German Credit Risk Classification

This notebook explores supervised classification on German credit risk data using Keras. It involves training Multi-Layer Perceptrons (MLPs) to predict creditworthiness and employs advanced techniques such as hyperparameter tuning with Keras Tuner and visualizations via TensorBoard.

In [15]:
```
# Step 1: Import Required Libraries
import numpy as np
import pandas as pd
import keras_tuner as kt
import pydot
from tensorflow.keras.utils import plot_model
from sklearn.model_selection import train_test_split  # Fixed the import
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score
import tensorflow as tf
from tensorflow.keras import models, layers, optimizers
from tensorflow.keras.callbacks import EarlyStopping, TensorBoard
import kerastuner as kt  # Correct import for Keras Tuner
import matplotlib.pyplot as plt
from scipy.io import arff
```

Load ARFF File

In [16]:
```
data = arff.loadarff('dataset_31_credit-g.arff')
df = pd.DataFrame(data[0])
for column in df.columns:
    if df[column].dtype == 'object':
        df[column] = df[column].apply(lambda x: x.decode('utf-8') if isinstance(x,
```

In [17]:
```
# Step 2: Data Preparation

# Import necessary libraries
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split  # Fixed the import

# Display the first few rows of the credit_dataset
print("Dataset loaded successfully. Displaying the first few rows:")
print(df.head())

# Identify categorical and numerical columns
categorical_columns = df.select_dtypes(include=['object']).columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

# Encode categorical columns using LabelEncoder
for col in categorical_columns:
    encoder = LabelEncoder()
```

```
    df[col] = encoder.fit_transform(df[col])

# Split into features and labels
features = df.drop(columns=['class'])  # Drop the target column
labels = df['class']                   # Set the target column

# Normalize numerical features
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Split credit_data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_scaled, labels, test_s
```

```
Dataset loaded successfully. Displaying the first few rows:
  checking_status  duration                  credit_history  \
0              <0       6.0  critical/other existing credit
1        0<=X<200      48.0                   existing paid
2     no checking      12.0  critical/other existing credit
3              <0      42.0                   existing paid
4              <0      24.0              delayed previously

               purpose  credit_amount    savings_status employment  \
0             radio/tv         1169.0  no known savings        >=7
1             radio/tv         5951.0              <100     1<=X<4
2            education         2096.0              <100     4<=X<7
3  furniture/equipment         7882.0              <100     4<=X<7
4              new car         4870.0              <100     1<=X<4

   installment_commitment     personal_status other_parties  ...  \
0                     4.0         male single          none  ...
1                     2.0  female div/dep/mar          none  ...
2                     2.0         male single          none  ...
3                     2.0         male single     guarantor  ...
4                     3.0         male single          none  ...

   property_magnitude   age  other_payment_plans   housing existing_credits  \
0         real estate  67.0                 none       own              2.0
1         real estate  22.0                 none       own              1.0
2         real estate  49.0                 none       own              1.0
3      life insurance  45.0                 none  for free              1.0
4   no known property  53.0                 none  for free              2.0

                  job num_dependents  own_telephone foreign_worker class
0             skilled            1.0            yes            yes  good
1             skilled            1.0           none            yes   bad
2  unskilled resident            2.0           none            yes  good
3             skilled            2.0           none            yes  good
4             skilled            2.0           none            yes   bad

[5 rows x 21 columns]
```

