```
# Financial Fraud Detection - Complete Balanced Implementation
## 1. Install Required Packages
!pip install tensorflow scikit-learn imbalanced-learn transformers > \underline{/dev/null}
## 2. Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')

→ Mounted at /content/drive
# 3. Load Data from Google Drive
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# Update this path to your dataset location in Drive
data_path = '/content/drive/MyDrive/Colab Notebooks/Fraud Detection/creditcard.csv'
df = pd.read_csv(data_path)
# Verify load
print("Data loaded successfully. Shape:", df.shape)
display(df.head())
Data loaded successfully. Shape: (284807, 31)
        Time
                    ۷1
                             ٧2
                                      ٧3
                                                ۷4
                                                          ۷5
                                                                   ۷6
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                                                                                                ۷9
                                                                                                              V21
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                                                                                                                                 V23
                                                                                                    . . .
                                                                       0.239599
     n
          0.0 -1.359807 -0.072781 2.536347
                                           1.378155 -0.338321
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                                                                                          0.363787
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                        0.266151 0.166480
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                                                    0.060018 -0.082361
                                                                       -0.078803
                                                                                 0.085102 -0.255425
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          1.0 -1.358354 -1.340163 1.773209
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                                                                       0.592941
                                                                                 -0.270533 0.817739
                                                                                                         -0.009431
                                                                                                                   0.798278 -0.137458 (
     5 rows × 31 columns
# Feature engineering
scaler = RobustScaler()
df['Amount'] = scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['Time'] = scaler.fit_transform(df['Time'].values.reshape(-1,1))
X = df.drop('Class', axis=1)
y = df['Class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
## 5. Data Preprocessing
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
# Normalize Time and Amount
scaler = RobustScaler()
df['Amount'] = scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['Time'] = scaler.fit_transform(df['Time'].values.reshape(-1,1))
# Train-test split
X = df.drop('Class', axis=1)
y = df['Class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
# Handle imbalance with SMOTE
sm = SMOTE(random state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
print("\nClass distribution after SMOTE:")
print(pd.Series(y_train_res).value_counts())
₹
     Class distribution after SMOTE:
     Class
     0
          227451
          227451
```

```
Name: count, dtype: int64
```

```
## 2. LSTM Model (Improved Version)
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
def create_sequences(data, labels, seq_length=30):
    seq, targets = [], []
    for i in range(seq_length, len(data)):
        seq.append(data.iloc[i-seq_length:i].values)
        targets.append(labels.iloc[i])
    return np.array(seq), np.array(targets)
X_train_seq, y_train_seq = create_sequences(pd.DataFrame(X_train), y_train)
X_test_seq, y_test_seq = create_sequences(pd.DataFrame(X_test), y_test)
lstm_model = Sequential([
    LSTM(64, input_shape=(X_train_seq.shape[1], X_train_seq.shape[2])),
    Dropout(0.3),
    Dense(1, activation='sigmoid')
lstm_model.compile(optimizer='adam', loss='binary_crossentropy',
                  metrics=['Precision', 'Recall', 'AUC'])
# Train with class weights
history = lstm_model.fit(X_train_seq, y_train_seq, epochs=15, batch_size=64,
                        validation_split=0.1, class_weight={0:1, 1:30})
🚁 /usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_di
       super().__init__(**kwargs)
     Epoch 1/15
     3204/3204 -
                                  - 111s 32ms/step - AUC: 0.4790 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2191 - va
     Epoch 2/15
     3204/3204
                                  - 90s 28ms/step - AUC: 0.5247 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2086 - val
     Epoch 3/15
     3204/3204
                                   - 85s 26ms/step - AUC: 0.5597 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2081 - val
     Epoch 4/15
     3204/3204 -
                                   - 138s 25ms/step - AUC: 0.5742 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2062 - va
     Epoch 5/15
     3204/3204 -
                                   - 102s 31ms/step - AUC: 0.5756 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2107 - va
     Epoch 6/15
     3204/3204 -
                                   - 131s 28ms/step - AUC: 0.6699 - Precision: 0.3161 - Recall: 0.0063 - loss: 0.1958 - val_AUC: 0
     Epoch 7/15
     3204/3204 -
                                   - 138s 27ms/step - AUC: 0.7162 - Precision: 0.2155 - Recall: 0.0159 - loss: 0.1801 - val_AUC: 0
     Epoch 8/15
     3204/3204 -
                                   - 141s 26ms/step - AUC: 0.7923 - Precision: 0.2654 - Recall: 0.0245 - loss: 0.1569 - val AUC: 0
     Epoch 9/15
     3204/3204 -
                                  – 87s 27ms/step – AUC: 0.8599 – Precision: 0.1438 – Recall: 0.0905 – loss: 0.1489 – val_AUC: 0.
     Epoch 10/15
     3204/3204 -
                                   - 86s 27ms/step - AUC: 0.9079 - Precision: 0.1688 - Recall: 0.1483 - loss: 0.1273 - val_AUC: 0.
     Epoch 11/15
     3204/3204 -
                                   - 146s 28ms/step - AUC: 0.9471 - Precision: 0.1432 - Recall: 0.2792 - loss: 0.1088 - val_AUC: 0
     Epoch 12/15
     3204/3204 -
                                   - 137s 27ms/step - AUC: 0.9733 - Precision: 0.1885 - Recall: 0.4542 - loss: 0.0810 - val_AUC: 0
     Epoch 13/15
     3204/3204 -
                                   - 139s 26ms/step - AUC: 0.9853 - Precision: 0.1866 - Recall: 0.5891 - loss: 0.0651 - val AUC: 0
     Epoch 14/15
     3204/3204 -
                                   - 144s 26ms/step — AUC: 0.9885 — Precision: 0.2264 — Recall: 0.7266 — loss: 0.0504 — val_AUC: 0
     Epoch 15/15
     3204/3204
                                   - 146s 28ms/step - AUC: 0.9924 - Precision: 0.2565 - Recall: 0.8238 - loss: 0.0401 - val AUC: 0
```

