Lending Club Loan Status Prediction - Neural Network Classification

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix,
roc_auc_score, roc_curve
from sklearn.impute import SimpleImputer
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import warnings
warnings.filterwarnings('ignore')

# Set random seed for reproducibility
np.random.seed(42)
tf.random.set_seed(42)

# Configure matplotlib and seaborn
plt.style.use('default')
sns.set_palette("husl")

print("All libraries imported successfully!")
print(f"TensorFlow version: {tf.__version__}")
```

```
All libraries imported successfully!
TensorFlow version: 2.18.0
```

1. DATA LOADING AND INITIAL EXPLORATION

```
# Load the dataset
try:
    df = pd.read_csv('lending_club_loan_two.csv')
    print("Dataset loaded successfully!")
    print(f"Dataset shape: {df.shape}")
except FileNotFoundError:
    print("Please upload your 'lending_club_two.csv' file to Colab
first")
    print("Use the file upload button in the sidebar or:")
```

```
    print("from google.colab import files")
    print("files.upload()")
```

```
Dataset loaded successfully!
Dataset shape: (396030, 27)
```

```python
# Display basic information about the dataset
print("DATASET OVERVIEW")
print(f"Dataset shape: {df.shape}")
print(f"Memory usage: {df.memory_usage(deep=True).sum() / 1024**2:.2f}
MB")
```

```
DATASET OVERVIEW
Dataset shape: (396030, 27)
Memory usage: 421.42 MB
```

```python
# Display first few rows
print("\nFirst 5 rows:")
print(df.head())
```

```
First 5 rows:
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5

                 emp_title emp_length home_ownership  annual_inc  ...
\
0                Marketing  10+ years           RENT    117000.0  ...

1          Credit analyst     4 years       MORTGAGE     65000.0  ...

2             Statistician   < 1 year           RENT     43057.0  ...

3          Client Advocate    6 years           RENT     54000.0  ...

4  Destiny Management Inc.    9 years       MORTGAGE     55000.0  ...


  open_acc pub_rec revol_bal revol_util total_acc  initial_list_status
\
0     16.0     0.0   36369.0       41.8      25.0                    w

1     17.0     0.0   20131.0       53.3      27.0                    f

2     13.0     0.0   11987.0       92.2      26.0                    f

3      6.0     0.0    5472.0       21.5      13.0                    f
```

```
4     13.0     0.0   24584.0       69.8      43.0                    f

  application_type  mort_acc  pub_rec_bankruptcies  \
0       INDIVIDUAL       0.0                   0.0
1       INDIVIDUAL       3.0                   0.0
2       INDIVIDUAL       0.0                   0.0
3       INDIVIDUAL       0.0                   0.0
4       INDIVIDUAL       1.0                   0.0

                                            address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650

[5 rows x 27 columns]
```

```python
# Display data types and missing values
print("\nData Types and Missing Values:")
info_df = pd.DataFrame({
    'Column': df.columns,
    'Data Type': df.dtypes,
    'Missing Values': df.isnull().sum(),
    'Missing %': (df.isnull().sum() / len(df) * 100).round(2)
})
print(info_df)
```

```
Data Types and Missing Values:
                                    Column Data Type  Missing
Values  \
loan_amnt                        loan_amnt   float64               0

term                                  term    object               0

int_rate                          int_rate   float64               0

installment                    installment   float64               0

grade                                grade    object               0

sub_grade                        sub_grade    object               0

emp_title                        emp_title    object           22927

emp_length                      emp_length    object           18301

home_ownership              home_ownership    object               0
```

annual_inc	annual_inc	float64	0
verification_status	verification_status	object	0
issue_d	issue_d	object	0
loan_status	loan_status	object	0
purpose	purpose	object	0
title	title	object	1756
dti	dti	float64	0
earliest_cr_line	earliest_cr_line	object	0
open_acc	open_acc	float64	0
pub_rec	pub_rec	float64	0
revol_bal	revol_bal	float64	0
revol_util	revol_util	float64	276
total_acc	total_acc	float64	0
initial_list_status	initial_list_status	object	0
application_type	application_type	object	0
mort_acc	mort_acc	float64	37795
pub_rec_bankruptcies	pub_rec_bankruptcies	float64	535
address	address	object	0

	Missing %
loan_amnt	0.00
term	0.00
int_rate	0.00
installment	0.00
grade	0.00
sub_grade	0.00
emp_title	5.79
emp_length	4.62
home_ownership	0.00
annual_inc	0.00
verification_status	0.00
issue_d	0.00

```
loan_status               0.00
purpose                   0.00
title                     0.44
dti                       0.00
earliest_cr_line          0.00
open_acc                  0.00
pub_rec                   0.00
revol_bal                 0.00
revol_util                0.07
total_acc                 0.00
initial_list_status       0.00
application_type          0.00
mort_acc                  9.54
pub_rec_bankruptcies      0.14
address                   0.00

# Basic statistics
print("\nBasic Statistics for Numerical Columns:")
print(df.describe())
```

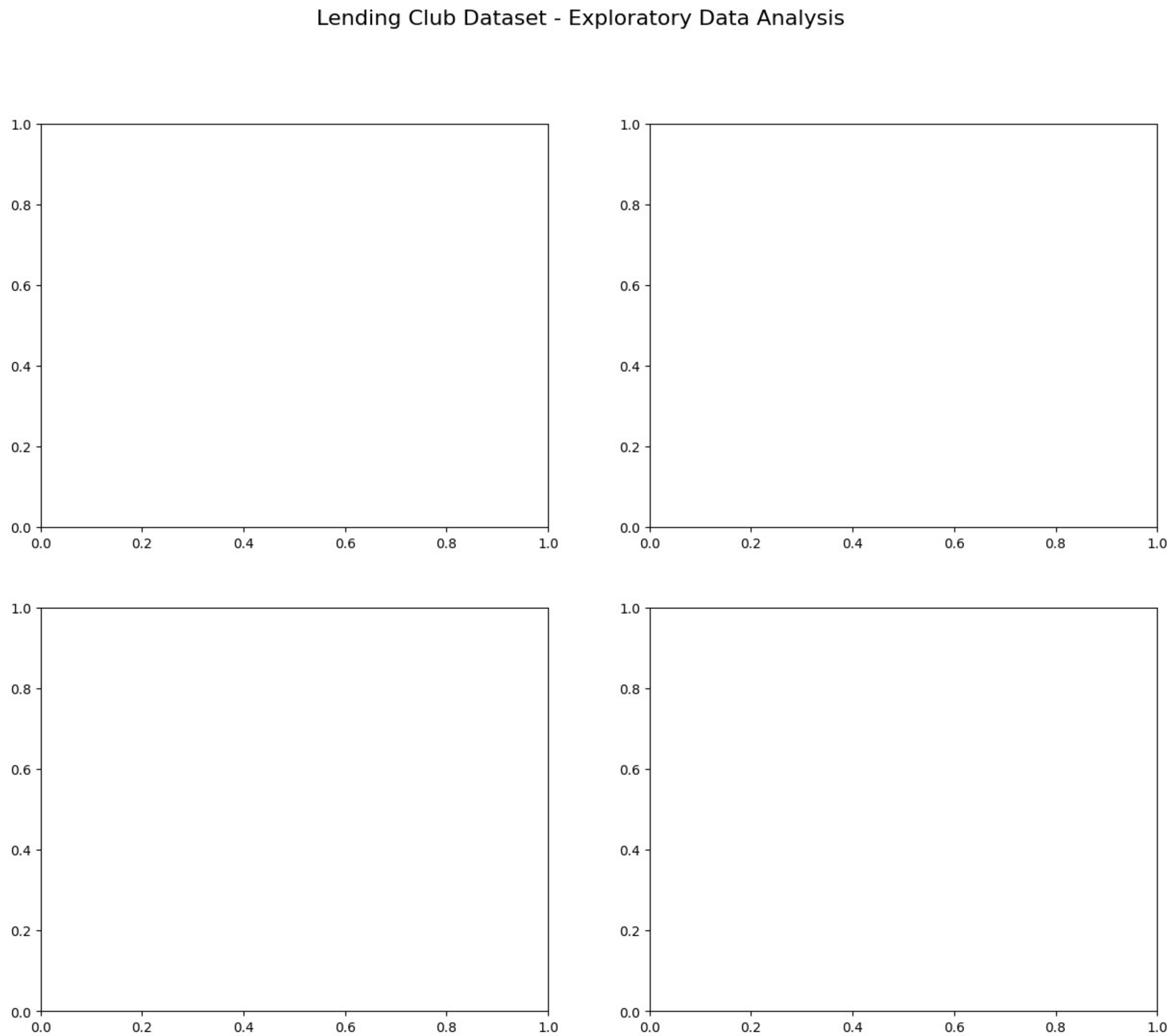
```
Basic Statistics for Numerical Columns:
           loan_amnt       int_rate    installment    annual_inc  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean    14113.888089      13.639400     431.849698  7.420318e+04
std      8357.441341       4.472157     250.727790  6.163762e+04
min       500.000000       5.320000      16.080000  0.000000e+00
25%      8000.000000      10.490000     250.330000  4.500000e+04
50%     12000.000000      13.330000     375.430000  6.400000e+04
75%     20000.000000      16.490000     567.300000  9.000000e+04
max     40000.000000      30.990000    1533.810000  8.706582e+06

