Project Title:"Credit-Risk Scoring with Explainable AI"

```
!pip install kagglehub --quiet

import kagglehub

# Download the dataset
path = kagglehub.dataset_download("laotse/credit-risk-dataset")

print("Dataset downloaded to:", path)
```

```
Downloading from https://www.kaggle.com/api/v1/datasets/download/laotse/credit-risk-dataset?dataset_
100%|██████████| 368k/368k [00:00<00:00, 1.01MB/s]Extracting files...
Dataset downloaded to: /root/.cache/kagglehub/datasets/laotse/credit-risk-dataset/versions/1
```

```
import pandas as pd
import os

# Load the dataset file
file_path = os.path.join(path, "credit_risk_dataset.csv")
df = pd.read_csv(file_path)

# Show data
print(df.head())
print("\n Data Info:\n", df.info())
print("\n Missing Values:\n", df.isnull().sum())
```

```
   person_age  person_income person_home_ownership  person_emp_length  \
0          22          59000                  RENT              123.0
1          21           9600                   OWN                5.0
2          25           9600              MORTGAGE                1.0
3          23          65500                  RENT                4.0
4          24          54400                  RENT                8.0

  loan_intent loan_grade  loan_amnt  loan_int_rate  loan_status  \
0    PERSONAL          D      35000          16.02            1
1   EDUCATION          B       1000          11.14            0
2     MEDICAL          C       5500          12.87            1
3     MEDICAL          C      35000          15.23            1
4     MEDICAL          C      35000          14.27            1

   loan_percent_income cb_person_default_on_file  cb_person_cred_hist_length
0                 0.59                         Y                           3
1                 0.10                         N                           2
2                 0.57                         N                           3
3                 0.53                         N                           2
4                 0.55                         Y                           4
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   person_age                  32581 non-null  int64
 1   person_income               32581 non-null  int64
```

```
 2   person_home_ownership       32581 non-null  object 
 3   person_emp_length           31686 non-null  float64
 4   loan_intent                 32581 non-null  object 
 5   loan_grade                  32581 non-null  object 
 6   loan_amnt                   32581 non-null  int64  
 7   loan_int_rate               29465 non-null  float64
 8   loan_status                 32581 non-null  int64  
 9   loan_percent_income         32581 non-null  float64
 10  cb_person_default_on_file   32581 non-null  object 
 11  cb_person_cred_hist_length  32581 non-null  int64  
dtypes: float64(3), int64(5), object(4)
memory usage: 3.0+ MB

 Data Info:
 None

 Missing Values:
 person_age                     0
person_income                  0
person_home_ownership          0
person_emp_length            895
loan_intent                    0
loan_grade                     0
loan_amnt                      0
loan_int_rate               3116
loan_status                    0
loan_percent_income            0
cb_person_default_on_file      0
cb_person_cred_hist_length     0
dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Drop rows with missing values (simplest method)
df.dropna(inplace=True)

# Encode categorical features
categorical_cols = ['person_home_ownership', 'loan_intent', 'loan_grade', 'cb_person_default_on_file']
