Importing Libraries

In [3]:
```
# Import relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.style as style
# Import tensorflow
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
sns.set()
pd.set_option('max_columns', None)
```

Loading Dataset

In [6]:
```
# Load the dataset
df = pd.read_csv('BankChurners.csv')
```

In [7]:
```
# Take a first glimpse at the data
df.head()
```

Out[7]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income
0	768805383	Existing Customer	45	M	3	High School	Married	
1	818770008	Existing Customer	49	F	5	Graduate	Single	Less
2	713982108	Existing Customer	51	M	3	Graduate	Married	
3	769911858	Existing Customer	40	F	4	High School	Unknown	Less
4	709106358	Existing Customer	40	M	3	Uneducated	Married	

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
CLIENTNUM                   0
Attrition_Flag              0
Customer_Age                0
Gender                      0
Dependent_count             0
Education_Level             0
Marital_Status              0
Income_Category             0
Card_Category               0
Months_on_book              0
Total_Relationship_Count    0
Months_Inactive_12_mon      0
Contacts_Count_12_mon       0
Credit_Limit                0
Total_Revolving_Bal         0
Avg_Open_To_Buy             0
Total_Amt_Chng_Q4_Q1        0
Total_Trans_Amt             0
Total_Trans_Ct              0
Total_Ct_Chng_Q4_Q1         0
Avg_Utilization_Ratio       0
dtype: int64
```

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

Out[9]:
```
Index(['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio'],
      dtype='object')
```

EDA

In [10]:
```
# Explore the variables
df.describe(include =  'all')
```

Out[10]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status
count	1.012700e+04	10127	10127.000000	10127	10127.000000	10127	10127
unique	NaN	2	NaN	2	NaN	7	4
top	NaN	Existing Customer	NaN	F	NaN	Graduate	Married
freq	NaN	8500	NaN	5358	NaN	3128	4687
mean	7.391776e+08	NaN	46.325960	NaN	2.346203	NaN	NaN
std	3.690378e+07	NaN	8.016814	NaN	1.298908	NaN	NaN
min	7.080821e+08	NaN	26.000000	NaN	0.000000	NaN	NaN