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## 3. Autoencoder Model
from tensorflow.keras import Model, Input

input_dim = X_train.shape[1]
encoding_dim = 14

input_layer = Input(shape=(input_dim,))
encoder = Dense(encoding_dim, activation='relu')(input_layer)
decoder = Dense(input_dim, activation='sigmoid')(encoder)

autoencoder = Model(inputs=input_layer, outputs=decoder)
autoencoder.compile(optimizer='adam', loss='mse')

# Train on normal transactions only
normal_idx = y_train == 0
```

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→ Epoch 1/20
    3199/3199
                                  - 10s 3ms/step - loss: 1.2769 - val_loss: 1.1652
    Epoch 2/20
    3199/3199 -
                                   - 10s 3ms/step - loss: 1.1764 - val_loss: 1.1460
    Epoch 3/20
    3199/3199 -
                                   - 9s 3ms/step - loss: 1.1446 - val_loss: 1.1405
    Epoch 4/20
    3199/3199 -
                                   - 9s 3ms/step - loss: 1.0911 - val_loss: 1.1377
    Epoch 5/20
    3199/3199
                                   - 11s 3ms/step - loss: 1.0813 - val_loss: 1.1357
    Epoch 6/20
    3199/3199
                                  - 10s 3ms/step - loss: 1.1152 - val_loss: 1.1348
    Epoch 7/20
    3199/3199
                                   - 10s 3ms/step - loss: 1.0850 - val_loss: 1.1338
    Epoch 8/20
    3199/3199 -
                                   - 11s 3ms/step - loss: 1.0925 - val_loss: 1.1335
    Epoch 9/20
    3199/3199 -
                                   - 18s 3ms/step - loss: 1.0768 - val_loss: 1.1331
    Epoch 10/20
    3199/3199 -
                                   - 10s 3ms/step - loss: 1.0467 - val_loss: 1.1325
    Epoch 11/20
    3199/3199 -
                                   - 11s 3ms/step - loss: 1.1283 - val_loss: 1.1322
    Epoch 12/20
    3199/3199 -
                                   - 11s 3ms/step - loss: 1.0775 - val_loss: 1.1320
    Epoch 13/20
    3199/3199 -
                                   - 10s 3ms/step - loss: 1.1499 - val_loss: 1.1319
    Epoch 14/20
    3199/3199 -
                                   - 12s 3ms/step - loss: 1.0789 - val_loss: 1.1317
    Epoch 15/20
    3199/3199 -
                                   - 11s 3ms/step - loss: 1.1134 - val_loss: 1.1317
    Epoch 16/20
    3199/3199 -
                                   - 18s 3ms/step - loss: 1.0629 - val_loss: 1.1318
    Epoch 17/20
    3199/3199 -
                                   - 11s 3ms/step - loss: 1.0853 - val_loss: 1.1315
    Epoch 18/20
    3199/3199 -
                                   - 9s 3ms/step - loss: 1.0458 - val_loss: 1.1314
    Epoch 19/20
    3199/3199 -
                                   - 10s 3ms/step - loss: 1.0556 - val_loss: 1.1315
    Epoch 20/20
                                    11s 3ms/step - loss: 1.0832 - val_loss: 1.1313
    3199/3199 -
    <keras.src.callbacks.history.History at 0x7d29aa7a4510>
# 1. TRANSFORMER IMPLEMENTATION
from tensorflow.keras.layers import LayerNormalization, MultiHeadAttention, Embedding, GlobalAveragePooling1D
from tensorflow.keras import Input, Model
class TransformerBlock(tf.keras.layers.Layer):
    def __init__(self, embed_dim, num_heads):
        super().__init__()
        self.att = MultiHeadAttention(num_heads=num_heads, key_dim=embed_dim)
        self.layernorm1 = LayerNormalization()
        self.layernorm2 = LayerNormalization()
        self.dense = tf.keras.Sequential([
            Dense(embed_dim, activation='gelu'),
            Dense(embed_dim)
        ])
    def call(self, inputs):
        attn_output = self.att(inputs, inputs)
        out1 = self.layernorm1(inputs + attn_output)
        ff_output = self.dense(out1)
        return self.layernorm2(out1 + ff output)
def build_transformer_model(input_shape):
    inputs = Input(shape=input_shape)
    # Feature Embedding
    x = Dense(64)(inputs)
    # Positional Encoding
    positions = tf.range(start=0, limit=input_shape[0], delta=1)