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

# Define features and target
X = df.drop(['loan_status'], axis=1)
y = df['loan_status']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Train/Test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)

# Logistic Regression
```

```
lr = LogisticRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

# Random Forest
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

# Performance
print("\n Logistic Regression Report:\n", classification_report(y_test, y_pred_lr))
print("Accuracy:", accuracy_score(y_test, y_pred_lr))

print("\n Random Forest Report:\n", classification_report(y_test, y_pred_rf))
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
```

```
 Logistic Regression Report:
               precision    recall  f1-score   support

           0       0.86      0.95      0.90      6715
           1       0.71      0.45      0.55      1877

    accuracy                           0.84      8592
   macro avg       0.79      0.70      0.73      8592
weighted avg       0.83      0.84      0.83      8592

Accuracy: 0.8405493482309124

 Random Forest Report:
               precision    recall  f1-score   support

           0       0.92      0.99      0.95      6715
           1       0.96      0.69      0.80      1877

    accuracy                           0.93      8592
   macro avg       0.94      0.84      0.88      8592
weighted avg       0.93      0.93      0.92      8592

Accuracy: 0.9264432029795159
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Build the model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compile and train
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2, verbose=1)

# Evaluate
loss, dl_accuracy = model.evaluate(X_test, y_test)
```

```
print("\n Deep Learning Accuracy:", dl_accuracy)
```

```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass a
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
502/502 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.8149 - loss: 0.4336 - val_accuracy: 0.8606 - v
Epoch 2/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8680 - loss: 0.3302 - val_accuracy: 0.8638 - v
Epoch 3/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.8742 - loss: 0.3194 - val_accuracy: 0.8633 - v
Epoch 4/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8764 - loss: 0.3130 - val_accuracy: 0.8756 - v
Epoch 5/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8822 - loss: 0.3039 - val_accuracy: 0.8783 - v
Epoch 6/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.8865 - loss: 0.2969 - val_accuracy: 0.8791 - v
Epoch 7/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.8837 - loss: 0.2945 - val_accuracy: 0.8763 - v
Epoch 8/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.8915 - loss: 0.2811 - val_accuracy: 0.8828 - v
Epoch 9/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8862 - loss: 0.2897 - val_accuracy: 0.8850 - v
Epoch 10/10
502/502 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8935 - loss: 0.2795 - val_accuracy: 0.8883 - v
269/269 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8862 - loss: 0.2940

 Deep Learning Accuracy: 0.8822160363197327
```

```
print("\n Final Model Accuracy Summary:")
print(f"Logistic Regression: {accuracy_score(y_test, y_pred_lr):.4f}")
print(f"Random Forest      : {accuracy_score(y_test, y_pred_rf):.4f}")
print(f"Deep Learning (Keras): {dl_accuracy:.4f}")
```

```

 Final Model Accuracy Summary:
Logistic Regression: 0.8405
Random Forest      : 0.9264
Deep Learning (Keras): 0.8822
```