25%	7.130368e+08	NaN	41.000000	NaN	1.000000	NaN	NaN
50%	7.179264e+08	NaN	46.000000	NaN	2.000000	NaN	NaN
75%	7.731435e+08	NaN	52.000000	NaN	3.000000	NaN	NaN
max	8.283431e+08	NaN	73.000000	NaN	5.000000	NaN	NaN

In [11]:
```
df['Education_Level'].value_counts()
```

Out[11]:
```
Graduate         3128
High School      2013
Unknown          1519
Uneducated       1487
College          1013
Post-Graduate     516
Doctorate         451
Name: Education_Level, dtype: int64
```

In [9]:
```
df['Marital_Status'].value_counts()
```

Out[9]:
```
Married     4687
Single      3943
Unknown      749
Divorced     748
Name: Marital_Status, dtype: int64
```

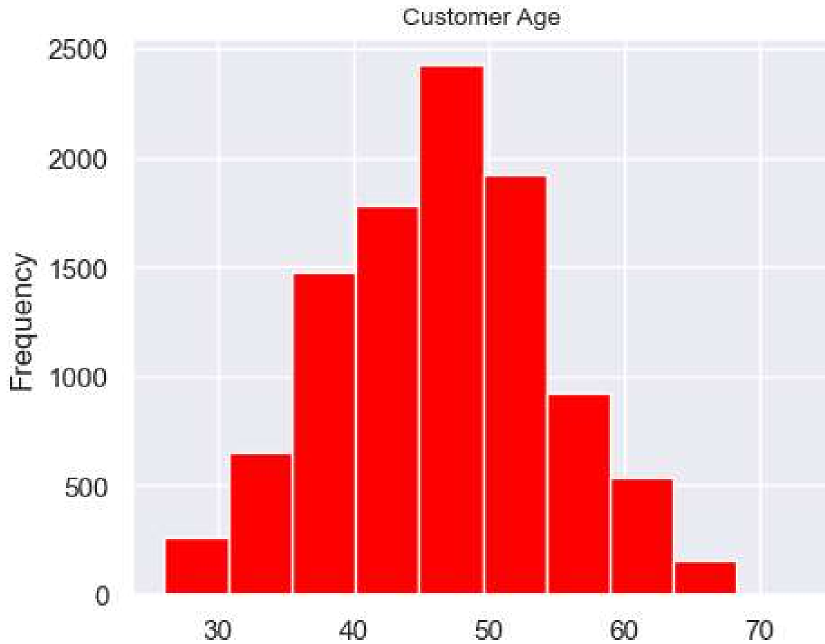
In [10]:
```
df['Income_Category'].value_counts()
```

Out[10]:
```
Less than $40K    3561
$40K - $60K       1790
$80K - $120K      1535
$60K - $80K       1402
Unknown           1112
$120K +            727
Name: Income_Category, dtype: int64
```

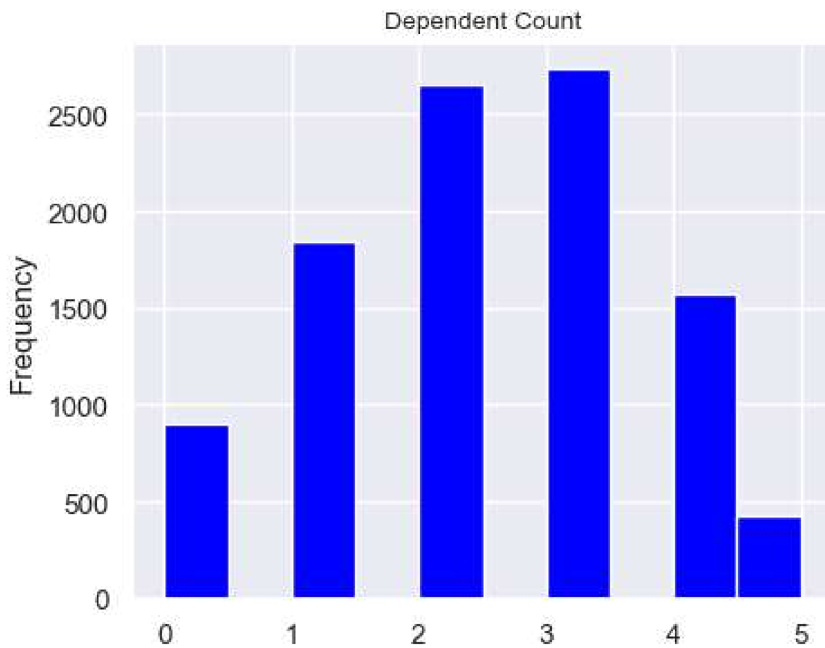
In [11]:
```
df['Card_Category'].value_counts()
```

Out[11]:
```
Blue        9436
Silver       555
Gold         116
Platinum      20
Name: Card_Category, dtype: int64
```

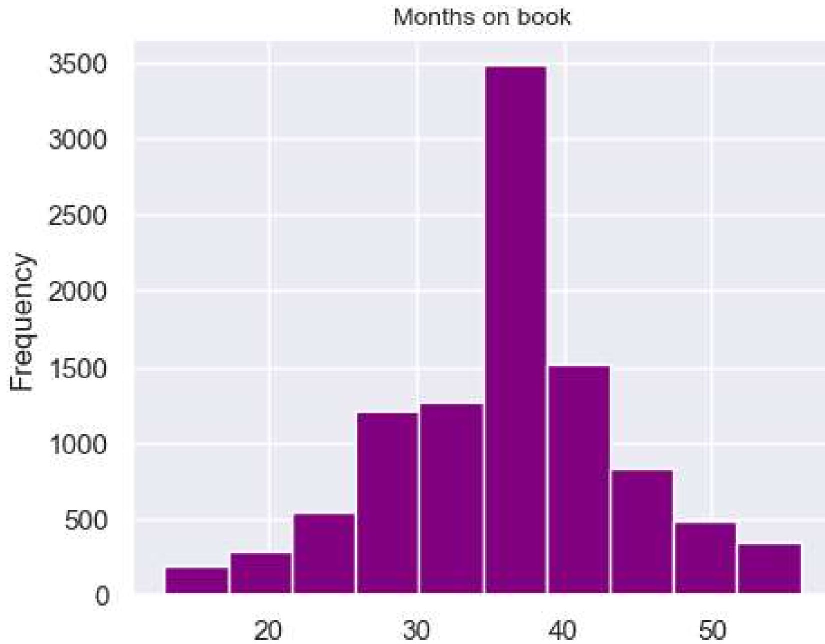
In [12]:
```
df['Customer_Age'].plot(kind = 'hist', figsize = (5, 4), color='red')
plt.title("Customer Age", size = 10)
plt.show()
```



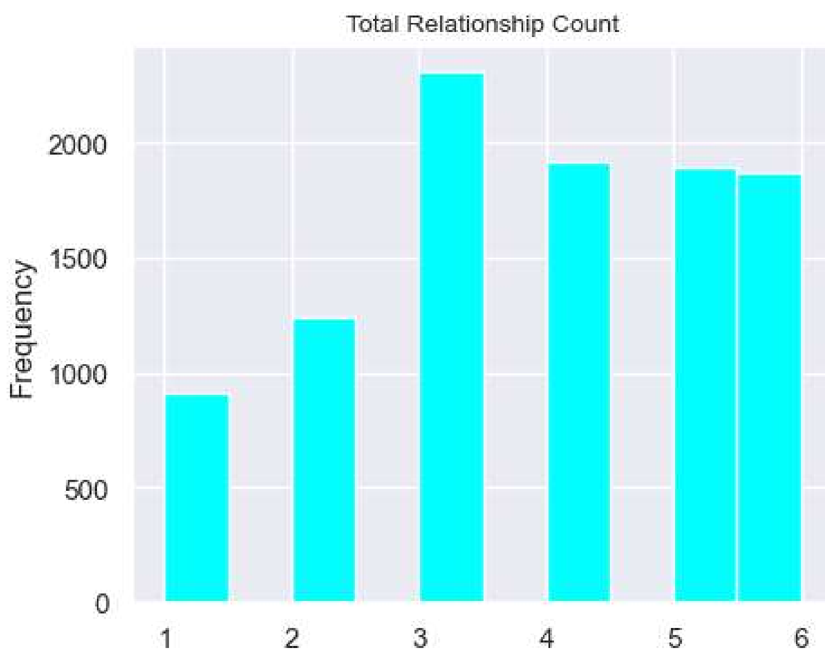
In [13]:
```
df['Dependent_count'].plot(kind = 'hist', figsize = (5, 4), color = 'blue')
plt.title("Dependent Count", size = 10)
plt.show()
```



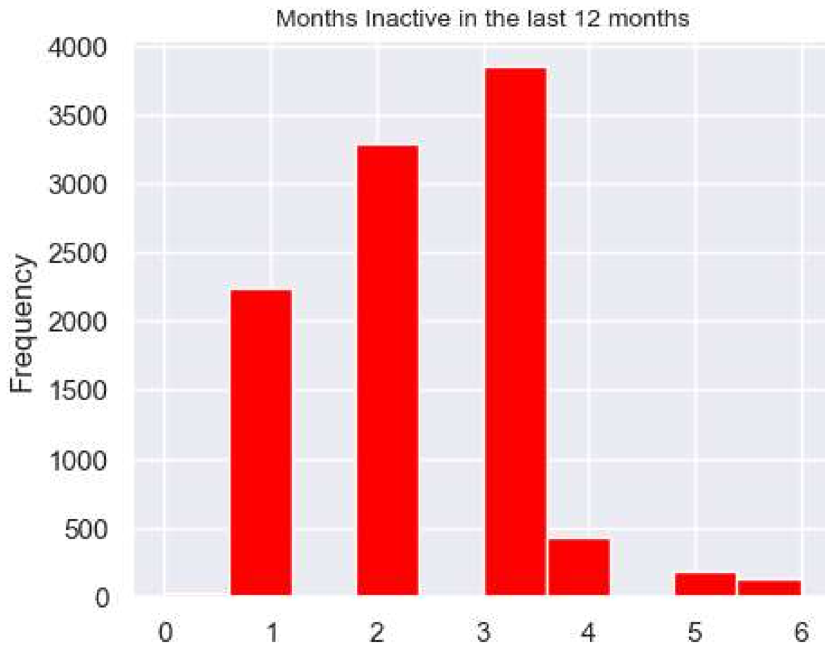
In [15]:
```
df['Months_on_book'].plot(kind = 'hist', figsize = (5, 4), color = 'purple')
plt.title("Months on book", size = 10)
plt.show()
```



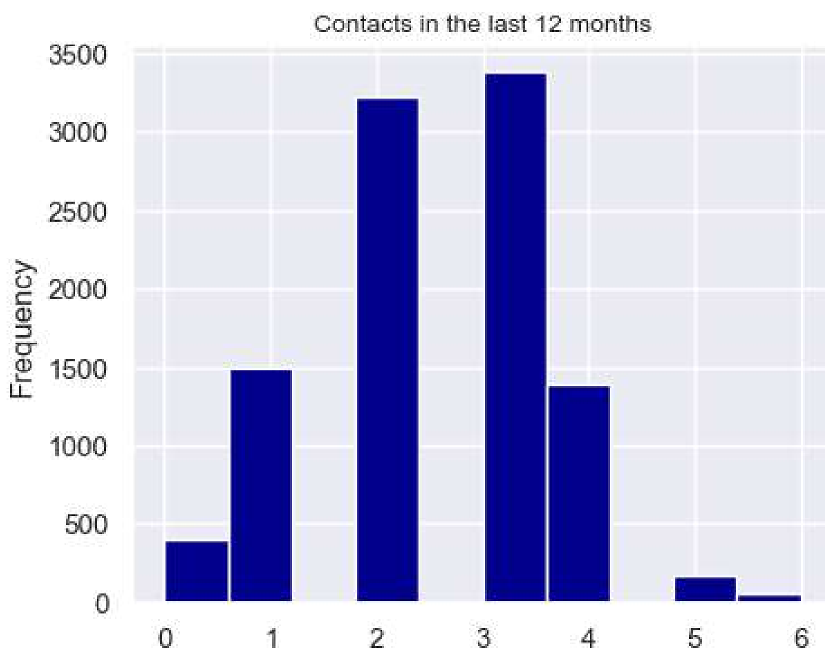
In [16]:
```
df['Total_Relationship_Count'].plot(kind = 'hist', figsize = (5, 4), color = 'cyan')
plt.title("Total Relationship Count", size = 10)
plt.show()
```



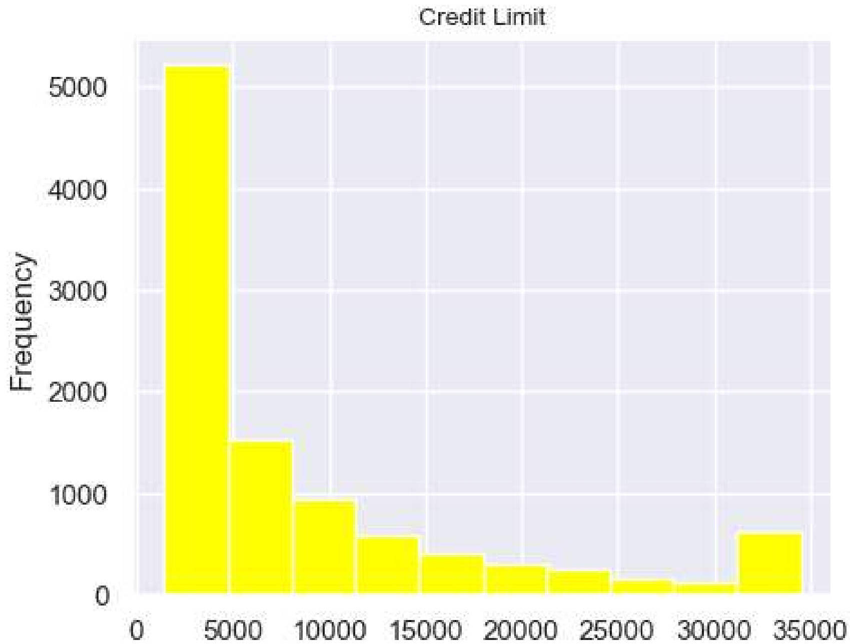
In [17]:
```
df['Months_Inactive_12_mon'].plot(kind = 'hist', figsize = (5, 4), color = 'red')
plt.title("Months Inactive in the last 12 months", size = 10)