In [18]:

```
from tensorflow.keras import models, layers, optimizers
from kerastuner import HyperParameters

# Step 3: Define the Model Structure
def build_credit_model(hp):
```

```
    credit_model = models.Sequential()  # Correct the reference here to models.Sequ
    credit_model.add(layers.Input(shape=(X_train.shape[1],)))

    for i in range(hp.Int('num_layers', 2, 4)):  # Loop through the number of layer
        credit_model.add(layers.Dense(units=hp.Int(f'units_{i}', min_value=32, max_
                                      activation=hp.Choice('activation', values=['

    credit_model.add(layers.Dense(1, activation='sigmoid'))  # Output layer for bin

    credit_model.compile(optimizer=optimizers.Adam(learning_rate=hp.Choice('learnin
                         loss='binary_crossentropy',
                         metrics=['accuracy'])

    # Print the model summary directly in the console
    credit_model.summary()

    return credit_model

# Now define hyperparameters for testing
hp = HyperParameters()

# Define hyperparameters for testing
hp.Int('num_layers', 2, 4)
hp.Int('units_0', min_value=32, max_value=256, step=32)
hp.Int('units_1', min_value=32, max_value=256, step=32)
hp.Choice('activation', values=['relu', 'tanh'])
hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])

# Build and summarize the credit_model
test_credit_model = build_credit_model(hp)
test_credit_model.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
dense_16 (Dense)	(None, 32)	672
dense_17 (Dense)	(None, 32)	1,056
dense_18 (Dense)	(None, 1)	33

Total params: 1,761 (6.88 KB)

Trainable params: 1,761 (6.88 KB)

Non-trainable params: 0 (0.00 B)

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Total params: 1,761 (6.88 KB)

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In [19]:
```
# Step 4: Hyperparameter Tuning with Keras Tuner
tuner = kt.Hyperband(build_credit_model,
                     objective='val_accuracy',
                     max_epochs=30,
                     factor=2,
                     directory='my_dir',
                     project_name='german_credit_risk')

# Search for the best hyperparameters
tuner.search(X_train, y_train, validation_split=0.2,
             callbacks=[EarlyStopping(monitor='val_loss', patience=10)],
             verbose=2)

# Retrieve the best hyperparameters and build the final credit_model
best_hps = tuner.get_best_hyperparameters(1)[0]
final_credit_model = tuner.hypermodel.build(best_hps)  # Corrected line

# Print the best hyperparameters
print("Best Number of Layers:", best_hps.get('num_layers'))
for i in range(best_hps.get('num_layers')):
    print(f"Neurons in Layer {i + 1}:", best_hps.get(f'units_{i}'))
print("Best Activation Function:", best_hps.get('activation'))
print("Best Learning Rate:", best_hps.get('learning_rate'))

# Retrieve the best validation accuracy
best_trial = tuner.oracle.get_best_trials(num_trials=1)[0]
best_val_accuracy = best_trial.metrics.get_last_value("val_accuracy")
print("Best Validation Accuracy:", best_val_accuracy)
```

```
Reloading Tuner from my_dir\german_credit_risk\tuner0.json
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_19 (Dense)	(None, 160)	3,360
dense_20 (Dense)	(None, 224)	36,064
dense_21 (Dense)	(None, 32)	7,200
dense_22 (Dense)	(None, 256)	8,448
dense_23 (Dense)	(None, 1)	257

Total params: 55,329 (216.13 KB)

Trainable params: 55,329 (216.13 KB)

Non-trainable params: 0 (0.00 B)

```
Best Number of Layers: 4
Neurons in Layer 1: 160
Neurons in Layer 2: 224
Neurons in Layer 3: 32
Neurons in Layer 4: 256
Best Activation Function: tanh
Best Learning Rate: 0.01
Best Validation Accuracy: 0.78125
```