    position_embedding = Embedding(input_dim=input_shape[0], output_dim=64)(positions)
    x += position_embedding
    # Transformer Blocks
    x = TransformerBlock(embed_dim=64, num_heads=4)(x)
    x = GlobalAveragePooling1D()(x)
```

```
outputs = Dense(1, activation='sigmoid')(x)
    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer='adam',
                 loss='binary_crossentropy',
                 metrics=['Precision', 'Recall', 'AUC'])
    return model
# 2. DATA PREPARATION FOR TRANSFORMER
# Using same sequences as LSTM for fair comparison
X_{train_{trans}} = X_{train_{seq}}
y_train_trans = y_train_seq
X test trans = X test seg
y_test_trans = y_test_seq
# 3. TRAINING THE TRANSFORMER
transformer = build_transformer_model(X_train_trans.shape[1:])
transformer.fit(X_train_trans, y_train_trans,
                epochs=15,
                batch_size=64,
                validation split=0.1,
                class_weight={0:1, 1:30})
→ Epoch 1/15
     3204/3204
                                  – 302s 91ms/step – AUC: 0.4615 – Precision: 0.0000e+00 – Recall: 0.0000e+00 – loss: 0.2202 – va
     Epoch 2/15
                                   - 315s 89ms/step - AUC: 0.5030 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2031 - va
     3204/3204 -
     Epoch 3/15
     3204/3204 -
                                   - 318s 88ms/step - AUC: 0.4955 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2096 - va
     Epoch 4/15
     3204/3204 -
                                   - 317s 86ms/step - AUC: 0.5604 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2226 - va
     Epoch 5/15
     3204/3204 -
                                   - 323s 87ms/step - AUC: 0.5077 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2015 - va
     Epoch 6/15
     3204/3204
                                  - 322s 87ms/step - AUC: 0.5277 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2009 - va
     Epoch 7/15
    3204/3204
                                   - 326s 88ms/step - AUC: 0.5523 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2023 - va
     Epoch 8/15
     3204/3204
                                   - 320s 87ms/step - AUC: 0.5449 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2030 - va
     Epoch 9/15
     3204/3204 -
                                   - 280s 87ms/step - AUC: 0.5455 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2057 - va
     Epoch 10/15
     3204/3204 -
                                   - 321s 87ms/step - AUC: 0.5271 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.1974 - va
     Epoch 11/15
     3204/3204 -
                                   - 279s 87ms/step - AUC: 0.5563 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2046 - va
     Epoch 12/15
     3204/3204 -
                                   - 334s 91ms/step - AUC: 0.5510 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2112 - va
     Epoch 13/15
     3204/3204 -
                                   - 277s 87ms/step - AUC: 0.5649 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.1943 - va
     Epoch 14/15
                                   - 301s 94ms/step - AUC: 0.5659 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2047 - va
    3204/3204 -
     Epoch 15/15
     3204/3204 -
                                   - 305s 89ms/step - AUC: 0.5742 - Precision: 0.0000e+00 - Recall: 0.0000e+00 - loss: 0.2151 - va
     <keras.src.callbacks.history.History at 0x7d29acf1f610>
## 5. Comparative Evaluation
def evaluate_model(model, X_test, y_test, model_type='lstm'):
    if model_type == 'autoencoder':
       reconstructions = model.predict(X_test)
        mse = np.mean(np.power(X_test - reconstructions, 2), axis=1)
        y_pred = (mse > np.percentile(mse, 95)).astype(int) # Anomaly threshold
        y_pred = (model.predict(X_test) > 0.5).astype(int)
    from sklearn.metrics import classification_report
    print(classification_report(y_test, y_pred))
```