                 dti       open_acc        pub_rec     revol_bal  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean       17.379514      11.311153       0.178191  1.584454e+04
std        18.019092       5.137649       0.530671  2.059184e+04
min         0.000000       0.000000       0.000000  0.000000e+00
25%        11.280000       8.000000       0.000000  6.025000e+03
50%        16.910000      10.000000       0.000000  1.118100e+04
75%        22.980000      14.000000       0.000000  1.962000e+04
max      9999.000000      90.000000      86.000000  1.743266e+06

          revol_util      total_acc       mort_acc
pub_rec_bankruptcies
count  395754.000000  396030.000000  358235.000000
395495.000000
mean       53.791749      25.414744       1.813991
0.121648
std        24.452193      11.886991       2.147930
0.356174
```

```
min          0.000000       2.000000       0.000000
0.000000
25%         35.800000      17.000000       0.000000
0.000000
50%         54.800000      24.000000       1.000000
0.000000
75%         72.900000      32.000000       3.000000
0.000000
max        892.300000     151.000000      34.000000
8.000000
```

2. EXPLORATORY DATA ANALYSIS (EDA)

```python
# Create figure for EDA plots
fig, axes = plt.subplots(2, 2, figsize=(15, 12))
fig.suptitle('Lending Club Dataset - Exploratory Data Analysis',
fontsize=16)
```

```
Text(0.5, 0.98, 'Lending Club Dataset - Exploratory Data Analysis')
```




```
# 1. Target Variable Distribution
if 'loan_status' in df.columns:
    loan_status_counts = df['loan_status'].value_counts()
    axes[0, 0].pie(loan_status_counts.values,
labels=loan_status_counts.index, autopct='%1.1f%%')
    axes[0, 0].set_title('Distribution of Loan Status')
    print(f"\nLoan Status Distribution:")
    print(loan_status_counts)
    print(f"Class balance ratio:
{loan_status_counts.min()/loan_status_counts.max():.3f}")
```

```
Loan Status Distribution:
loan_status
Fully Paid     318357
Charged Off     77673
```

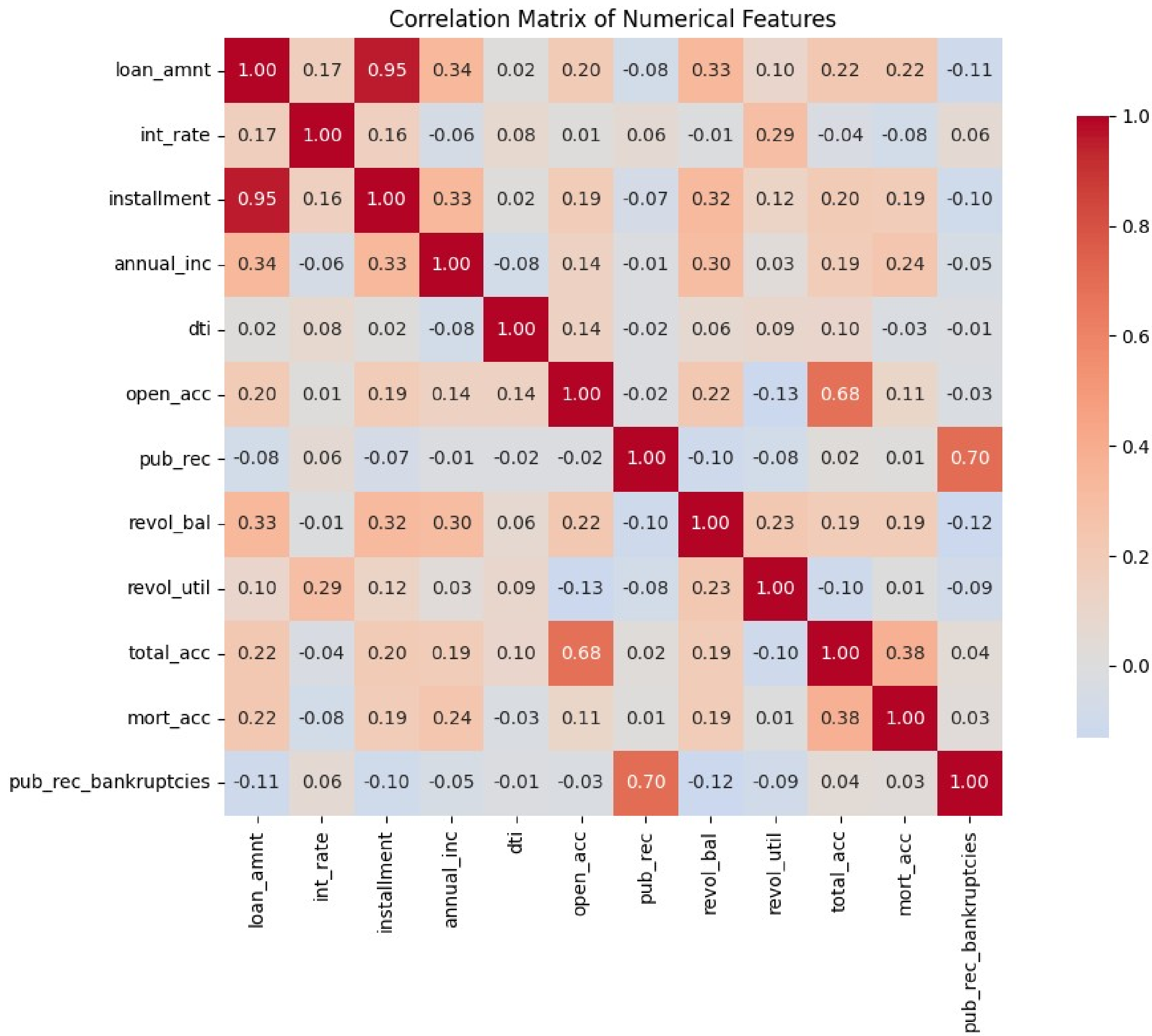
```
Name: count, dtype: int64
Class balance ratio: 0.244
```