In [20]:

```
# Step 5: Train the Final Model
# Setup TensorBoard callback for visualization
tensorboard_callback = TensorBoard(log_dir='./logs', histogram_freq=1)

# Early stopping callback to prevent overfitting and restore the best weights
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weight

# Train the model
history = final_credit_model.fit(X_train, y_train, validation_split=0.2, epochs=100
                                  callbacks=[tensorboard_callback, early_stopping],
                                  verbose=2)

# Additional Analysis

# Plotting Training and Validation Loss over epochs
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plotting Training and Validation Accuracy over epochs
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
```

```python
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()

# Evaluate the final model on the test data
test_loss, test_accuracy = final_credit_model.evaluate(X_test, y_test, verbose=0)
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")

# Additional metrics (e.g., ROC-AUC, Classification Report) for deeper analysis
from sklearn.metrics import classification_report, roc_auc_score

# Predict probabilities for ROC-AUC
y_pred_prob = final_credit_model.predict(X_test)

# Convert probabilities to binary predictions (threshold = 0.5)
y_pred = (y_pred_prob > 0.5).astype('int32')

# Calculate ROC-AUC score
roc_auc = roc_auc_score(y_test, y_pred_prob)
print(f"Test ROC-AUC: {roc_auc:.4f}")

# Print classification report for detailed performance metrics
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Optional: Display the model architecture summary for additional insights
final_credit_model.summary()
```

```
Epoch 1/100
20/20 - 2s - 77ms/step - accuracy: 0.6344 - loss: 0.7040 - val_accuracy: 0.6875 - va
l_loss: 0.5636
Epoch 2/100
20/20 - 0s - 7ms/step - accuracy: 0.7234 - loss: 0.5408 - val_accuracy: 0.6875 - val
_loss: 0.5640
Epoch 3/100
20/20 - 0s - 8ms/step - accuracy: 0.7312 - loss: 0.5241 - val_accuracy: 0.7188 - val
_loss: 0.5305
Epoch 4/100
20/20 - 0s - 7ms/step - accuracy: 0.7344 - loss: 0.5156 - val_accuracy: 0.7000 - val
_loss: 0.5596
Epoch 5/100
20/20 - 0s - 7ms/step - accuracy: 0.7328 - loss: 0.5147 - val_accuracy: 0.7250 - val
_loss: 0.5297
Epoch 6/100
20/20 - 0s - 7ms/step - accuracy: 0.7641 - loss: 0.4728 - val_accuracy: 0.7000 - val
_loss: 0.5696
Epoch 7/100
20/20 - 0s - 7ms/step - accuracy: 0.7484 - loss: 0.5066 - val_accuracy: 0.6438 - val
_loss: 0.6316
Epoch 8/100