plt.show()
```



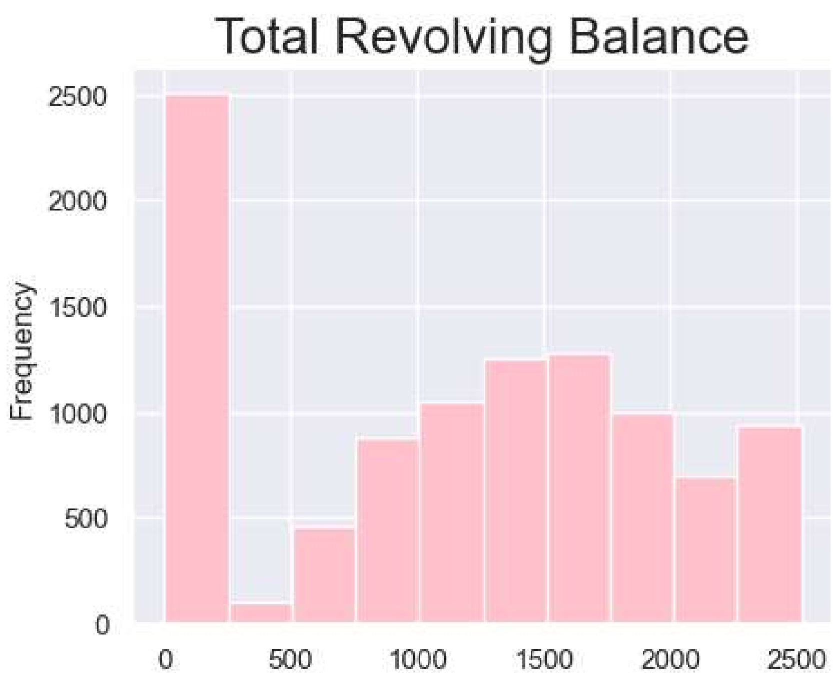
In [18]:
```
df['Contacts_Count_12_mon'].plot(kind = 'hist', figsize = (5, 4), color = 'darkblue')
plt.title("Contacts in the last 12 months", size = 10)
plt.show()
```



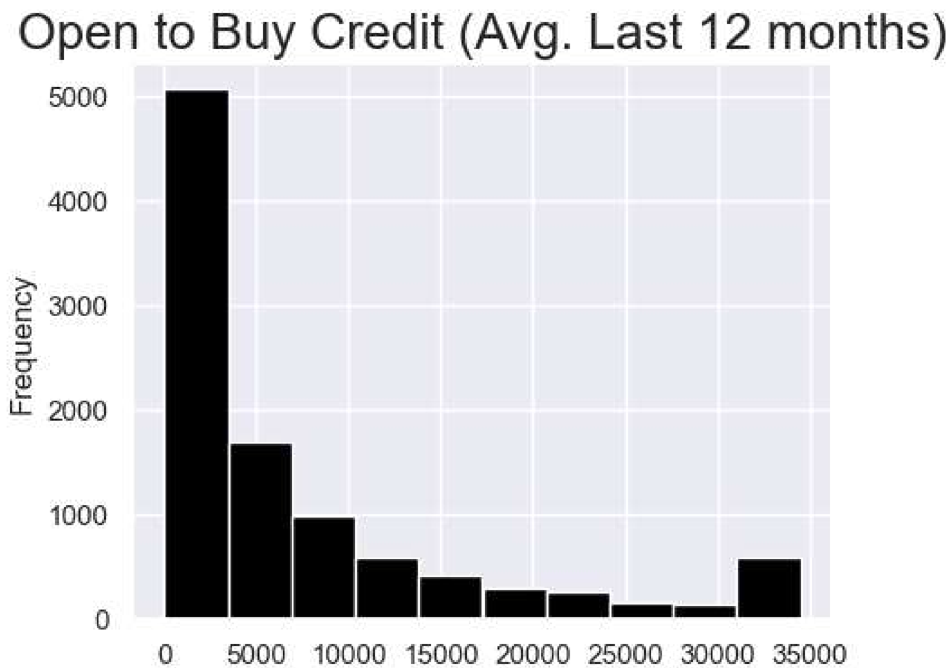
In [19]:
```
df['Credit_Limit'].plot(kind = 'hist', figsize = (5, 4), color = 'yellow')
plt.title("Credit Limit", size = 10)
plt.show()
```



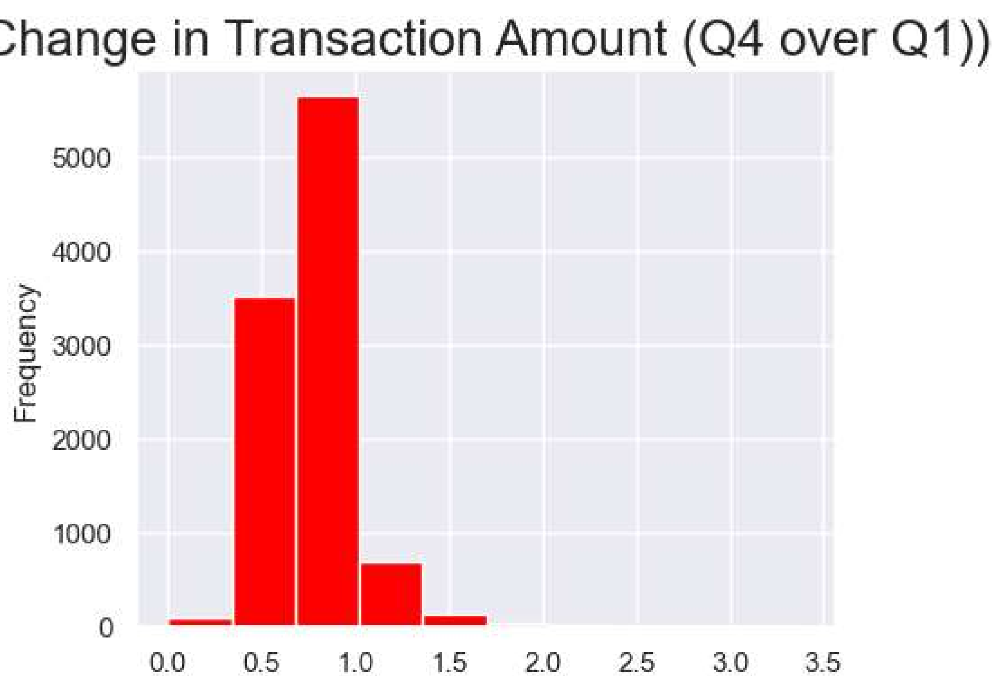
In [20]:
```
df['Total_Revolving_Bal'].plot(kind = 'hist', figsize = (5, 4), color = 'pink')
plt.title("Total Revolving Balance", size = 20)
plt.show()
```



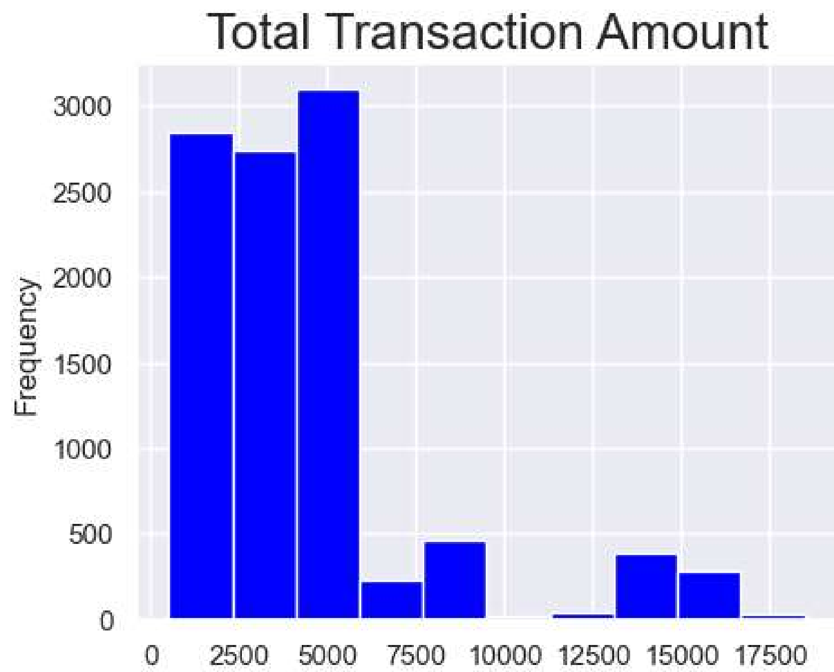
In [22]:
```
df['Avg_Open_To_Buy'].plot(kind = 'hist', figsize = (5, 4), color = 'black')
plt.title("Open to Buy Credit (Avg. Last 12 months)", size = 20)
plt.show()
```



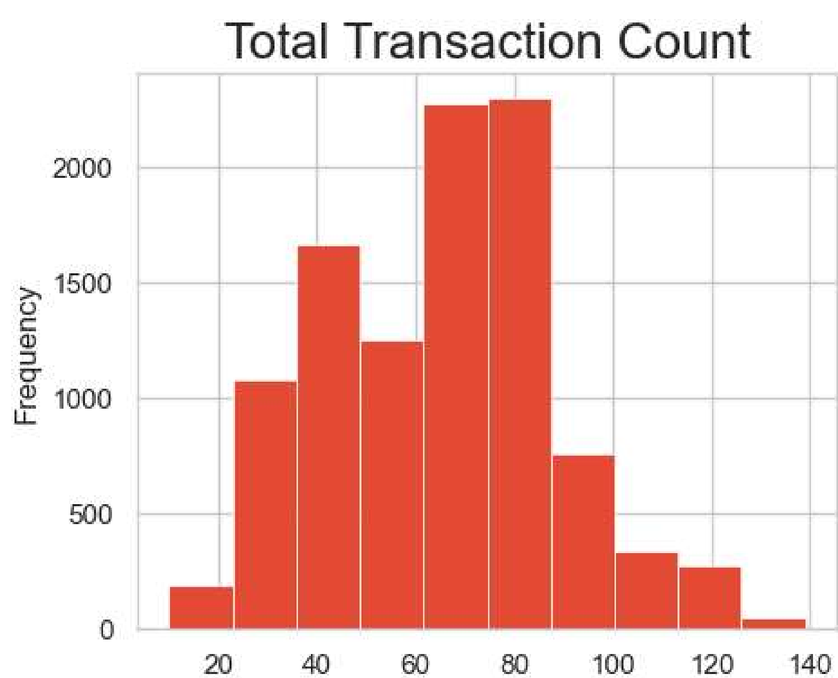
In [23]:
```
df['Total_Amt_Chng_Q4_Q1'].plot(kind = 'hist', figsize = (5, 4), color = 'red')
plt.title("Change in Transaction Amount (Q4 over Q1))", size = 20)
plt.show()
```



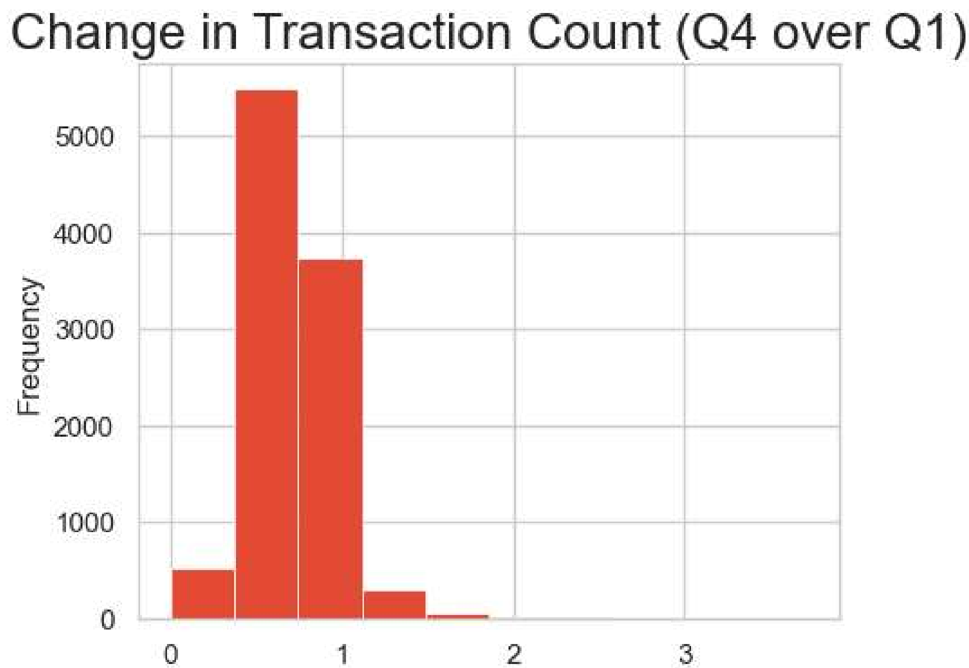
In [25]:
```
df['Total_Trans_Amt'].plot(kind = 'hist', figsize = (5, 4), color = 'blue')
plt.title("Total Transaction Amount", size = 20)
plt.show()
```



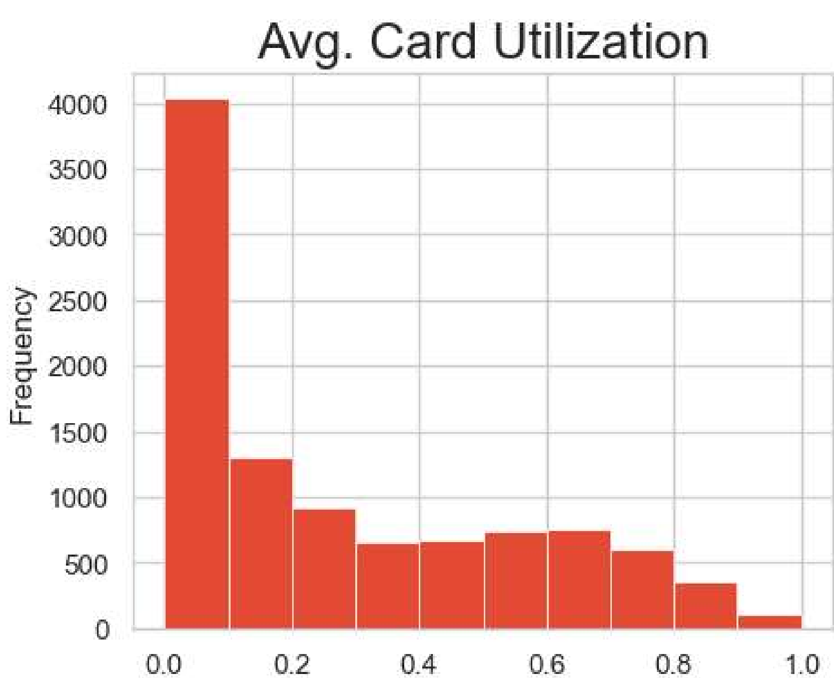
In [33]:
```
df['Total_Trans_Ct'].plot(kind = 'hist', figsize = (5, 4))
plt.title("Total Transaction Count", size = 20)
plt.show()
```



In [34]:
```
df['Total_Ct_Chng_Q4_Q1'].plot(kind = 'hist', figsize = (5, 4))
plt.title("Change in Transaction Count (Q4 over Q1)", size = 20)
plt.show()
```



In [78]:
```
df['Avg_Utilization_Ratio'].plot(kind = 'hist', figsize = (5, 4))
plt.title("Avg. Card Utilization", size = 20)
plt.show()
```

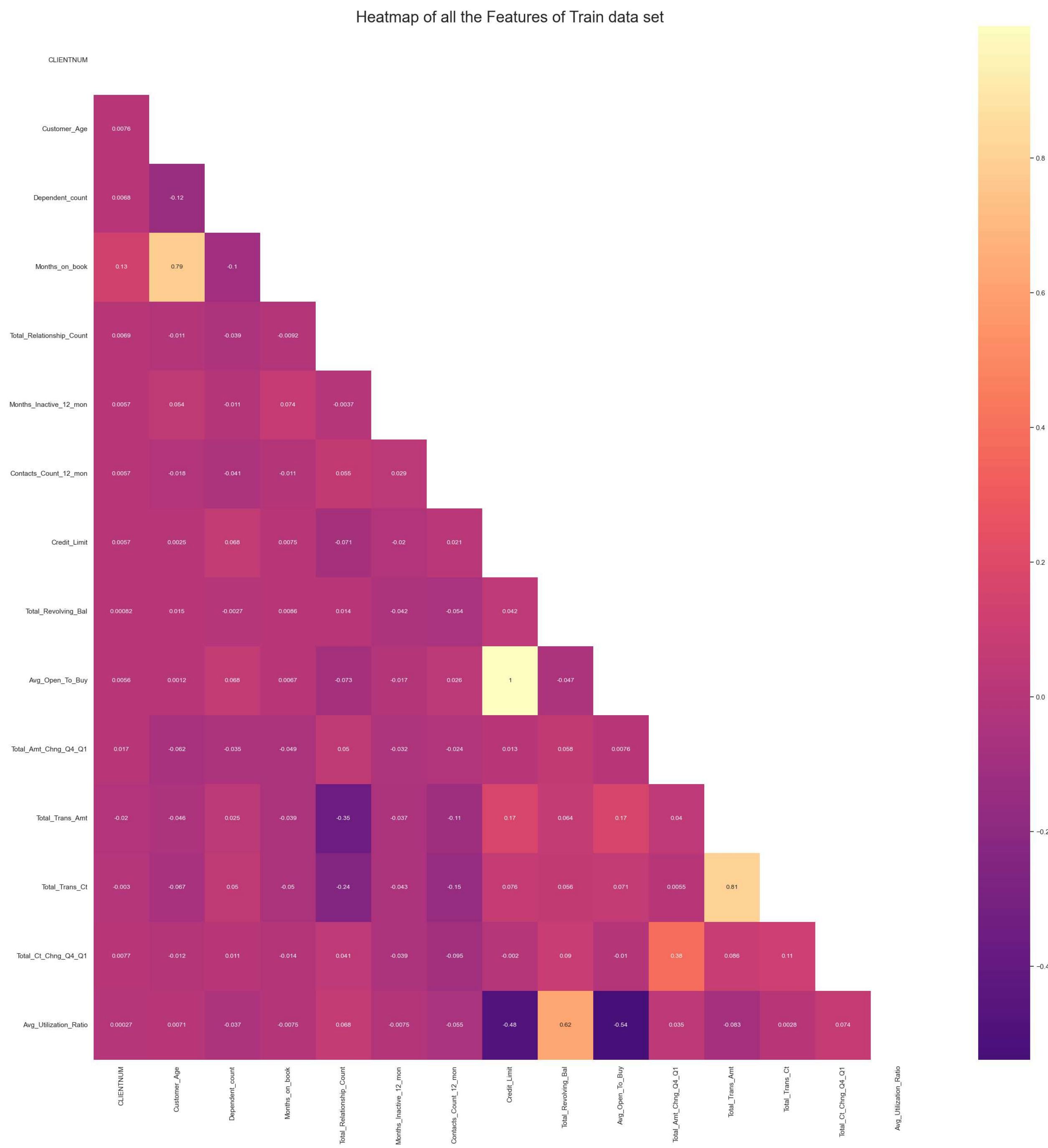


In [22]:
```
#Churn vs. normal
counts = df.Attrition_Flag.value_counts()
normal = counts[0]
Churn = counts[1]
perc_normal = (normal/(normal+Churn))*100
perc_Churn = (Churn/(normal+Churn))*100
print('There were {} non-Churn ({:.3f}%) and {} Churn ({:.3f}%).'.format(normal, perc_norma
```

