=(12, 6))

train_accuracy = model_history.history['accuracy']
val_accuracy = model_history.history['val_accuracy']
epoch = range(1, 51)

sns.lineplot(x=epoch, y=train_accuracy, label='Training Accuracy')
sns.lineplot(x=epoch, y=val_accuracy, label='Validation Accuracy')

plt.title('Training and Validation Accuracy\n')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



[32]:

```python
from sklearn.metrics import classification_report

y_pred = model.predict(X_test)

# Convert the one-hot encoded predictions to class labels
y_pred_classes = np.argmax(y_pred, axis=1)
y_test_classes = np.argmax(y_test, axis=1)

# Calculate and print the classification report
print(classification_report(y_test_classes, y_pred_classes))
```

```
63/63 [==============================] - 0s 2ms/step
              precision    recall  f1-score   support

           0       0.86      0.97      0.91      1598
           1       0.76      0.36      0.48       402

    accuracy                           0.85      2000
   macro avg       0.81      0.66      0.70      2000
weighted avg       0.84      0.85      0.83      2000
```