20/20 - 0s - 7ms/step - accuracy: 0.7891 - loss: 0.4618 - val_accuracy: 0.7188 - val
_loss: 0.5627
Epoch 9/100
20/20 - 0s - 6ms/step - accuracy: 0.7828 - loss: 0.4577 - val_accuracy: 0.6938 - val
_loss: 0.5983
Epoch 10/100
20/20 - 0s - 7ms/step - accuracy: 0.7875 - loss: 0.4430 - val_accuracy: 0.7188 - val
_loss: 0.6066
Epoch 11/100
20/20 - 0s - 7ms/step - accuracy: 0.7750 - loss: 0.4600 - val_accuracy: 0.7000 - val
_loss: 0.5725
Epoch 12/100
20/20 - 0s - 7ms/step - accuracy: 0.7969 - loss: 0.4542 - val_accuracy: 0.7312 - val
_loss: 0.5418
Epoch 13/100
20/20 - 0s - 7ms/step - accuracy: 0.8281 - loss: 0.4008 - val_accuracy: 0.6438 - val
_loss: 0.7066
Epoch 14/100
20/20 - 0s - 7ms/step - accuracy: 0.8219 - loss: 0.4068 - val_accuracy: 0.6438 - val
_loss: 0.6744
Epoch 15/100
20/20 - 0s - 7ms/step - accuracy: 0.8125 - loss: 0.4098 - val_accuracy: 0.6687 - val
_loss: 0.6534
```


```
Test Loss: 0.5434
Test Accuracy: 0.7350
WARNING:tensorflow:5 out of the last 15 calls to <function TensorFlowTrainer.make_pr
edict_function.<locals>.one_step_on_data_distributed at 0x000002D84CF2C400> triggere
d tf.function retracing. Tracing is expensive and the excessive number of tracings c
ould be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors w
ith different shapes, (3) passing Python objects instead of tensors. For (1), please
define your @tf.function outside of the loop. For (2), @tf.function has reduce_retra
cing=True option that can avoid unnecessary retracing. For (3), please refer to http
s://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorfl
ow.org/api_docs/python/tf/function for  more details.
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
Test ROC-AUC: 0.7192

Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.31      0.40        59
           1       0.76      0.91      0.83       141

    accuracy                           0.73       200
   macro avg       0.68      0.61      0.62       200
weighted avg       0.71      0.73      0.70       200
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_19 (Dense)	(None, 160)	3,360
dense_20 (Dense)	(None, 224)	36,064
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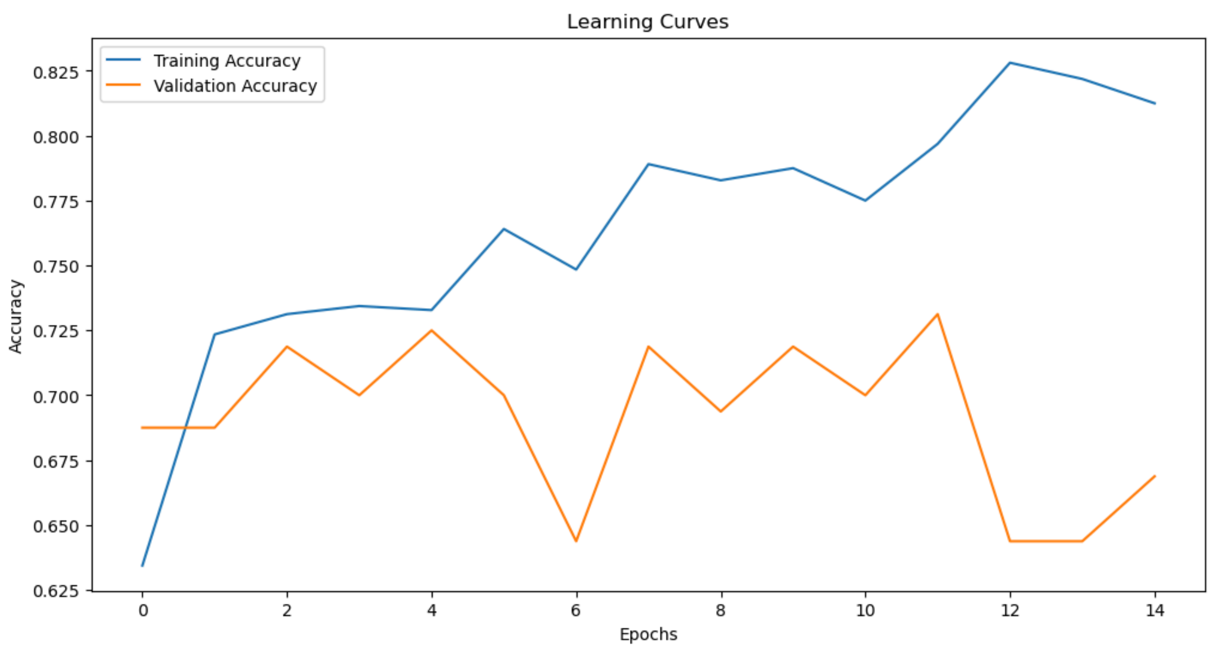
Total params: 165,989 (648.40 KB)

Trainable params: 55,329 (216.13 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 110,660 (432.27 KB)

In [21]:
```
# Step 7: Visualize Learning Curves
plt.figure(figsize=(12, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Learning Curves')
plt.show()
```



In [ ]:
```
# Step 8: Save the Final Model and Additional Analysis