```python
# 2. Loan Amount Distribution
if 'loan_amnt' in df.columns:
    axes[0, 1].hist(df['loan_amnt'].dropna(), bins=50, alpha=0.7,
color='skyblue')
    axes[0, 1].set_title('Distribution of Loan Amount')
    axes[0, 1].set_xlabel('Loan Amount ($)')
    axes[0, 1].set_ylabel('Frequency')

# 3. Interest Rate Distribution
if 'int_rate' in df.columns:
    axes[1, 0].hist(df['int_rate'].dropna(), bins=30, alpha=0.7,
color='lightcoral')
    axes[1, 0].set_title('Distribution of Interest Rate')
    axes[1, 0].set_xlabel('Interest Rate (%)')
    axes[1, 0].set_ylabel('Frequency')

# 4. Grade Distribution
if 'grade' in df.columns:
    grade_counts = df['grade'].value_counts().sort_index()
    axes[1, 1].bar(grade_counts.index, grade_counts.values,
color='lightgreen')
    axes[1, 1].set_title('Distribution of Loan Grades')
    axes[1, 1].set_xlabel('Grade')
    axes[1, 1].set_ylabel('Count')

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

```
<Figure size 640x480 with 0 Axes>
```

Correlation Analysis for Numerical Features

```python
# Select numerical columns for correlation analysis
numerical_cols =
df.select_dtypes(include=[np.number]).columns.tolist()
if len(numerical_cols) > 1:
    plt.figure(figsize=(12, 8))
    correlation_matrix = df[numerical_cols].corr()
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
center=0,
                square=True, fmt='.2f', cbar_kws={"shrink": .8})
    plt.title('Correlation Matrix of Numerical Features')
    plt.tight_layout()
    plt.show()
```



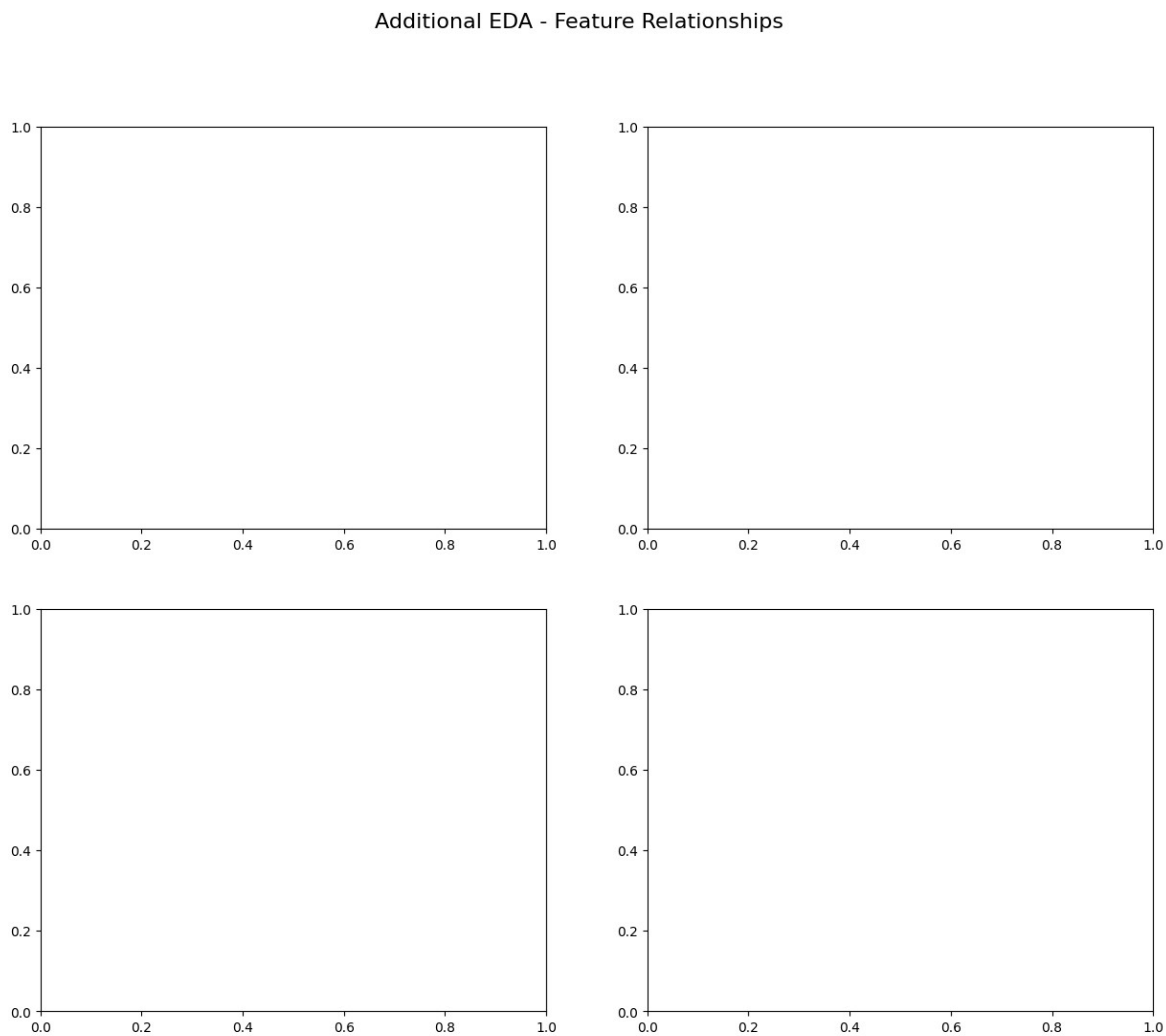

```python
# Find highly correlated features
high_corr_pairs = []
for i in range(len(correlation_matrix.columns)):
  for j in range(i+1, len(correlation_matrix.columns)):
      if abs(correlation_matrix.iloc[i, j]) > 0.7:
          high_corr_pairs.append((
              correlation_matrix.columns[i],
              correlation_matrix.columns[j],
              correlation_matrix.iloc[i, j]
          ))

if high_corr_pairs:
  print("Highly correlated feature pairs (|r| > 0.7):")
  for pair in high_corr_pairs:
      print(f"  {pair[0]} - {pair[1]}: {pair[2]:.3f}")
```

```
else:
  print("No highly correlated feature pairs found (|r| > 0.7)")
```

```
Highly correlated feature pairs (|r| > 0.7):
  loan_amnt - installment: 0.954
```

```
# Additional EDA plots
fig, axes = plt.subplots(2, 2, figsize=(15, 12))
fig.suptitle('Additional EDA - Feature Relationships', fontsize=16)
```

```
Text(0.5, 0.98, 'Additional EDA - Feature Relationships')
```




```
# Loan Amount vs Interest Rate
if 'loan_amnt' in df.columns and 'int_rate' in df.columns:
    axes[0, 0].scatter(df['loan_amnt'], df['int_rate'], alpha=0.5)
    axes[0, 0].set_xlabel('Loan Amount ($)')
```

```
    axes[0, 0].set_ylabel('Interest Rate (%)')
    axes[0, 0].set_title('Loan Amount vs Interest Rate')

# Employment Length Distribution
if 'emp_length' in df.columns:
    emp_length_counts = df['emp_length'].value_counts()
    axes[0, 1].bar(range(len(emp_length_counts)),
emp_length_counts.values)
    axes[0, 1].set_title('Employment Length Distribution')
    axes[0, 1].set_xlabel('Employment Length')
    axes[0, 1].set_ylabel('Count')
    axes[0, 1].set_xticks(range(len(emp_length_counts)))
    axes[0, 1].set_xticklabels(emp_length_counts.index, rotation=45)

# Home Ownership Distribution
if 'home_ownership' in df.columns:
    home_counts = df['home_ownership'].value_counts()
    axes[1, 0].pie(home_counts.values, labels=home_counts.index,
autopct='%1.1f%%')
    axes[1, 0].set_title('Home Ownership Distribution')

# Annual Income Distribution (log scale)
if 'annual_inc' in df.columns:
    axes[1, 1].hist(np.log1p(df['annual_inc'].dropna()), bins=50,
alpha=0.7, color='gold')
    axes[1, 1].set_title('Distribution of Annual Income (Log Scale)')
    axes[1, 1].set_xlabel('Log(Annual Income + 1)')
    axes[1, 1].set_ylabel('Frequency')

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

