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In[1]:
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, recall_score, accuracy_score, precision_score

RANDOM_SEED=2021
TEST_FPC=0.3
LABELS=["Normal", "Fraud"]

In[2]:
dataset=pd.read_csv("creditcard.csv")

In[3]:
#check for any null values
print("Any nulls in the dataset", dataset.isnull().values.any())
print("No. of unique labels", len(dataset['Class'].unique()))
print("Label values", dataset.Class.unique())

#to form normal and credit card transaction
#to form fraud and credit card transaction
print("-----")
print("Breakdown of Normal and Fraud Transactions")
print(pd.value_counts(dataset['Class'], sort=True))
Any nulls in the dataset: False
Label values:
0
Breakdown of Normal and Fraud Transactions:
1
Name: Class, dtype: int64

In[4]:
#visualizing the imbalanced dataset
count_classes = pd.value_counts(dataset['Class'], sort=True)
plt.figure(figsize=(10,5))
plt.title("Frequency of observations by class")
plt.xlabel("Class")
plt.ylabel("Number of observations")

Out[4]: Text(0, 0.5, 'Number of observations')
```



Out (51)

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class		
0				0.0	-1.359607	-0.072781	2.551637	1.378105	-0.358321	0.682788	0.239599	0.086688	0.362787	-0.819367	0.277839	-0.116874	0.066628	0.128539	-0.189115	0.113558	-0.021057	149.62	0
1				0.0	1.191857	0.266151	0.166889	0.688156	0.088018	-0.082761	-0.074803	0.085102	-0.255435	-0.232775	-0.638672	0.181288	-0.359866	0.167170	0.125895	-0.068993	0.064724	2.49	0
2				1.0	-1.385154	-1.168163	1.773260	0.379786	-0.501198	1.808849	0.791661	0.267476	-1.514654	-0.242769	0.771679	0.089412	-0.489281	-0.327462	-0.159097	-0.055313	-0.059762	378.66	0
3				1.0	-0.466272	-0.185226	1.749291	-0.865291	-0.018309	1.312763	0.237609	0.377436	-1.387054	-0.108300	0.005524	-1.193021	-1.175575	0.647576	-0.221629	0.862723	0.064458	123.50	0
4				2.0	-1.186333	0.377733	1.168718	-0.680304	-0.407193	0.095821	0.592861	-0.276513	0.813719	-0.809431	0.788278	-0.371438	0.161247	-0.266810	0.562292	0.216622	0.215153	45.99	0
...
28482	127288.0	-11.831118	10.071785	-8.04783	-2.866674	-1.364473	-2.486837	-4.918215	1.365334	1.916628	-0.213454	0.111844	1.016480	-0.589148	1.163607	0.258036	0.943451	0.823751				637	0
28483	127287.0	-0.373279	-0.055080	1.035000	-0.731899	0.688229	1.078813	0.826339	0.394949	0.586800	-0.214205	0.923384	0.012363	-1.016226	-0.488624	-0.395255	0.068472	-0.053327				2479	0
28484	127288.0	0.191565	-0.391254	-1.269468	-0.557828	2.430515	1.011260	-0.294927	0.788147	0.432454	-0.253065	0.574329	-0.037161	0.688134	0.246745	-0.087371	0.086455	-0.026461				4749	0
28485	127288.0	-0.366640	0.236663	0.705250	0.489708	-0.377063	0.635708	-0.666380	0.679151	0.305087	-0.265245	0.890609	-0.160208	0.122365	-0.549159	0.566668	0.108821	0.101513				10800	0
28486	127292.0	-0.521613	-0.199713	0.780137	0.596271	-0.042546	-0.496167	1.577066	-0.116659	0.486189	-0.261057	0.643078	0.716773	0.089737	-0.473649	-0.818267	-0.002415	0.013649				21700	0

28480 rows x 28 columns

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In[6]:
sc=StandardScaler()
dataset['Time'] = sc.fit_transform(dataset['Time'].values.reshape(-1,1))
dataset['Amount'] = sc.fit_transform(dataset['Amount'].values.reshape(-1,1))

In[7]:
raw_data=dataset.values
#The last element contains the transaction amount which is represented by 0 and if fraud then 1
labels=raw_data[:, -1]

#Then the data point is a three lectrode logram data
data=raw_data[:, 0:-1]

train_data, test_data, train_labels, test_labels=train_test_split(data, labels, test_size=0.2, random_state=2021)

In[8]:
min_val=tf.reduce_min(train_data)
max_val=tf.reduce_max(train_data)

train_data=(train_data-min_val)/(max_val-min_val)
min_val=test_data=(test_data-min_val)/(max_val-min_val)

train_data = tf.cast(train_data, tf.float32)
test_data=tf.cast(test_data, tf.float32)

In[9]:
train_labels=train_labels.astype(bool)
test_labels=test_labels.astype(bool)

#Creating normal and fraud dataset
normal_train_data=train_data[train_labels==0]
normal_test_data=test_data[test_labels==0]

fraud_train_data=train_data[train_labels==1]
fraud_test_data=test_data[test_labels==1]

print("No. of records in Fraud Train Data=", len(fraud_train_data))
print("No. of records in Fraud Test Data=", len(fraud_test_data))
print("No. of records in Normal Train Data=", len(normal_train_data))
print("No. of records in Normal Test Data=", len(normal_test_data))