```
There were 8500 non-Churn (83.934%) and 1627 Churn (16.066%).
```

In [28]:
```
style.use('ggplot')
sns.set_style('whitegrid')
plt.subplots(figsize = (30,30))
## Plotting heatmap. Generate a mask for the upper triangle (taken from seaborn example gal
mask = np.zeros_like(df.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(df.corr(), cmap = "magma", annot=True, mask=mask, center = 0, );
plt.title("Heatmap of all the Features of Train data set", fontsize = 25);
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_9772\3171721159.py:5: DeprecationWarning: `np.b
ool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bool` by
itself. Doing this will not modify any behavior and is safe. If you specifically wanted th
e numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/releas
e/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/1.20.0-notes.html#depr
ecations)
  mask = np.zeros_like(dataset.corr(), dtype=np.bool)
```



Pre-processing

In [29]:
```
X = df.iloc[:,2:]
```

In [30]:
```
y = df.iloc[:,1]
```

In [31]:
```
# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 1
```

In [32]:
```
# Encode the response variables to 0s and 1s
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.fit_transform(y_test)
print(y_train)
print(y_test)
```

```
[1 1 1 ... 0 1 1]
[1 1 1 ... 1 1 1]
```

In [33]:
```
# Perform feature scaling to the continuous variables
sc = StandardScaler()
X_train.iloc[:,[0,2,7,8,9,10,11,12,13,14,15,16,17,18]] = sc.fit_transform(X_train.iloc[:,[0
X_test.iloc[:,[0,2,7,8,9,10,11,12,13,14,15,16,17,18]] = sc.transform(X_test.iloc[:,[0,2,7,8
```

In [34]:
```
# Turn the categorical variables into dummy variables

ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1, 3, 4, 5, 6])], remain
X_train = np.array(ct.fit_transform(X_train))
X_test = np.array(ct.fit_transform(X_test))
```

ML algorithms and Evaluation

knn

In [79]:
```
# Train the model
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)
```

Out[79]:
```
KNeighborsClassifier()
```

In [80]:
```
# Test the model
y_pred_knn = classifier.predict(X_test)
print(np.concatenate((y_pred_knn.reshape(len(y_pred_knn),1), y_test.reshape(len(y_test),1))
```

```
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

```
C:\Users\DELL\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: Future
Warning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default behavior
of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will
change: the default value of `keepdims` will become False, the `axis` over which the stati
stic is taken will be eliminated, and the value None will no longer be accepted. Set `keep
dims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

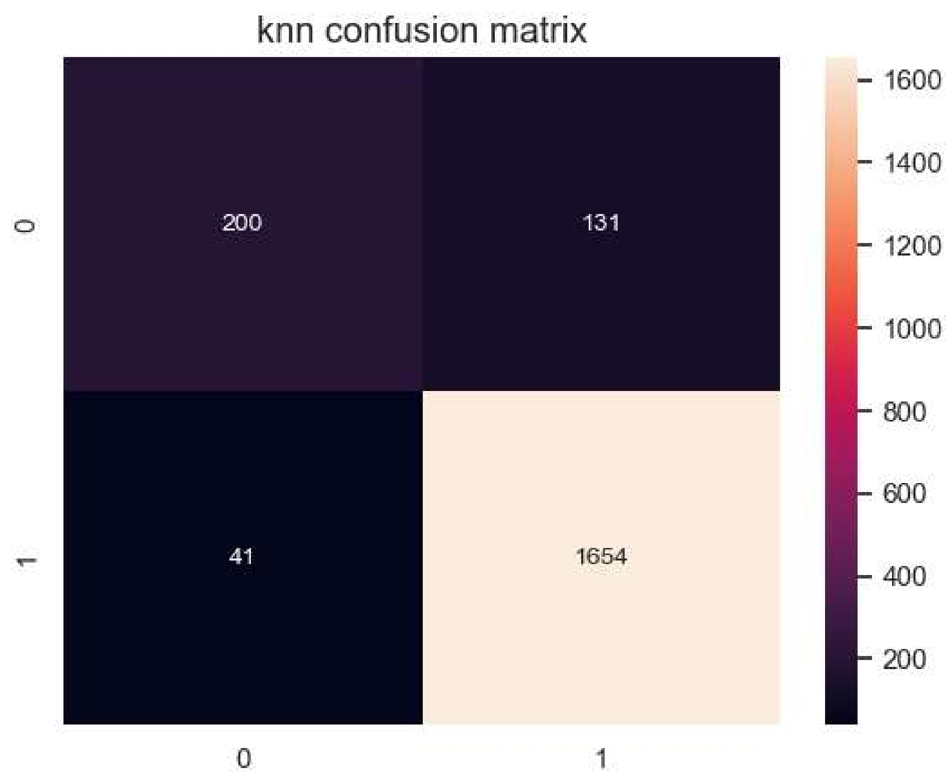
In [81]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
cm = confusion_matrix(y_test, y_pred_knn)
print(cm)
print(accuracy_score(y_test, y_pred_knn))
print(classification_report(y_test,y_pred_knn))
sns.heatmap(cm, annot=True, fmt='d').set_title('knn confusion matrix')
```

```
[[ 200  131]
 [  41 1654]]
0.9151036525172754
              precision    recall  f1-score   support

           0       0.83      0.60      0.70       331
           1       0.93      0.98      0.95      1695

    accuracy                           0.92      2026
   macro avg       0.88      0.79      0.82      2026
weighted avg       0.91      0.92      0.91      2026
```