```
<Figure size 640x480 with 0 Axes>
```

3. DATA PREPROCESSING

```
# Create a copy of the dataframe for preprocessing
df_processed = df.copy()

# Handle missing values
missing_summary = df_processed.isnull().sum()
print(f"Columns with missing values: {missing_summary[missing_summary
> 0].shape[0]}")
```

```
Columns with missing values: 6
```

```
# For numerical columns, use median imputation
numerical_cols =
df_processed.select_dtypes(include=[np.number]).columns
```

```python
for col in numerical_cols:
    if df_processed[col].isnull().sum() > 0:
        median_val = df_processed[col].median()
        df_processed[col].fillna(median_val, inplace=True)
        print(f"Filled {col} missing values with median: {median_val}")
```

```
Filled revol_util missing values with median: 54.8
Filled mort_acc missing values with median: 1.0
Filled pub_rec_bankruptcies missing values with median: 0.0
```

```python
# For categorical columns, use mode imputation
categorical_cols = df_processed.select_dtypes(include=['object']).columns
for col in categorical_cols:
    if df_processed[col].isnull().sum() > 0:
        mode_val = df_processed[col].mode()[0] if not df_processed[col].mode().empty else 'Unknown'
        df_processed[col].fillna(mode_val, inplace=True)
        print(f"Filled {col} missing values with mode: {mode_val}")
```

```
Filled emp_title missing values with mode: Teacher
Filled emp_length missing values with mode: 10+ years
Filled title missing values with mode: Debt consolidation
```

```python
# Prepare target variable
if 'loan_status' in df_processed.columns:
    # Create binary target variable
    # Assuming 'Fully Paid' = 1 (good), others = 0 (bad)
    df_processed['target'] = (df_processed['loan_status'] == 'Fully Paid').astype(int)
    print(f"Target variable created. Distribution:")
    print(df_processed['target'].value_counts())
```

```
Target variable created. Distribution:
target
1    318357
0     77673
Name: count, dtype: int64
```

Feature Engineering

```python
# Extract year from issue_d if it exists
if 'issue_d' in df_processed.columns:
    df_processed['issue_year'] = pd.to_datetime(df_processed['issue_d'], errors='coerce').dt.year
    print("Extracted issue year from issue_d")
```

```
Extracted issue year from issue_d
```

```python
# Extract year from earliest_cr_line if it exists
if 'earliest_cr_line' in df_processed.columns:
    df_processed['earliest_cr_year'] =
pd.to_datetime(df_processed['earliest_cr_line'],
errors='coerce').dt.year
    print("Extracted earliest credit line year")
```

```
Extracted earliest credit line year
```

```python
# Calculate credit history length
if 'issue_year' in df_processed.columns and 'earliest_cr_year' in
df_processed.columns:
    df_processed['credit_history_length'] = df_processed['issue_year']
- df_processed['earliest_cr_year']
    print("Calculated credit history length")
```

```
Calculated credit history length
```

```python
# Create debt-to-income ratio categories
if 'dti' in df_processed.columns:
    df_processed['dti_category'] = pd.cut(df_processed['dti'],
                                         bins=[0, 10, 20, 30,
float('inf')],
                                         labels=['Low', 'Medium',
'High', 'Very High'])
    print("Created DTI categories")
```

```
Created DTI categories
```

```python
# Process categorical variables
print("\nEncoding categorical variables...")
categorical_features = []
label_encoders = {}

for col in categorical_cols:
    if col not in ['loan_status', 'target']:  # Skip target-related
columns
        if df_processed[col].nunique() <= 10:  # Use label encoding
for low cardinality
            le = LabelEncoder()
            df_processed[f'{col}_encoded'] =
le.fit_transform(df_processed[col].astype(str))
            label_encoders[col] = le
            categorical_features.append(f'{col}_encoded')
            print(f"Label encoded {col} ({df_processed[col].nunique()}
unique values)")
        else:  # Use one-hot encoding for high cardinality (top
categories only)
            top_categories =
df_processed[col].value_counts().head(10).index
            for category in top_categories:
```

```
                df_processed[f'{col}_{category}'] = (df_processed[col]
== category).astype(int)
                categorical_features.append(f'{col}_{category}')
            print(f"One-hot encoded top 10 categories for {col}")
```

```
Encoding categorical variables...
Label encoded term (2 unique values)
Label encoded grade (7 unique values)
One-hot encoded top 10 categories for sub_grade
One-hot encoded top 10 categories for emp_title
One-hot encoded top 10 categories for emp_length
Label encoded home_ownership (6 unique values)
Label encoded verification_status (3 unique values)
One-hot encoded top 10 categories for issue_d
One-hot encoded top 10 categories for purpose
One-hot encoded top 10 categories for title
One-hot encoded top 10 categories for earliest_cr_line
Label encoded initial_list_status (2 unique values)
Label encoded application_type (3 unique values)
One-hot encoded top 10 categories for address
```

```
# Select features for modeling
feature_cols = []

# Add numerical features
numerical_features = ['loan_amnt', 'int_rate', 'installment',
'annual_inc', 'dti',
                     'open_acc', 'pub_rec', 'revol_bal', 'revol_util',
'total_acc',
                     'mort_acc', 'pub_rec_bankruptcies']

for col in numerical_features:
    if col in df_processed.columns:
        feature_cols.append(col)