LSTM Performance: 1780/1780 13s 7ms/step

evaluate\_model(lstm\_model, X\_test\_seq, y\_test\_seq)

evaluate\_model(autoencoder, X\_test, y\_test, 'autoencoder')

evaluate\_model(transformer, X\_test\_trans, y\_test\_trans)

print("LSTM Performance:")

print("\nAutoencoder Performance:")

print("\n=== Transformer Evaluation ===")

	precision	recall	f1-score	support	
0	1.00	0.99	1.00	56834	
1	0.00	0.00	0.00	98	
accuracy			0.99	56932	
macro avq	0.50	0.50	0.50	56932	
weighted avg	1.00	0.99	0.99	56932	
Autoencoder P	erformance:				
1781/1781		2s	1ms/step		
	precision	recall	f1-score	support	
0	1.00	0.95	0.97	56864	
1	0.03	0.87	0.06	98	
1	0.05	0.07	0.00	90	
accuracy			0.95	56962	
macro avg	0.51	0.91	0.52	56962	
weighted avg	1.00	0.95	0.97	56962	
weighted avg	1.00	0.93	0.37	30302	
=== Transform	ner Evaluation				
1780/1780		25s	14ms/step		
	precision	recall	f1-score	support	
0	1.00	1.00	1.00	56834	
1	0.00	0.00	0.00	98	
accuracy			1.00	56932	
macro avg	0.50	0.50	0.50	56932	
weighted avg	1.00	1.00	1.00	56932	

<sup>/</sup>usr/local/lib/python3.11/dist-packages/sklearn/metrics/\_classification.py:1565: UndefinedMetricWarning: Precision is ill-de \_warn\_prf(average, modifier, f"{metric.capitalize()} is", len(result))

<sup>/</sup>usr/local/lib/python3.11/dist-packages/sklearn/metrics/\_classification.py:1565: UndefinedMetricWarning: Precision is ill-de \_warn\_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/\_classification.py:1565: UndefinedMetricWarning: Precision is ill-de

\_warn\_prf(average, modifier, f"{metric.capitalize()} is", len(result))