Out[81]: Text(0.5, 1.0, 'knn confusion matrix')



Logistic Regression

In [82]:
```
# Train the model
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

Out[82]: LogisticRegression(random_state=0)

In [83]:
```
# Test the model
y_pred_lr = classifier.predict(X_test)
print(np.concatenate((y_pred_lr.reshape(len(y_pred_lr),1), y_test.reshape(len(y_test),1)),1
```

```
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

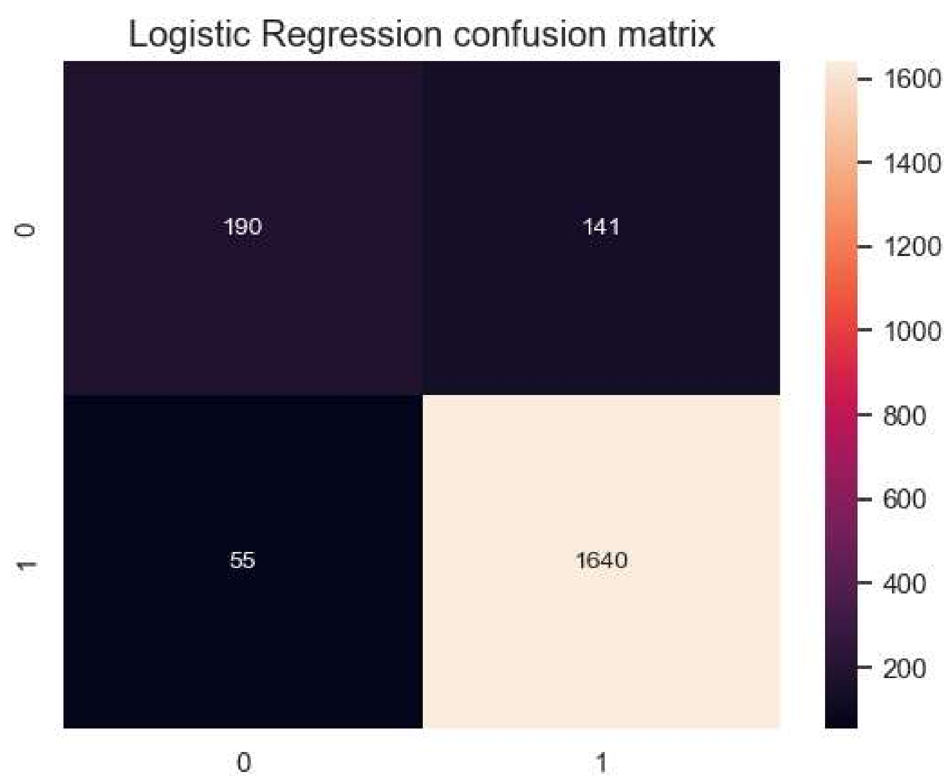
In [84]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_lr)
print(cm)
print(accuracy_score(y_test, y_pred_lr))
print(classification_report(y_test,y_pred_lr))
sns.heatmap(cm, annot=True, fmt='d').set_title('Logistic Regression confusion matrix')
```

```
[[ 190  141]
 [  55 1640]]
0.9032576505429417
              precision    recall  f1-score   support

           0       0.78      0.57      0.66       331
           1       0.92      0.97      0.94      1695

    accuracy                           0.90      2026
   macro avg       0.85      0.77      0.80      2026
weighted avg       0.90      0.90      0.90      2026
```

Out[84]: Text(0.5, 1.0, 'Logistic Regression confusion matrix')



SVM

In [90]:
```
# Train the model
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)
```

Out[90]:
```
SVC(kernel='linear', random_state=0)
```

In [91]:
```
# Test the model
y_pred_svm = classifier.predict(X_test)
print(np.concatenate((y_pred_svm.reshape(len(y_pred_svm),1), y_test.reshape(len(y_test),1))
```

```
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

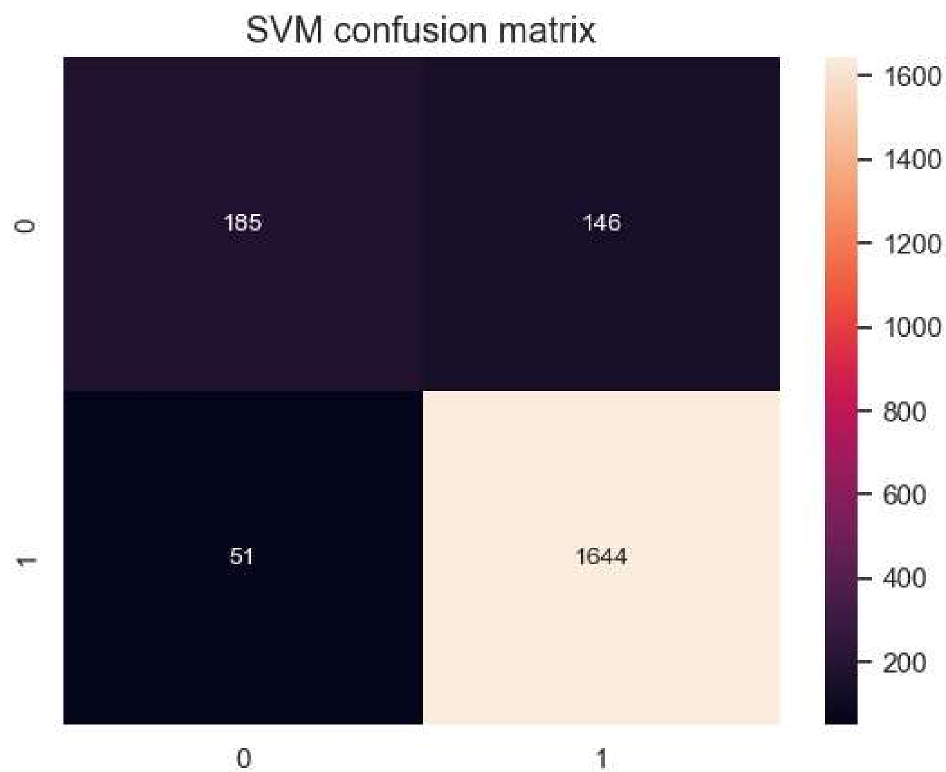
In [92]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_svm)
print(cm)
print(accuracy_score(y_test, y_pred_svm))
print(classification_report(y_test,y_pred_svm))
sns.heatmap(cm, annot=True, fmt='d').set_title('SVM confusion matrix')
```

```
[[ 185  146]
 [  51 1644]]
0.9027640671273445
              precision    recall  f1-score   support

           0       0.78      0.56      0.65       331
           1       0.92      0.97      0.94      1695

    accuracy                           0.90      2026
   macro avg       0.85      0.76      0.80      2026
weighted avg       0.90      0.90      0.90      2026
```

Out[92]: `Text(0.5, 1.0, 'SVM confusion matrix')`



Decision Tree

In [93]:
```
# Train the model
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)
```

Out[93]: `DecisionTreeClassifier(criterion='entropy', random_state=0)`

In [94]:
```
# Test the model
y_pred_dt = classifier.predict(X_test)
print(np.concatenate((y_pred_dt.reshape(len(y_pred_dt),1), y_test.reshape(len(y_test),1)),1
```