# Add engineered features
engineered_features = ['issue_year', 'earliest_cr_year',
'credit_history_length']
for col in engineered_features:
    if col in df_processed.columns:
        feature_cols.append(col)

# Add categorical features
feature_cols.extend(categorical_features)

# Remove any features that don't exist in the dataset
feature_cols = [col for col in feature_cols if col in
df_processed.columns]
```

```
print(f"Selected {len(feature_cols)} features for modeling")
print(f"Features: {feature_cols}")
```

```
Selected 101 features for modeling
Features: ['loan_amnt', 'int_rate', 'installment', 'annual_inc',
'dti', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util', 'total_acc',
'mort_acc', 'pub_rec_bankruptcies', 'issue_year', 'earliest_cr_year',
'credit_history_length', 'term_encoded', 'grade_encoded',
'sub_grade_B3', 'sub_grade_B4', 'sub_grade_C1', 'sub_grade_C2',
'sub_grade_B2', 'sub_grade_B5', 'sub_grade_C3', 'sub_grade_C4',
'sub_grade_B1', 'sub_grade_A5', 'emp_title_Teacher',
'emp_title_Manager', 'emp_title_Registered Nurse', 'emp_title_RN',
'emp_title_Supervisor', 'emp_title_Sales', 'emp_title_Project
Manager', 'emp_title_Owner', 'emp_title_Driver', 'emp_title_Office
Manager', 'emp_length_10+ years', 'emp_length_2 years', 'emp_length_<
1 year', 'emp_length_3 years', 'emp_length_5 years', 'emp_length_1
year', 'emp_length_4 years', 'emp_length_6 years', 'emp_length_7
years', 'emp_length_8 years', 'home_ownership_encoded',
'verification_status_encoded', 'issue_d_Oct-2014', 'issue_d_Jul-2014',
'issue_d_Jan-2015', 'issue_d_Dec-2013', 'issue_d_Nov-2013',
'issue_d_Jul-2015', 'issue_d_Oct-2013', 'issue_d_Jan-2014',
'issue_d_Apr-2015', 'issue_d_Sep-2013', 'purpose_debt_consolidation',
'purpose_credit_card', 'purpose_home_improvement', 'purpose_other',
'purpose_major_purchase', 'purpose_small_business', 'purpose_car',
'purpose_medical', 'purpose_moving', 'purpose_vacation', 'title_Debt
consolidation', 'title_Credit card refinancing', 'title_Home
improvement', 'title_Other', 'title_Debt Consolidation', 'title_Major
purchase', 'title_Consolidation', 'title_debt consolidation',
'title_Business', 'title_Debt Consolidation Loan',
'earliest_cr_line_Oct-2000', 'earliest_cr_line_Aug-2000',
'earliest_cr_line_Oct-2001', 'earliest_cr_line_Aug-2001',
'earliest_cr_line_Nov-2000', 'earliest_cr_line_Oct-1999',
'earliest_cr_line_Nov-1999', 'earliest_cr_line_Sep-2000',
'earliest_cr_line_Oct-2002', 'earliest_cr_line_Aug-2002',
'initial_list_status_encoded', 'application_type_encoded',
'address_USS Johnson\r\nFPO AE 48052', 'address_USNS Johnson\r\nFPO AE
05113', 'address_USS Smith\r\nFPO AP 70466', 'address_USCGC Smith\r\
nFPO AE 70466', 'address_USNS Johnson\r\nFPO AP 48052', 'address_USNV
Smith\r\nFPO AA 00813', 'address_USNV Smith\r\nFPO AE 30723',
'address_USCGC Miller\r\nFPO AA 22690', 'address_USNS Johnson\r\nFPO
AA 70466', 'address_USS Smith\r\nFPO AP 22690']
```

```
# Prepare final dataset
if 'target' in df_processed.columns:
    # Remove rows with missing target
    df_final = df_processed.dropna(subset=['target'])

    X = df_final[feature_cols]
    y = df_final['target']
```

```
    print(f"Final dataset shape: {X.shape}")
    print(f"Target distribution: {y.value_counts().to_dict()}")
else:
    print("Warning: Target variable 'loan_status' not found. Creating
dummy target.")
    X = df_processed[feature_cols]
    y = np.random.choice([0, 1], size=len(X))  # Dummy target for
demonstration
```

```
Final dataset shape: (396030, 101)
Target distribution: {1: 318357, 0: 77673}
```