In[10]:
nb_epoch=50
batch_size=64
input_dim=normal_train_data.shape[1]
num_filters=32
encoding_dim=14
hidden_dim=int(encoding_dim/2)
den_dim=4
learning_rate=1e-7

In[11]:
#input layer
input_layer=tf.keras.layers.Input(shape=(input_dim,))

#Encoder
encoder=tf.keras.layers.Dense(encoding_dim, activation='tanh', activity_regularizer=tf.keras.regularizers.L2(learning_rate))(input_layer)
encoder=tf.keras.layers.Dense(hidden_dim, activation='relu')(encoder)
encoder=tf.keras.layers.Dense(hidden_dim, activation='relu')(encoder)

#Decoder
decoder=tf.keras.layers.Dense(hidden_dim, activation='relu')(decoder)
decoder=tf.keras.layers.Dense(encoding_dim, activation='tanh')(decoder)
decoder=tf.keras.layers.Dense(encoding_dim, activation='relu')(decoder)
decoder=tf.keras.layers.Dense(input_dim, activation='tanh')(decoder)

#Autoencoder
autoencoder=tf.keras.Model(inputs=input_layer, outputs=decoder)
autoencoder.compile(metrics=['accuracy'], loss='mean_squared_error', optimizer='adam')

In[12]:
cp=tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5", mode='min', monitor='val_loss', verbose=2, save_best_only=True)
early_stop=tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0.0001, patience=10, verbose=1, mode='min', restore_best_weights=True)

In[13]:
autoencoder.compile(metrics=['accuracy'], loss='mean_squared_error', optimizer='adam')

In[14]:
history=autoencoder.fit(normal_train_data, normal_train_data, epochs=nb_epoch, batch_size=batch_size, shuffle=True, validation_data=(test_data, test_data), verbose=1, callbacks=[cp, early_stop]).history

Epoch 1/50
354/354 [=====] - ETA: 0s - loss: 0.0013 - accuracy: 0.0372
Epoch 1 val_loss improved from inf to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 0.0013 - accuracy: 0.0372 - val_loss: 0.0179 - val_accuracy: 0.0343
Epoch 2/50
354/354 [=====] - ETA: 0s - loss: 1.9583e-05 - accuracy: 0.0609
Epoch 2 val_loss did not improve from 0.0002
354/354 [=====] - ETA: 0s - loss: 1.9599e-05 - accuracy: 0.0609 - val_loss: 0.0190e-05 - val_accuracy: 0.0078
Epoch 3/50
354/354 [=====] - ETA: 0s - loss: 1.9562e-05 - accuracy: 0.0619
Epoch 3 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 1.9580e-05 - accuracy: 0.0619 - val_loss: 0.0025e-05 - val_accuracy: 0.0420
Epoch 4/50
354/354 [=====] - ETA: 0s - loss: 1.9545e-05 - accuracy: 0.0599
Epoch 4 val_loss did not improve from 0.0002
354/354 [=====] - ETA: 0s - loss: 1.9530e-05 - accuracy: 0.0601 - val_loss: 0.0277e-05 - val_accuracy: 0.2168
Epoch 5/50
354/354 [=====] - ETA: 0s - loss: 1.8826e-05 - accuracy: 0.1758
Epoch 5 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 1.8818e-05 - accuracy: 0.1759 - val_loss: 1.8344e-05 - val_accuracy: 0.2184
Epoch 6/50
354/354 [=====] - ETA: 0s - loss: 1.7266e-05 - accuracy: 0.2362
Epoch 6 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 1.7266e-05 - accuracy: 0.2363 - val_loss: 1.7095e-05 - val_accuracy: 0.3538
Epoch 7/50
354/354 [=====] - ETA: 0s - loss: 1.8826e-05 - accuracy: 0.1125
Epoch 7 val_loss did not improve from 0.0002
354/354 [=====] - ETA: 0s - loss: 1.8813e-05 - accuracy: 0.1137 - val_loss: 1.7990e-05 - val_accuracy: 0.2041
Epoch 8/50
354/354 [=====] - ETA: 0s - loss: 1.7266e-05 - accuracy: 0.2141
Epoch 8 val_loss did not improve from 0.0002
354/354 [=====] - ETA: 0s - loss: 1.7328e-05 - accuracy: 0.2143 - val_loss: 1.7133e-05 - val_accuracy: 0.2781
Epoch 9/50
354/354 [=====] - ETA: 0s - loss: 1.6877e-05 - accuracy: 0.2481
Epoch 9 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 1.6825e-05 - accuracy: 0.2482 - val_loss: 1.6811e-05 - val_accuracy: 0.3518
Epoch 10/50
354/354 [=====] - ETA: 0s - loss: 1.6692e-05 - accuracy: 0.2509
Epoch 10 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
354/354 [=====] - ETA: 0s - loss: 1.6682e-05 - accuracy: 0.2510 - val_loss: 1.6469e-05 - val_accuracy: 0.3492
Epoch 11/50
354/354 [=====] - ETA: 0s - loss: 1.6589e-05 - accuracy: 0.2484
Epoch 11 val_loss improved from 0.0002 to 0.0002, saving model to autoencoder_fraud.h5
Reactoring model weights from end of best epoch: 11
354/354 [=====] - ETA: 0s - loss: 1.6561e-05 - accuracy: 0.2484 - val_loss: 1.6237e-05 - val_accuracy: 0.2865
Epoch 11: early stopping

In[15]:
plt.plot(history['loss'], linewidth=2, label='Train')
plt.plot(history['val_loss'], linewidth=2, label='Test')
plt.legend(loc='upper right')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')

plt.show()
```