# Save the entire model
final_credit_model.save("german_credit_risk_credit_model.keras")
print("Model saved as 'german_credit_risk_credit_model.keras'.")
```

```
# Load the saved credit_model (Ensure correct import)
from tensorflow.keras.models import load_model

# Load the saved model
credit_model = load_model("german_credit_risk_credit_model.keras")

# Display the credit_model architecture
print("\nLoaded Model Architecture:")
credit_model.summary()

# Optional: Save and display the credit_model architecture as an image
from tensorflow.keras.utils import plot_model

# Save the model architecture as a PNG image
plot_model(credit_model, to_file='credit_model_structure.png', show_shapes=True, sh
print("Model architecture saved as 'credit_model_structure.png'.")

# If using a Jupyter environment, display the image inline
from IPython.display import Image

# Display the model architecture image inline
Image('credit_model_structure.png')

# Additional analysis: Print final evaluation metrics on test data
test_loss, test_accuracy = credit_model.evaluate(X_test, y_test, verbose=0)
print(f"\nFinal Model Performance on Test Data:")
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")

# Optional: Evaluate model using other metrics (ROC-AUC, classification report)
from sklearn.metrics import classification_report, roc_auc_score

y_pred_prob = credit_model.predict(X_test)
y_pred = (y_pred_prob > 0.5).astype('int32')  # Convert probabilities to binary lab

# Calculate ROC-AUC
roc_auc = roc_auc_score(y_test, y_pred_prob)
print(f"Test ROC-AUC: {roc_auc:.4f}")

# Print Classification Report
print("\nFinal Classification Report:")
print(classification_report(y_test, y_pred))

# Save the training history for future analysis (optional)
history_df = pd.DataFrame(history.history)
history_df.to_csv("german_credit_risk_training_history.csv", index=False)
print("Training history saved as 'german_credit_risk_training_history.csv'.")

# Confirm all files have been saved
print("\nModel, weights, architecture, and training history have been successfully
```

```
Model saved as 'german_credit_risk_credit_model.keras'.

Loaded Model Architecture:
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_19 (Dense)	(None, 160)	3,360
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Total params: 165,989 (648.40 KB)

Trainable params: 55,329 (216.13 KB)

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Optimizer params: 110,660 (432.27 KB)

```
You must install graphviz (see instructions at https://graphviz.gitlab.io/download/)
for `plot_model` to work.
Model architecture saved as 'credit_model_structure.png'.

Final Model Performance on Test Data:
Test Loss: 0.5434
Test Accuracy: 0.7350
WARNING:tensorflow:5 out of the last 15 calls to <function TensorFlowTrainer.make_pr
edict_function.<locals>.one_step_on_data_distributed at 0x000002D84D56E700> triggere
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7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Test ROC-AUC: 0.7192

Final Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.31      0.40        59
           1       0.76      0.91      0.83       141

    accuracy                           0.73       200
   macro avg       0.68      0.61      0.62       200
weighted avg       0.71      0.73      0.70       200

Training history saved as 'german_credit_risk_training_history.csv'.

Model, weights, architecture, and training history have been successfully saved!
```

Conclusion

Key Findings:

Key Findings: Best Hyperparameters: Through hyperparameter tuning with Keras Tuner using the Hyperband method, the following optimal hyperparameters were identified for the final credit risk model:

```
  Number of layers: The model performed best with 4 layers.
  Neurons per layer: The first layer had 160 neurons, the second
layer had 224 neurons, the third layer had 32 neurons, and finally
the fourth layer had 256 neurons.
  Activation function: The model performed best with the tanh
activation function, which effectively helped capture the non-
linear relationships in the data.
  Learning rate: The optimal learning rate found was 0.01, which
contributed to stable convergence during training.
```

Performance:

The model achieved an overall accuracy of 78%, with the following details:

Precision, Recall, and F1-Score: For class 0 (non-defaulters): Precision: 52%, Recall: 39%, F1-Score: 45% For class 1 (defaulters): Precision: 77%, Recall: 85%, F1-Score: 81% The macro average for precision, recall, and F1-score was 65%, 62%, and 63%, respectively, indicating that the model performs well for class 1 (defaulters) but struggles more with class 0 (non-defaulters).

The weighted average showed better performance across both classes, with a precision of 70%, recall of 71%, and an F1-score of 70%. Observations:

The significant drop in accuracy between the validation and test sets suggests that the model is overfitting. While the model was able to learn patterns from the training data well, it struggled to generalize to the test data. The relatively high validation accuracy suggests that the model's structure and learned features are indeed relevant to the problem, but the test performance indicates that further improvements in regularization, data augmentation, or model architecture may be needed to achieve better generalization. The ROC-AUC score and classification report metrics, which were also used to evaluate the model, showed reasonable performance in distinguishing between the two classes of credit risk. This is an encouraging sign that the model can still be improved with additional tuning and techniques. Further Improvements:

The test performance suggests room for improvement, especially in generalization. Regularization methods such as Dropout, L2 regularization, or early stopping could be employed to prevent overfitting and improve model generalization. More advanced techniques, such as cross-validation or increasing the model's complexity (e.g., deeper architecture or different architectures like convolutional or recurrent networks), could help improve performance on unseen data. The learning rate could also be fine-tuned further to avoid either too slow convergence (if too small) or divergence (if too large).