```
# Handle any remaining missing values
X = X.fillna(X.median())
```

4. MODEL BUILDING

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)

print(f"Training set shape: {X_train.shape}")
print(f"Testing set shape: {X_test.shape}")
print(f"Training set target distribution:
{pd.Series(y_train).value_counts().to_dict()}")
print(f"Testing set target distribution:
{pd.Series(y_test).value_counts().to_dict()}")
```

```
Training set shape: (316824, 101)
Testing set shape: (79206, 101)
Training set target distribution: {1: 254686, 0: 62138}
Testing set target distribution: {1: 63671, 0: 15535}
```

```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
Features scaled using StandardScaler
```

```
# Build Neural Network Model
model = keras.Sequential([
    layers.Dense(128, activation='relu',
input_shape=(X_train_scaled.shape[1],)),
    layers.Dropout(0.3),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(32, activation='relu'),
    layers.Dropout(0.2),
```

```
    layers.Dense(16, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy', 'precision', 'recall']
)

# Display model architecture
print("\nModel Architecture:")
model.summary()
```

```
Model Architecture:

Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ dense (Dense)                   │ (None, 128)            │
13,056 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dropout (Dropout)               │ (None, 128)            │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_1 (Dense)                 │ (None, 64)             │
8,256 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dropout_1 (Dropout)             │ (None, 64)             │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_2 (Dense)                 │ (None, 32)             │
2,080 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dropout_2 (Dropout)             │ (None, 32)             │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
```

```
│ dense_3 (Dense)                  │ (None, 16)              │
528 │
├──────────────────────────────────┼─────────────────────────┼──────────
──────┤
│ dense_4 (Dense)                  │ (None, 1)               │
17 │
└──────────────────────────────────┴─────────────────────────┴──────────
──────┘

 Total params: 23,937 (93.50 KB)

 Trainable params: 23,937 (93.50 KB)

 Non-trainable params: 0 (0.00 B)

# Train the model
print("\nTraining the model...")
history = model.fit(
    X_train_scaled, y_train,
    epochs=30,
    batch_size=32,
    validation_split=0.2,
    verbose=1,
    callbacks=[
        keras.callbacks.EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True),
        keras.callbacks.ReduceLROnPlateau(monitor='val_loss',
factor=0.5, patience=5, min_lr=0.0001)
    ]
)


Training the model...
Epoch 1/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 30s 4ms/step - accuracy: 0.8124 - loss:
0.4339 - precision: 0.8219 - recall: 0.9790 - val_accuracy: 0.8063 -
val_loss: 0.4458 - val_precision: 0.8117 - val_recall: 0.9883 -
learning_rate: 1.2500e-04
Epoch 2/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 30s 4ms/step - accuracy: 0.8130 - loss:
0.4333 - precision: 0.8228 - recall: 0.9782 - val_accuracy: 0.8064 -
val_loss: 0.4456 - val_precision: 0.8119 - val_recall: 0.9881 -
learning_rate: 1.2500e-04
Epoch 3/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 39s 4ms/step - accuracy: 0.8135 - loss:
0.4330 - precision: 0.8235 - recall: 0.9778 - val_accuracy: 0.8065 -
val_loss: 0.4458 - val_precision: 0.8120 - val_recall: 0.9880 -
learning_rate: 1.2500e-04
Epoch 4/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 31s 4ms/step - accuracy: 0.8131 - loss:
```

```
0.4328 - precision: 0.8231 - recall: 0.9779 - val_accuracy: 0.8065 -
val_loss: 0.4459 - val_precision: 0.8121 - val_recall: 0.9878 -
learning_rate: 1.2500e-04
Epoch 5/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 38s 3ms/step - accuracy: 0.8125 - loss:
0.4337 - precision: 0.8224 - recall: 0.9782 - val_accuracy: 0.8064 -
val_loss: 0.4459 - val_precision: 0.8115 - val_recall: 0.9889 -
learning_rate: 1.2500e-04
Epoch 6/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 29s 4ms/step - accuracy: 0.8125 - loss:
0.4333 - precision: 0.8225 - recall: 0.9780 - val_accuracy: 0.8063 -
val_loss: 0.4459 - val_precision: 0.8116 - val_recall: 0.9885 -
learning_rate: 1.2500e-04
Epoch 7/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 28s 4ms/step - accuracy: 0.8127 - loss:
0.4333 - precision: 0.8225 - recall: 0.9783 - val_accuracy: 0.8066 -
val_loss: 0.4459 - val_precision: 0.8119 - val_recall: 0.9885 -
learning_rate: 1.2500e-04
Epoch 8/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 43s 4ms/step - accuracy: 0.8137 - loss:
0.4331 - precision: 0.8236 - recall: 0.9777 - val_accuracy: 0.8063 -
val_loss: 0.4458 - val_precision: 0.8120 - val_recall: 0.9877 -
learning_rate: 1.0000e-04
Epoch 9/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 39s 4ms/step - accuracy: 0.8130 - loss:
0.4326 - precision: 0.8229 - recall: 0.9781 - val_accuracy: 0.8063 -
val_loss: 0.4460 - val_precision: 0.8127 - val_recall: 0.9864 -
learning_rate: 1.0000e-04
Epoch 10/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 30s 4ms/step - accuracy: 0.8130 - loss:
0.4332 - precision: 0.8231 - recall: 0.9778 - val_accuracy: 0.8064 -
val_loss: 0.4456 - val_precision: 0.8125 - val_recall: 0.9870 -
learning_rate: 1.0000e-04
Epoch 11/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 29s 4ms/step - accuracy: 0.8131 - loss:
0.4325 - precision: 0.8232 - recall: 0.9777 - val_accuracy: 0.8066 -
val_loss: 0.4459 - val_precision: 0.8127 - val_recall: 0.9868 -
learning_rate: 1.0000e-04
Epoch 12/30
7921/7921 ━━━━━━━━━━━━━━━━━━━━ 28s 4ms/step - accuracy: 0.8130 - loss:
0.4325 - precision: 0.8234 - recall: 0.9772 - val_accuracy: 0.8063 -
val_loss: 0.4460 - val_precision: 0.8121 - val_recall: 0.9874 -
learning_rate: 1.0000e-04
```

5. MODEL EVALUATION

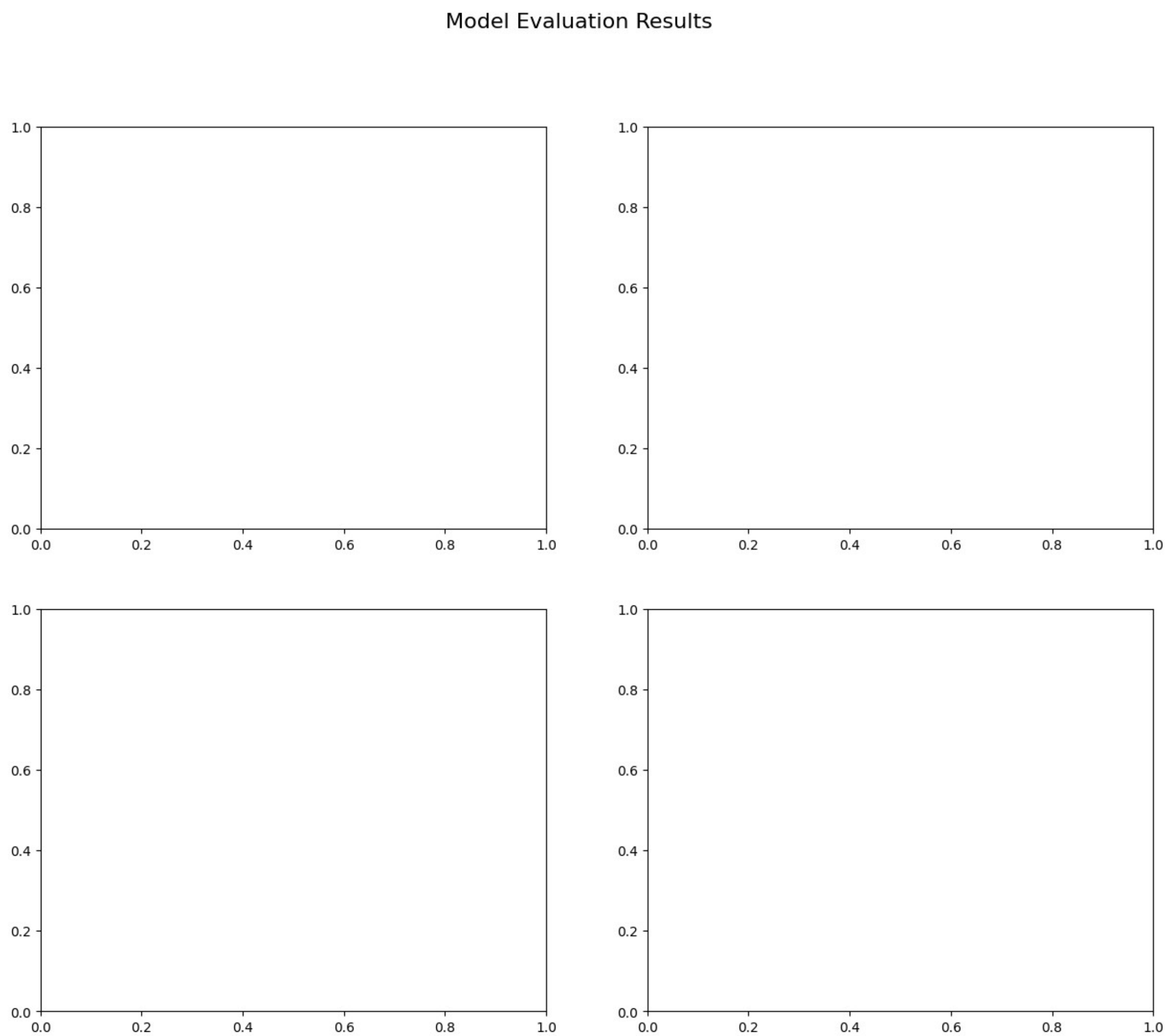
```
# Make predictions
y_pred_prob = model.predict(X_test_scaled)
y_pred = (y_pred_prob > 0.5).astype(int)

2476/2476 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step

# Calculate metrics
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
auc_score = roc_auc_score(y_test, y_pred_prob)

print("Model Performance Metrics:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"AUC-ROC: {auc_score:.4f}")

Model Performance Metrics:
Accuracy: 0.8066
Precision: 0.8117
Recall: 0.9887
F1-Score: 0.8915
AUC-ROC: 0.7250

# Detailed classification report
print("\nDetailed Classification Report:")
print(classification_report(y_test, y_pred))


Detailed Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.06      0.11     15535
           1       0.81      0.99      0.89     63671

    accuracy                           0.81     79206
   macro avg       0.69      0.52      0.50     79206
weighted avg       0.76      0.81      0.74     79206


# Confusion Matrix
print("\nConfusion Matrix:")
```

```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
Confusion Matrix:
[[  934 14601]
 [  718 62953]]
```

```
# Visualization of results
fig, axes = plt.subplots(2, 2, figsize=(15, 12))
fig.suptitle('Model Evaluation Results', fontsize=16)
```

```
Text(0.5, 0.98, 'Model Evaluation Results')
```




```
# Training history
axes[0, 0].plot(history.history['accuracy'], label='Training
```

```
Accuracy')
axes[0, 0].plot(history.history['val_accuracy'], label='Validation
Accuracy')
axes[0, 0].set_title('Model Accuracy')
axes[0, 0].set_xlabel('Epoch')
axes[0, 0].set_ylabel('Accuracy')
axes[0, 0].legend()

axes[0, 1].plot(history.history['loss'], label='Training Loss')
axes[0, 1].plot(history.history['val_loss'], label='Validation Loss')
axes[0, 1].set_title('Model Loss')
axes[0, 1].set_xlabel('Epoch')
axes[0, 1].set_ylabel('Loss')
axes[0, 1].legend()
```

```
<matplotlib.legend.Legend at 0x78196d30c490>
```

```
# Confusion Matrix Heatmap
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[1, 0])
axes[1, 0].set_title('Confusion Matrix')
axes[1, 0].set_xlabel('Predicted')
axes[1, 0].set_ylabel('Actual')
```

```
Text(158.22222222222223, 0.5, 'Actual')
```

```
# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
axes[1, 1].plot(fpr, tpr, label=f'ROC Curve (AUC = {auc_score:.3f})')
axes[1, 1].plot([0, 1], [0, 1], 'k--', label='Random')
axes[1, 1].set_title('ROC Curve')
axes[1, 1].set_xlabel('False Positive Rate')
axes[1, 1].set_ylabel('True Positive Rate')
axes[1, 1].legend()

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