```
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

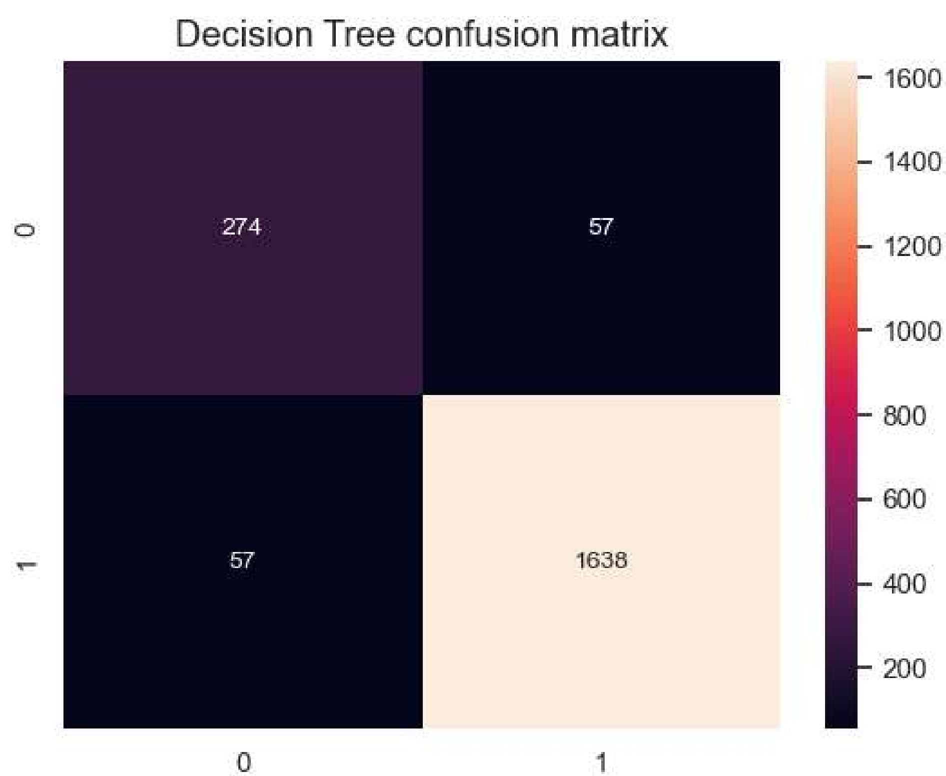
In [95]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_dt)
print(cm)
print(accuracy_score(y_test, y_pred_dt))
print(classification_report(y_test,y_pred_dt))
sns.heatmap(cm, annot=True, fmt='d').set_title('Decision Tree confusion matrix')
```

```
[[ 274   57]
 [  57 1638]]
0.9437314906219151
              precision    recall  f1-score   support

           0       0.83      0.83      0.83       331
           1       0.97      0.97      0.97      1695

    accuracy                           0.94      2026
   macro avg       0.90      0.90      0.90      2026
weighted avg       0.94      0.94      0.94      2026
```

Out[95]: Text(0.5, 1.0, 'Decision Tree confusion matrix')



Random Forest

In [96]:
```
# Train the model
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state
classifier.fit(X_train, y_train)
```

Out[96]:
```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)
```

In [97]:
```
# Test the model
y_pred_rf = classifier.predict(X_test)
print(np.concatenate((y_pred_rf.reshape(len(y_pred_rf),1), y_test.reshape(len(y_test),1)),1
```

```
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

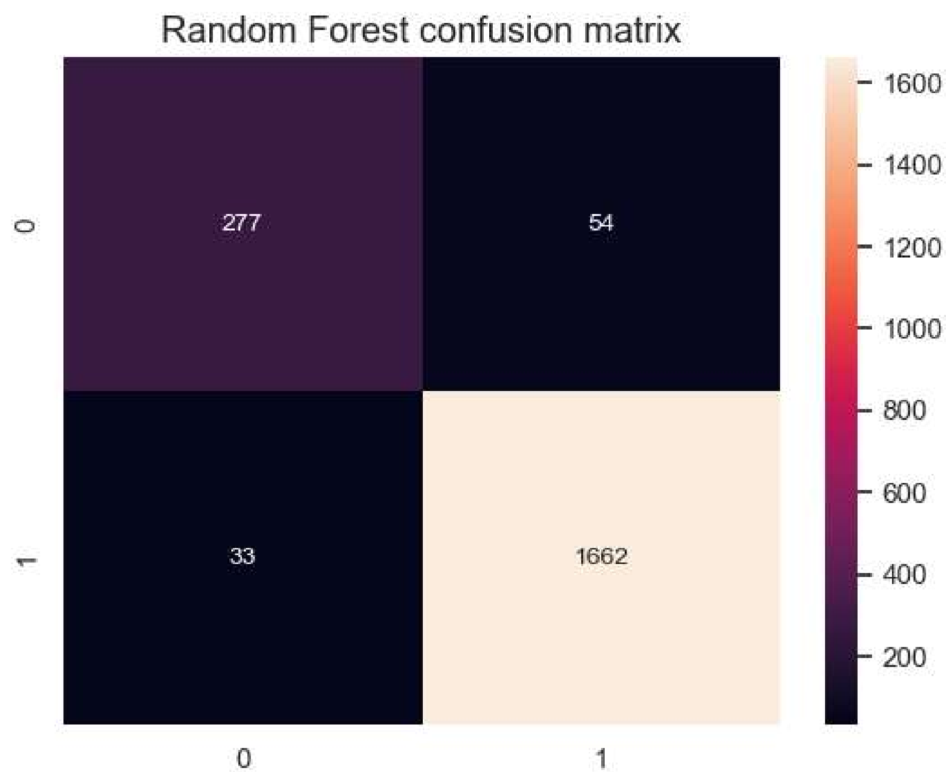
In [98]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_rf)
print(cm)
print(accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test,y_pred_rf))
sns.heatmap(cm, annot=True, fmt='d').set_title('Random Forest confusion matrix')
```

```
[[ 277   54]
 [  33 1662]]
0.9570582428430404
              precision    recall  f1-score   support

           0       0.89      0.84      0.86       331
           1       0.97      0.98      0.97      1695

    accuracy                           0.96      2026
   macro avg       0.93      0.91      0.92      2026
weighted avg       0.96      0.96      0.96      2026
```

Out[98]:
```
Text(0.5, 1.0, 'Random Forest confusion matrix')
```



ANN

In [99]:
```
# Import tensorflow
import tensorflow as tf
```

In [100]:
```
# Initialzing the ANN
ann = tf.keras.models.Sequential()
# Adding the input layer and the first hidden layer
ann.add(tf.keras.layers.Dense(units=12, activation='relu'))
# Adding the second hidden layer
ann.add(tf.keras.layers.Dense(units=12, activation='relu'))
# Adding the output layer
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

In [101]:
```
# Compile the ANN
ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

In [102]:
```
# Train the ANN
ann.fit(X_train, y_train, batch_size = 32, epochs = 50)
```

```
Epoch 1/50
254/254 [==============================] - 2s 2ms/step - loss: 0.4616 - accuracy: 0.7736
Epoch 2/50
254/254 [==============================] - 1s 2ms/step - loss: 0.2856 - accuracy: 0.8874
Epoch 3/50
254/254 [==============================] - 1s 2ms/step - loss: 0.2431 - accuracy: 0.9047
Epoch 4/50
254/254 [==============================] - 1s 2ms/step - loss: 0.2210 - accuracy: 0.9115
Epoch 5/50
254/254 [==============================] - 1s 2ms/step - loss: 0.2042 - accuracy: 0.9193
Epoch 6/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1896 - accuracy: 0.9252
Epoch 7/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1794 - accuracy: 0.9295
Epoch 8/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1718 - accuracy: 0.9332
Epoch 9/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1649 - accuracy: 0.9333
Epoch 10/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1614 - accuracy: 0.9353
Epoch 11/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1583 - accuracy: 0.9385
Epoch 12/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1564 - accuracy: 0.9374
Epoch 13/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1534 - accuracy: 0.9396
Epoch 14/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1509 - accuracy: 0.9407
Epoch 15/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1501 - accuracy: 0.9409
Epoch 16/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1480 - accuracy: 0.9425
Epoch 17/50
254/254 [==============================] - 1s 4ms/step - loss: 0.1474 - accuracy: 0.9416
Epoch 18/50
254/254 [==============================] - 1s 4ms/step - loss: 0.1467 - accuracy: 0.9430
Epoch 19/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1456 - accuracy: 0.9426
Epoch 20/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1448 - accuracy: 0.9424
Epoch 21/50
254/254 [==============================] - 1s 4ms/step - loss: 0.1435 - accuracy: 0.9440
Epoch 22/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1426 - accuracy: 0.9458
Epoch 23/50
254/254 [==============================] - 1s 5ms/step - loss: 0.1421 - accuracy: 0.9451
Epoch 24/50
254/254 [==============================] - 1s 5ms/step - loss: 0.1414 - accuracy: 0.9452
Epoch 25/50
254/254 [==============================] - 1s 4ms/step - loss: 0.1394 - accuracy: 0.9475
Epoch 26/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1388 - accuracy: 0.9459
Epoch 27/50
254/254 [==============================] - 1s 4ms/step - loss: 0.1383 - accuracy: 0.9451
Epoch 28/50
254/254 [==============================] - 1s 6ms/step - loss: 0.1367 - accuracy: 0.9462
Epoch 29/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1372 - accuracy: 0.9465
Epoch 30/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1360 - accuracy: 0.9465
Epoch 31/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1350 - accuracy: 0.9480
Epoch 32/50
```

