Crisis Prediction in African Economies

Given data about financial climates in various African countries throughout the years, let's try to predict whether a banking crisis occurred or not in a given year in a given country.

We will use a TensorFlow ANN to make our predictions.

In [1]:
```
import numpy as np
import pandas as pd
import plotly.express as px

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split

import tensorflow as tf
```

In [2]:
```
data = pd.read_csv('/Users/shikarichacha/Desktop/GSsoC24/african_cr
data
```

Out[2]:

	case	cc3	country	year	systemic_crisis	exch_usd	domestic_debt_in_default	s
0	1	DZA	Algeria	1870	1	0.052264	0	
1	1	DZA	Algeria	1871	0	0.052798	0	
2	1	DZA	Algeria	1872	0	0.052274	0	
3	1	DZA	Algeria	1873	0	0.051680	0	
4	1	DZA	Algeria	1874	0	0.051308	0	
...	...	...	...	...	...	...	...	
1054	70	ZWE	Zimbabwe	2009	1	354.800000	1	
1055	70	ZWE	Zimbabwe	2010	0	378.200000	1	
1056	70	ZWE	Zimbabwe	2011	0	361.900000	1	
1057	70	ZWE	Zimbabwe	2012	0	361.900000	1	
1058	70	ZWE	Zimbabwe	2013	0	361.900000	1	

1059 rows × 14 columns

In [3]:
```
((data['banking_crisis'] == 'crisis').astype(int) == data['systemic
```

Out[3]:
```
False
```

In [4]:
```
data.isna().sum()
```

Out[4]:
```
case                               0
cc3                                0
country                            0
year                               0
systemic_crisis                    0
exch_usd                           0
domestic_debt_in_default           0
sovereign_external_debt_default    0
gdp_weighted_default               0
inflation_annual_cpi               0
independence                       0
currency_crises                    0
inflation_crises                   0
banking_crisis                     0
dtype: int64
```

In [5]:
```
data = data.drop(['case', 'country'], axis=1)
```

In [6]:
```
data
```

Out[6]:

	cc3	year	systemic_crisis	exch_usd	domestic_debt_in_default	sovereign_external_
0	DZA	1870	1	0.052264	0	
1	DZA	1871	0	0.052798	0	
2	DZA	1872	0	0.052274	0	
3	DZA	1873	0	0.051680	0	
4	DZA	1874	0	0.051308	0	
...	...	...	...	...	...	
1054	ZWE	2009	1	354.800000	1	
1055	ZWE	2010	0	378.200000	1	
1056	ZWE	2011	0	361.900000	1	
1057	ZWE	2012	0	361.900000	1	
1058	ZWE	2013	0	361.900000	1	

1059 rows × 12 columns

In [7]:
```
cc3_dummies = pd.get_dummies(data['cc3'])
data = pd.concat([data, cc3_dummies], axis=1)
data = data.drop('cc3', axis=1)
```