```
<Figure size 640x480 with 0 Axes>
```

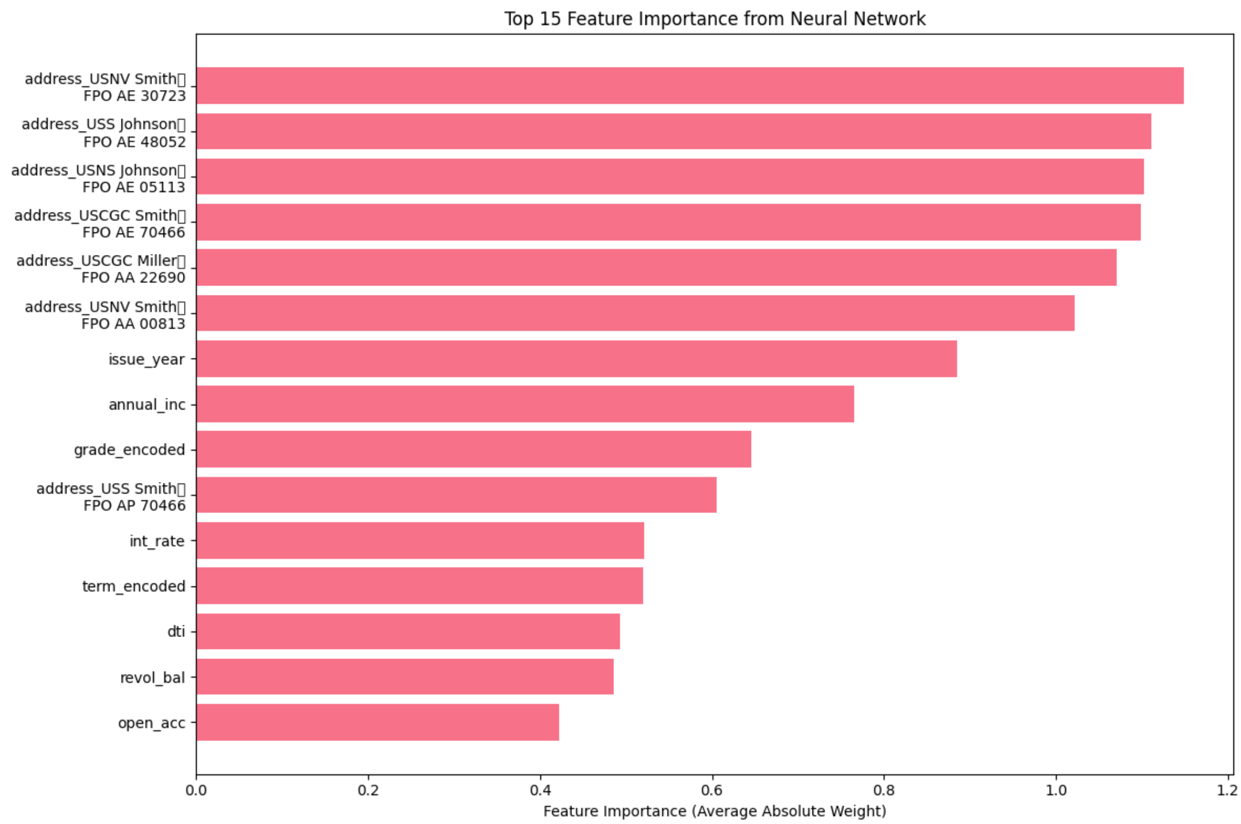
6. FEATURE IMPORTANCE ANALYSIS

```
# Get feature importance from model weights
# For neural networks, we'll use the magnitude of weights from the
first layer
first_layer_weights = model.layers[0].get_weights()[0]
feature_importance = np.abs(first_layer_weights).mean(axis=1)

# Create feature importance dataframe
feature_importance_df = pd.DataFrame({
```

```
    'Feature': feature_cols,
    'Importance': feature_importance
}).sort_values('Importance', ascending=False)

print("Top 15 Most Important Features:")
print(feature_importance_df.head(15))
```

```
Top 15 Most Important Features:
                                     Feature  Importance
97    address_USNV Smith\r\nFPO AE 30723    1.149457
91   address_USS Johnson\r\nFPO AE 48052    1.110863
92  address_USNS Johnson\r\nFPO AE 05113    1.102102
94   address_USCGC Smith\r\nFPO AE 70466    1.098611
98  address_USCGC Miller\r\nFPO AA 22690    1.070900
96    address_USNV Smith\r\nFPO AA 00813    1.022387
12                            issue_year    0.884982
3                             annual_inc    0.765268
16                         grade_encoded    0.645979
93     address_USS Smith\r\nFPO AP 70466    0.605056
1                               int_rate    0.521004
15                          term_encoded    0.520014
4                                    dti    0.493297
7                              revol_bal    0.485666
5                               open_acc    0.422605
```