Visualized the performance of different models (Logistic Regression, Random Forest, and Deep Learning) using bar plots for accuracy, confusion matrices, and ROC curves.

```
# Create a dictionary of model accuracies
model_accuracies = {
    'Logistic Regression': accuracy_score(y_test, y_pred_lr),
    'Random Forest': accuracy_score(y_test, y_pred_rf),
    'Deep Learning': dl_accuracy
}

# Convert the dictionary to a DataFrame
accuracy_df = pd.DataFrame.from_dict(model_accuracies, orient='index', columns=['Accuracy'])

# Rename the index to 'Model'
```

```
accuracy_df.index.name = 'Model'

# Reset index to make 'Model' a column
accuracy_df = accuracy_df.reset_index()

display(accuracy_df)
```

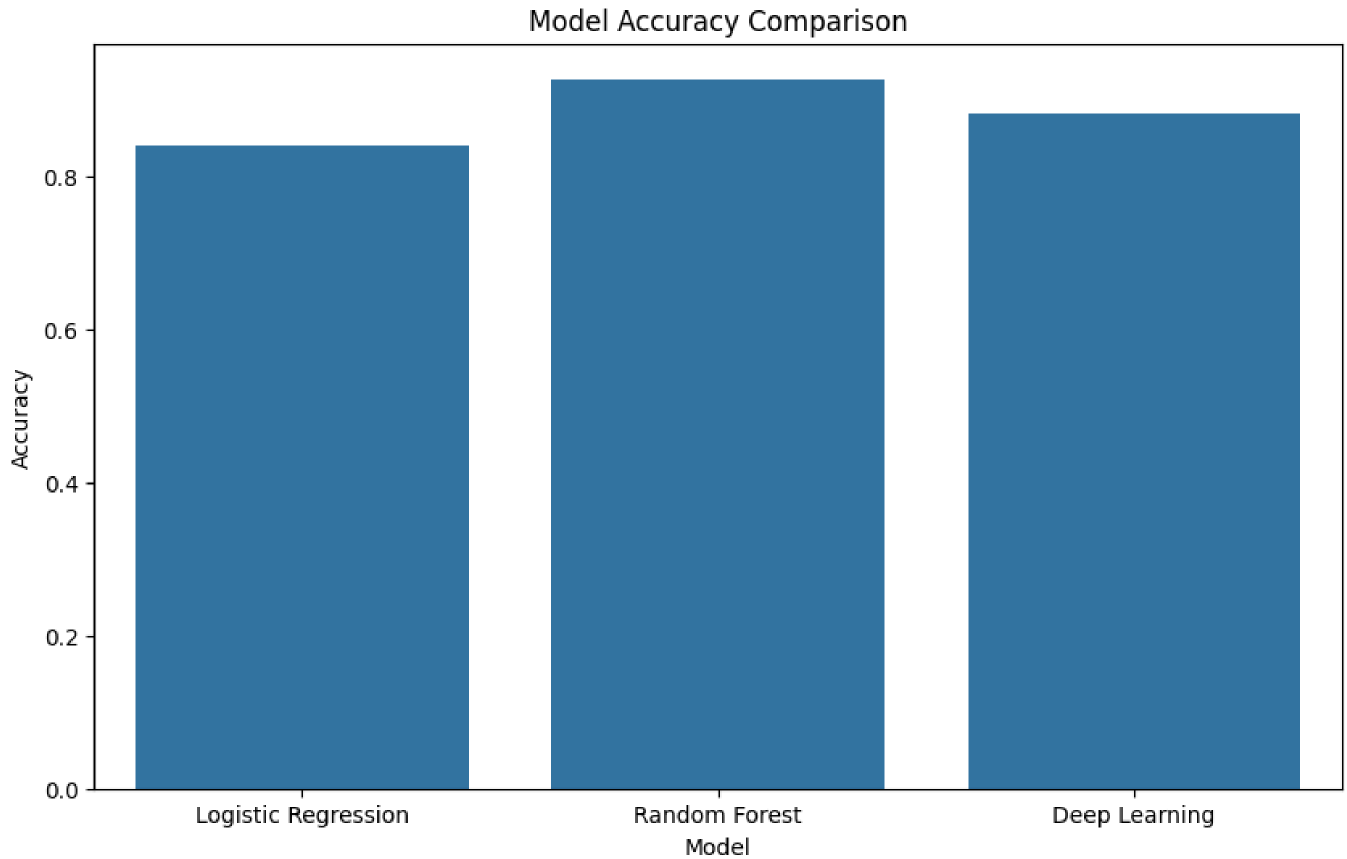
	Model	Accuracy
0	Logistic Regression	0.840549
1	Random Forest	0.926443
2	Deep Learning	0.882216

Visualized model accuracy

Subtask:

Created a bar plot to compare the accuracy of the Logistic Regression, Random Forest, and Deep Learning models.