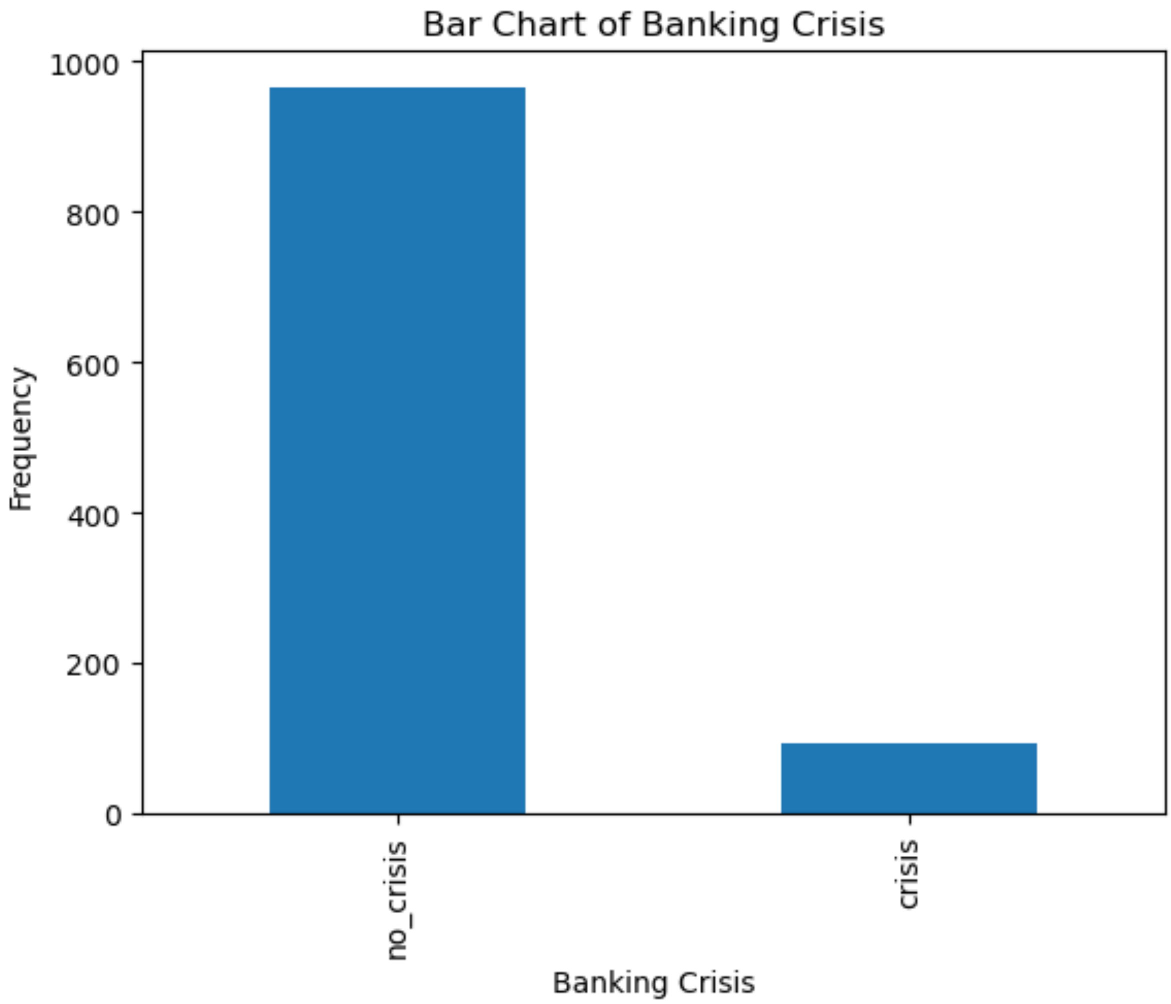
In [8]:
```
data
```

Out[8]:

	year	systemic_crisis	exch_usd	domestic_debt_in_default	sovereign_external_debt_(
0	1870	1	0.052264	0	
1	1871	0	0.052798	0	
2	1872	0	0.052274	0	
3	1873	0	0.051680	0	
4	1874	0	0.051308	0	
...	...	...	...	...	
1054	2009	1	354.800000	1	
1055	2010	0	378.200000	1	
1056	2011	0	361.900000	1	
1057	2012	0	361.900000	1	
1058	2013	0	361.900000	1	

1059 rows × 24 columns

In [22]:
```
import matplotlib.pyplot as plt

data['banking_crisis'].value_counts().plot(kind='bar')
plt.xlabel('Banking Crisis')
plt.ylabel('Frequency')
plt.title('Bar Chart of Banking Crisis')
plt.show()
```



In [9]:
```
y = data['banking_crisis']
X = data.drop('banking_crisis', axis=1)
```

In [10]:
```
y
```

Out[10]:
```
0         crisis
1      no_crisis
2      no_crisis
3      no_crisis
4      no_crisis
         ...
1054      crisis
1055   no_crisis
1056   no_crisis
1057   no_crisis
1058   no_crisis
Name: banking_crisis, Length: 1059, dtype: object
```

In [11]:
```
label_encoder = LabelEncoder()

y = label_encoder.fit_transform(y)
{index: label for index, label in enumerate(label_encoder.classes_)}
```

Out[11]:
```
{0: 'crisis', 1: 'no_crisis'}
```

In [12]:
```
y = pd.Series(y).apply(lambda x: 1 - x)
y
```

Out[12]:
```
0       1
1       0
2       0
3       0
4       0
       ..
1054    1
1055    0
1056    0
1057    0
1058    0
Length: 1059, dtype: int64
```