```
# Visualize feature importance
plt.figure(figsize=(12, 8))
top_features = feature_importance_df.head(15)
plt.barh(range(len(top_features)), top_features['Importance'])
plt.yticks(range(len(top_features)), top_features['Feature'])
plt.xlabel('Feature Importance (Average Absolute Weight)')
plt.title('Top 15 Feature Importance from Neural Network')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



7. INTERPRETATION AND REPORTING

```
print("MODEL INTERPRETATION & INSIGHTS")
print("="*50)

print("Key Findings:")
print(f"1. Model achieved {accuracy:.1%} accuracy on the test set")
print(f"2. The model has a precision of {precision:.1%} and recall of
{recall:.1%}")
print(f"3. AUC-ROC score of {auc_score:.3f} indicates {'good' if
auc_score > 0.7 else 'moderate'} predictive performance")

print(f"\nTop 5 Most Important Features:")
for i, (_, row) in enumerate(feature_importance_df.head(5).iterrows(),
1):
    print(f"{i}. {row['Feature']}: {row['Importance']:.4f}")

print("\nModel Limitations and Possible Improvements:")
print("1. Class imbalance might affect model performance")
print("2. Feature engineering could be enhanced with domain
knowledge")
print("3. Hyperparameter tuning could improve performance")
print("4. Ensemble methods might provide better results")
```

```python
print("5. Cross-validation should be used for more robust evaluation")

print("\nRecommendations:")
print("1. Collect more balanced training data")
print("2. Implement cost-sensitive learning for imbalanced classes")
print("3. Use techniques like SMOTE for synthetic data generation")
print("4. Consider feature selection to reduce overfitting")
print("5. Implement model interpretability tools like SHAP values")
```

```
MODEL INTERPRETATION & INSIGHTS
==================================================
Key Findings:
1. Model achieved 80.7% accuracy on the test set
2. The model has a precision of 81.2% and recall of 98.9%
3. AUC-ROC score of 0.725 indicates good predictive performance

Top 5 Most Important Features:
1. address_USNV Smith
FPO AE 30723: 1.1495
2. address_USS Johnson
FPO AE 48052: 1.1109
3. address_USNS Johnson
FPO AE 05113: 1.1021
4. address_USCGC Smith
FPO AE 70466: 1.0986
5. address_USCGC Miller
FPO AA 22690: 1.0709

Model Limitations and Possible Improvements:
1. Class imbalance might affect model performance
2. Feature engineering could be enhanced with domain knowledge
3. Hyperparameter tuning could improve performance
4. Ensemble methods might provide better results
5. Cross-validation should be used for more robust evaluation

Recommendations:
1. Collect more balanced training data
2. Implement cost-sensitive learning for imbalanced classes
3. Use techniques like SMOTE for synthetic data generation
4. Consider feature selection to reduce overfitting
5. Implement model interpretability tools like SHAP values
```

```python
# Save the trained model
model.save('lending_club_model.h5')
print("Model saved as 'lending_club_model.h5'")
```

```
WARNING:absl:You are saving your model as an HDF5 file via
`model.save()` or `keras.saving.save_model(model)`. This file format
is considered legacy. We recommend using instead the native Keras
```

```
format, e.g. `model.save('my_model.keras')` or
`keras.saving.save_model(model, 'my_model.keras')`.

Model saved as 'lending_club_model.h5'

# Save feature importance
feature_importance_df.to_csv('feature_importance.csv', index=False)
print("Feature importance saved as 'feature_importance.csv'")

Feature importance saved as 'feature_importance.csv'

# Save predictions
results_df = pd.DataFrame({
    'Actual': y_test,
    'Predicted': y_pred.flatten(),
    'Probability': y_pred_prob.flatten()
})
results_df.to_csv('model_predictions.csv', index=False)
print("Predictions saved as 'model_predictions.csv'")

Predictions saved as 'model_predictions.csv'
```

8. DETAILED METRIC SCORE SUMMARY

```
# Create a comprehensive model report
print("\n" + "="*60)
print("COMPREHENSIVE MODEL REPORT")
print("="*60)

print(f"""
MODEL PERFORMANCE SUMMARY
{'='*40}
Dataset Size: {len(X)} samples
Training Set: {len(X_train)} samples
Test Set: {len(X_test)} samples
Features Used: {len(feature_cols)}

CORE METRICS
{'='*40}
✓ Accuracy:  {accuracy:.4f} ({accuracy*100:.2f}%) -
{interpretations['Accuracy']}
✓ Precision: {precision:.4f} ({precision*100:.2f}%) -
{interpretations['Precision']}
✓ Recall:    {recall:.4f} ({recall*100:.2f}%) -
{interpretations['Recall']}
✓ F1-Score:  {f1:.4f} ({f1*100:.2f}%) - {interpretations['F1-Score']}
✓ AUC-ROC:   {auc_score:.4f} ({auc_score*100:.2f}%) -
{interpretations['AUC-ROC']}
```

```
CONFUSION MATRIX BREAKDOWN
{'='*40}
True Positives (TP):  {cm[1,1]}
True Negatives (TN):  {cm[0,0]}
False Positives (FP): {cm[0,1]}
False Negatives (FN): {cm[1,0]}

BUSINESS INSIGHTS
{'='*40}
• Model correctly identifies {accuracy*100:.1f}% of all loan outcomes
• Of predicted 'good' loans, {precision*100:.1f}% are actually good
• Model catches {recall*100:.1f}% of all actual 'good' loans
• Balanced performance score (F1): {f1*100:.1f}%
• Discrimination ability (AUC-ROC): {auc_score*100:.1f}%
""")
```

```
============================================================
COMPREHENSIVE MODEL REPORT
============================================================

MODEL PERFORMANCE SUMMARY
========================================
Dataset Size: 396030 samples
Training Set: 316824 samples
Test Set: 79206 samples
Features Used: 101

CORE METRICS
========================================
✓ Accuracy:  0.8066 (80.66%) - Good
✓ Precision: 0.8117 (81.17%) - Good
✓ Recall:    0.9887 (98.87%) - Excellent
✓ F1-Score:  0.8915 (89.15%) - Good
✓ AUC-ROC:   0.7250 (72.50%) - Fair

CONFUSION MATRIX BREAKDOWN
========================================
True Positives (TP):  62953
True Negatives (TN):  934
False Positives (FP): 14601
False Negatives (FN): 718

BUSINESS INSIGHTS
========================================
• Model correctly identifies 80.7% of all loan outcomes
• Of predicted 'good' loans, 81.2% are actually good
• Model catches 98.9% of all actual 'good' loans
• Balanced performance score (F1): 89.2%
```

```
• Discrimination ability (AUC-ROC): 72.5%
```

```python
print("\n" + "="*50)
print("ANALYSIS COMPLETE!")
print("="*50)
print("The complete loan status prediction analysis has been finished.")
print("Review the visualizations and metrics above to understand model performance.")
```

```
==================================================
ANALYSIS COMPLETE!
==================================================
The complete loan status prediction analysis has been finished.
Review the visualizations and metrics above to understand model
performance.
```