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Accuracy', data=accuracy_df)
plt.title("Model Accuracy Comparison")
plt.show()
```



Visualized confusion matrices

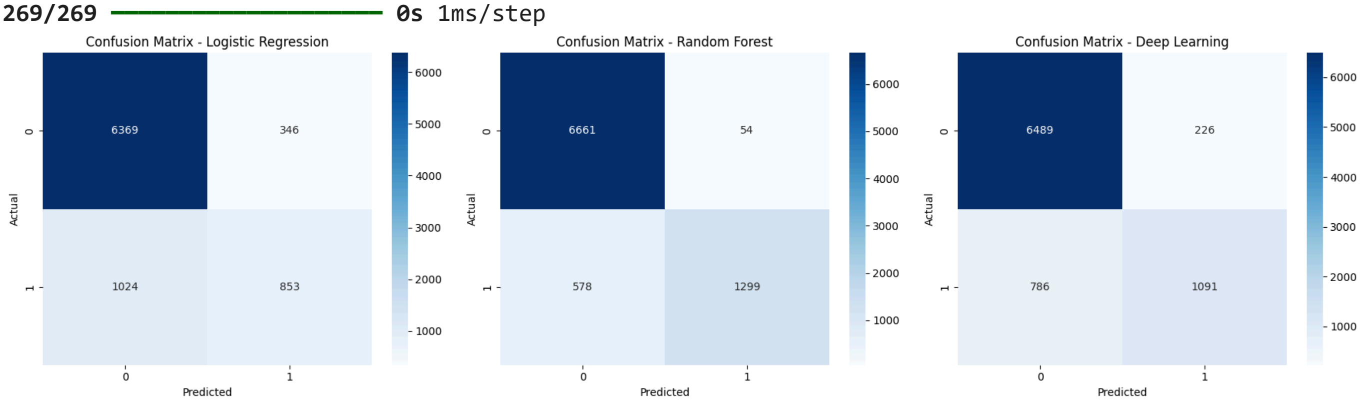
Subtask:

Generated confusion matrices for each model to assess their performance in more detail.

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Calculate confusion matrices
cm_lr = confusion_matrix(y_test, y_pred_lr)
cm_rf = confusion_matrix(y_test, y_pred_rf)

# For Deep Learning, convert probabilities to class labels
y_pred_dl_classes = (model.predict(X_test) > 0.5).astype("int32")
cm_dl = confusion_matrix(y_test, y_pred_dl_classes)

# Plot confusion matrices
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

sns.heatmap(cm_lr, annot=True, fmt='d', cmap='Blues', ax=axes[0])
axes[0].set_title("Confusion Matrix - Logistic Regression")
axes[0].set_xlabel("Predicted")
```

```
axes[0].set_ylabel("Actual")

sns.heatmap(cm_rf, annot=True, fmt='d', cmap='Blues', ax=axes[1])
axes[1].set_title("Confusion Matrix - Random Forest")
axes[1].set_xlabel("Predicted")
axes[1].set_ylabel("Actual")

sns.heatmap(cm_dl, annot=True, fmt='d', cmap='Blues', ax=axes[2])
axes[2].set_title("Confusion Matrix - Deep Learning")
axes[2].set_xlabel("Predicted")
axes[2].set_ylabel("Actual")

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