```
254/254 [==============================] - 1s 3ms/step - loss: 0.1344 - accuracy: 0.9484
Epoch 33/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1319 - accuracy: 0.9489
Epoch 34/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1324 - accuracy: 0.9493
Epoch 35/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1303 - accuracy: 0.9507
Epoch 36/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1289 - accuracy: 0.9505
Epoch 37/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1286 - accuracy: 0.9509
Epoch 38/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1281 - accuracy: 0.9525
Epoch 39/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1266 - accuracy: 0.9522
Epoch 40/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1257 - accuracy: 0.9516
Epoch 41/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1247 - accuracy: 0.9532
Epoch 42/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1244 - accuracy: 0.9522
Epoch 43/50
254/254 [==============================] - 1s 2ms/step - loss: 0.1227 - accuracy: 0.9528
Epoch 44/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1217 - accuracy: 0.9542
Epoch 45/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1219 - accuracy: 0.9542
Epoch 46/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1218 - accuracy: 0.9533
Epoch 47/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1197 - accuracy: 0.9559
Epoch 48/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1195 - accuracy: 0.9548
Epoch 49/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1178 - accuracy: 0.9579
Epoch 50/50
254/254 [==============================] - 1s 3ms/step - loss: 0.1174 - accuracy: 0.9565
```

Out[102]:
```
<keras.callbacks.History at 0x1bb3b07db80>
```

In [103]:
```
# Test the model
y_pred_ann = ann.predict(X_test)
y_pred_ann = (y_pred_ann > 0.5)
print(np.concatenate((y_pred_ann.reshape(len(y_pred_ann),1), y_test.reshape(len(y_test),1))
```

```
64/64 [==============================] - 0s 2ms/step
[[1 1]
 [1 1]
 [1 1]
 ...
 [1 1]
 [1 1]
 [1 1]]
```

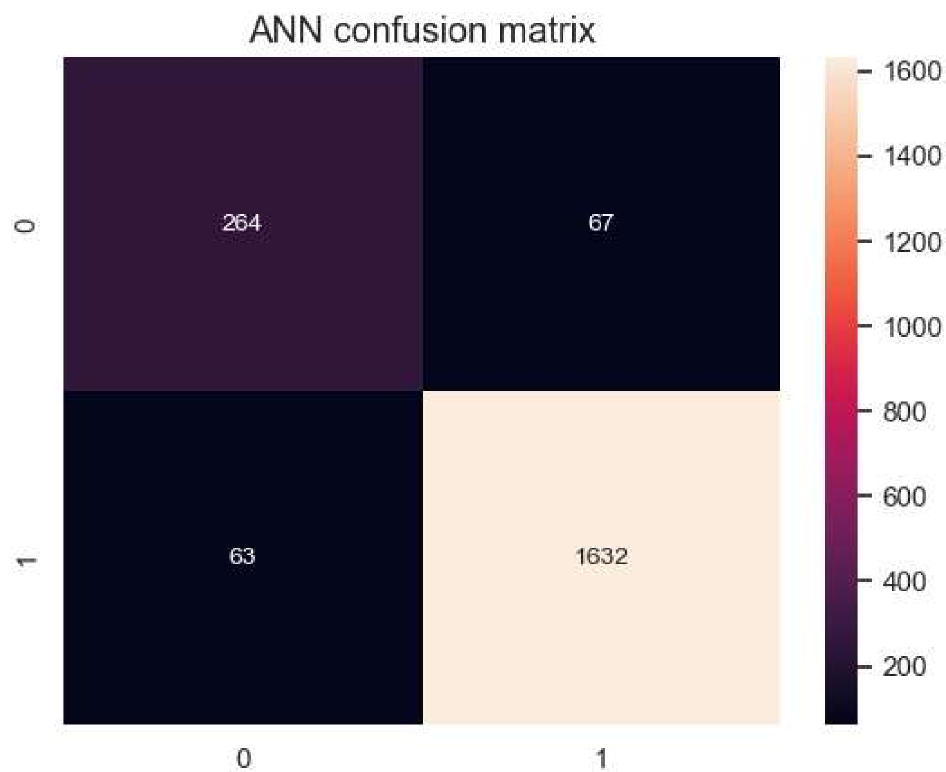
In [105]:
```
# Build the confusion matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_ann)
print(cm)
print(accuracy_score(y_test, y_pred_ann))
print(classification_report(y_test,y_pred_ann))
sns.heatmap(cm, annot=True, fmt='d').set_title('ANN confusion matrix')
```

```
[[ 264   67]
 [  63 1632]]
0.9358341559723593
              precision    recall  f1-score   support

           0       0.81      0.80      0.80       331
           1       0.96      0.96      0.96      1695

    accuracy                           0.94      2026
   macro avg       0.88      0.88      0.88      2026
weighted avg       0.94      0.94      0.94      2026
```

Out[105]:
```
Text(0.5, 1.0, 'ANN confusion matrix')
```



In [113]:

```
import pandas as pd
from sklearn.metrics import confusion_matrix, accuracy_score
from tabulate import tabulate

# Define the model names and corresponding predictions
model_names = ['k-NN', 'Logistic Regression', 'SVM', 'Decision Tree', 'Random Forest', 'ANN
predictions = [y_pred_knn, y_pred_lr, y_pred_svm, y_pred_dt, y_pred_rf, y_pred_ann]
test_labels = [y_test] * len(model_names)

# Initialize empty lists to store accuracy scores and confusion matrices
accuracy_scores = []
confusion_matrices = []

# Calculate accuracy scores and confusion matrices for each model
for prediction, test_label in zip(predictions, test_labels):
    accuracy = accuracy_score(test_label, prediction)
    matrix = confusion_matrix(test_label, prediction)
    accuracy_scores.append(accuracy)
    confusion_matrices.append(matrix)

# Create a DataFrame to store the results
results_df = pd.DataFrame({
    'Model': model_names,
    'Accuracy': accuracy_scores,
    'Confusion Matrix': confusion_matrices
})

# Sort the DataFrame by accuracy in ascending order
results_df.sort_values(by='Accuracy', ascending=True, inplace=True)

# Convert the DataFrame to an interactive table with color coding
table = tabulate(results_df, headers='keys', tablefmt='html',
                 numalign="center", stralign="center",
                 colalign=("center", "center", "center"),
                 floatfmt=".4f",
                 disable_numparse=True,
                 showindex=True)

# Apply color coding to the table rows based on accuracy
color_table = table.replace('<tr>', '<tr style="background-color: #FFCCCC;">', 1)
color_table = color_table.replace('<tr>', '<tr style="background-color: #CCFFCC;">', -1)

# Display the colorful interactive table
from IPython.display import display, HTML
display(HTML(color_table))
```

	Model	Accuracy	Confusion Matrix
2	SVM	0.9027640671273445	[[185 146] [51 1644]]
1	Logistic Regression	0.9032576505429417	[[190 141] [55 1640]]
0	k-NN	0.9151036525172754	[[200 131] [41 1654]]
5	ANN	0.9358341559723593	[[264 67] [63 1632]]
3	Decision Tree	0.9437314906219151	[[274 57] [57 1638]]
4	Random Forest	0.9570582428430404	[[277 54] [33 1662]]