In [13]:
```
scaler = StandardScaler()

X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

In [14]:
```
X
```

Out[14]:

	year	systemic_crisis	exch_usd	domestic_debt_in_default	sovereign_external_de
0	-2.917150	3.451758	-0.386713	-0.203219	
1	-2.887313	-0.289707	-0.386708	-0.203219	
2	-2.857475	-0.289707	-0.386712	-0.203219	
3	-2.827638	-0.289707	-0.386718	-0.203219	
4	-2.797800	-0.289707	-0.386721	-0.203219	
...	...	...	...	...	
1054	1.230271	3.451758	2.797088	4.920801	
1055	1.260109	-0.289707	3.007099	4.920801	
1056	1.289946	-0.289707	2.860809	4.920801	
1057	1.319784	-0.289707	2.860809	4.920801	
1058	1.349622	-0.289707	2.860809	4.920801	

1059 rows × 23 columns

In [15]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_siz
```

In [16]:
```
X.shape
```

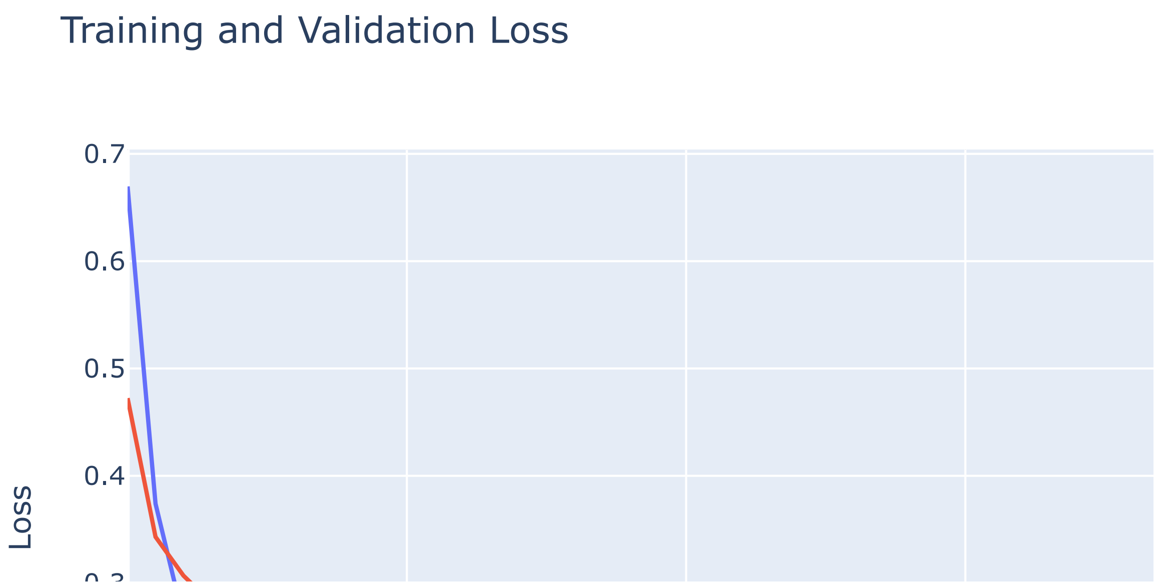
Out[16]: (1059, 23)

In [17]:
```
y.sum() / len(y)
```

Out[17]: 0.08876298394711993

In [18]:
```
inputs = tf.keras.Input(shape=(23,))
x = tf.keras.layers.Dense(64, activation='relu')(inputs)
x = tf.keras.layers.Dense(64, activation='relu')(x)
outputs = tf.keras.layers.Dense(1, activation='sigmoid')(x)

model = tf.keras.Model(inputs=inputs, outputs=outputs)


model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=[tf.keras.metrics.AUC(name="auc")]
)


batch_size = 64
epochs = 60

history = model.fit(
    X_train,
    y_train,
    validation_split=0.2,
    batch_size=batch_size,
    epochs=epochs,
    callbacks=[tf.keras.callbacks.ReduceLROnPlateau()],
    verbose=0
)
```

In [19]:
```
fig = px.line(
    history.history,
    y=['loss', 'val_loss'],
    labels={'index': "Epoch", 'value': "Loss"},
    title="Training and Validation Loss"
)

fig.show()
```



In [20]:
```
model.evaluate(X_test, y_test)
```

```
10/10 [==============================] - 0s 498us/step - loss: 0.0
377 - auc: 0.9979
```

Out[20]:
```
[0.03768949210643768, 0.9978998899459839]
```