```
269/269 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```



Visualized roc curves

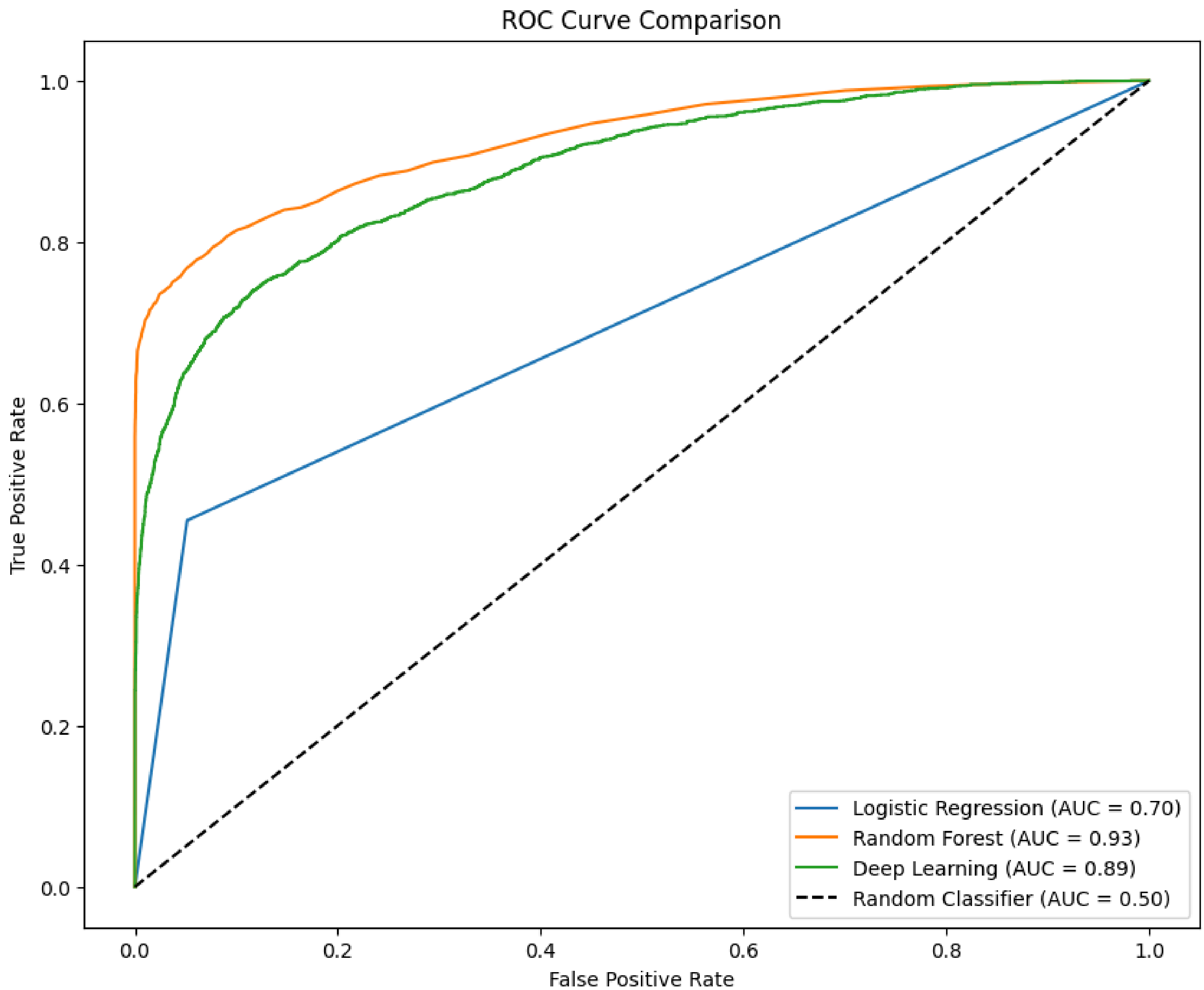
Subtask:

Ploted ROC curves for each model to evaluate their ability to distinguish between the two classes.

```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Calculate ROC curve and AUC for Logistic Regression
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_pred_lr)
auc_lr = roc_auc_score(y_test, y_pred_lr)

# Calculate ROC curve and AUC for Random Forest
# Get predicted probabilities for the positive class (index 1)
y_pred_proba_rf = rf.predict_proba(X_test)[:, 1]
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_pred_proba_rf)
auc_rf = roc_auc_score(y_test, y_pred_proba_rf)

# Calculate ROC curve and AUC for Deep Learning
# Get predicted probabilities from the Keras model
y_pred_proba_dl = model.predict(X_test).ravel()
fpr_dl, tpr_dl, thresholds_dl = roc_curve(y_test, y_pred_proba_dl)
auc_dl = roc_auc_score(y_test, y_pred_proba_dl)

# Plot ROC curves
```

```
plt.figure(figsize=(10, 8))
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {auc_lr:.2f})')
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {auc_rf:.2f})')
plt.plot(fpr_dl, tpr_dl, label=f'Deep Learning (AUC = {auc_dl:.2f})')

# Plot random classifier line
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier (AUC = 0.50)')

plt.title("ROC Curve Comparison")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()
```

```
269/269 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Summary:

Data Analysis Key Findings

- A bar plot comparing the accuracy of Logistic Regression, Random Forest, and Deep Learning models was successfully generated.
- Confusion matrices for each model were calculated and visualized as heatmaps, showing the distribution of true positives, true negatives, false positives, and false negatives.
- ROC curves for all three models were plotted on a single figure, along with their respective AUC scores, to compare their ability to distinguish between classes.