Sri Sivasubramaniya Nadar College of Engineering, Chennai
(An autonomous Institution affiliated to Anna University)

Degree & Branch	B.E. Computer Science & Engineering	Semester	V
Subject Code & Name	ICS1512 & Machine Learning Algorithms Laboratory		
Academic Year	2025-2026 (Odd)	Batch: 2023-2028	**Due Date:**

Experiment #2: Loan Amount Prediction using Linear Regression

Aim:
To apply linear regression to predict the loan amount based on customer features using the train dataset.

Libraries Used:

- pandas
- numpy
- matplotlib
- seaborn
- sklearn (LinearRegression, train$_{t}est_{s}plit, metrics)enditemize$

Objective:
To preprocess the dataset, explore it using EDA, apply feature engineering, build a regression model, and evaluate it using MSE, MAE, and R^2 Score.

Mathematical Description:
Linear Regression tries to model the relationship between a scalar dependent variable y and one or more explanatory variables X using the linear equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$$

where β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients, and ϵ is the error term.

CODE:

```
# 1. Import required 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.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

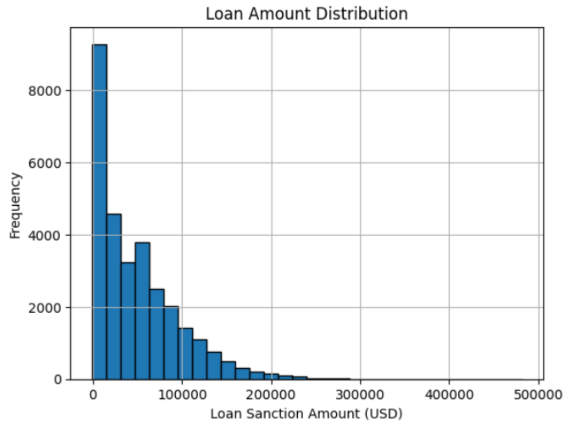
```
# 2. Load the dataset
df = pd.read_csv('train.csv')
print("Original dataset shape:", df.shape)

# 3. Preprocessing function (without scaling target)
def preprocess(df, target=None):
    df = df.copy()

    # Drop unnecessary identifier columns
    drop_cols = ['Customer ID', 'Name', 'Property ID']
    for col in drop_cols:
        if col in df.columns:
            df.drop(columns=col, inplace=True)

    # Fill missing numeric values with mean
    for col in df.select_dtypes(include='number').columns:
        df[col] = df[col].fillna(df[col].mean())

    # Fill missing categorical values with mode
    for col in df.select_dtypes(include='object').columns:
        df[col] = df[col].fillna(df[col].mode()[0])

    # One-hot encoding for categoricals
    df = pd.get_dummies(df, drop_first=True)

    # Scale numeric features EXCEPT target
    scaler = StandardScaler()
    num_cols = df.select_dtypes(include='number').columns
    if target and target in num_cols:
        num_cols = num_cols.drop(target)
    df[num_cols] = scaler.fit_transform(df[num_cols])

    return df

# 4. Apply preprocessing
target_col = 'Loan Sanction Amount (USD)'
df = preprocess(df, target=target_col)

# 5. Split into features and target
X = df.drop(columns=[target_col])
y = df[target_col]

# 6. Split the data: 60% train, 20% validation, 20% test
X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.25, random_s

# 7. Train Linear Regression
model = LinearRegression()
```

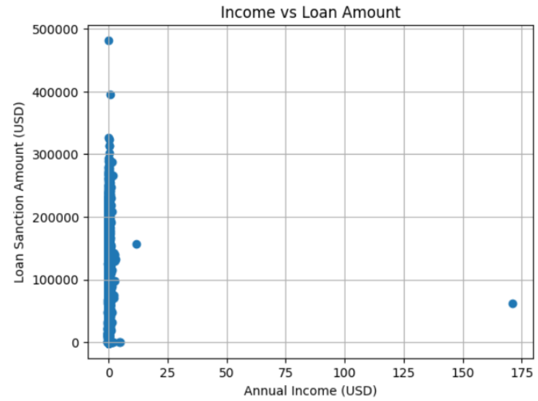
```
model.fit(X_train, y_train)

# 8. Predictions
y_val_pred = model.predict(X_val)
y_test_pred = model.predict(X_test)

# 9. Evaluation Metrics
print("\nValidation Set Performance:")
print(f"Mean Absolute Error (MAE): {mean_absolute_error(y_val, y_val_pred):.2f}")
print(f"Mean Squared Error (MSE): {mean_squared_error(y_val, y_val_pred):.2f}")
print(f"R² Score: {r2_score(y_val, y_val_pred):.2f}")

print("\nTest Set Performance:")
print(f"Mean Absolute Error (MAE): {mean_absolute_error(y_test, y_test_pred):.2f}")
print(f"Mean Squared Error (MSE): {mean_squared_error(y_test, y_test_pred):.2f}")
print(f"R² Score: {r2_score(y_test, y_test_pred):.2f}")

# 10. EDA Visualizations
# Histogram of Target
plt.hist(y, bins=30, edgecolor='black')
plt.title("Loan Amount Distribution")
plt.xlabel("Loan Sanction Amount (USD)")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()

# Scatter Plot
plt.scatter(X['Income (USD)'], y)
plt.xlabel("Annual Income (USD)")
plt.ylabel("Loan Sanction Amount (USD)")
plt.title("Income vs Loan Amount")
plt.grid(True)
plt.show()

# Correlation Heatmap
corr = df.corr(numeric_only=True)
plt.figure(figsize=(16, 14))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap")
plt.tight_layout()
plt.show()

# Boxplot for Income
sns.boxplot(x=X['Income (USD)'])
plt.title("Boxplot: Annual Income")
plt.show()

# 11. Evaluation Visuals
```

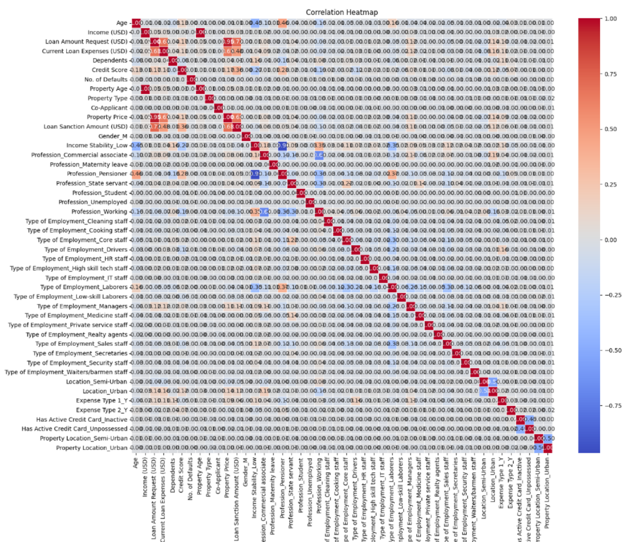
```
# Actual vs Predicted Plot (Validation)
plt.scatter(y_val, y_val_pred, alpha=0.6)
plt.xlabel("Actual Loan Amount")
plt.ylabel("Predicted Loan Amount")
plt.title("Actual vs Predicted (Validation Set)")
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')
plt.grid(True)
plt.show()

# Residual Plot
residuals = y_val - y_val_pred
sns.residplot(x=y_val_pred, y=residuals, lowess=True, line_kws={'color': 'red'})
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.grid(True)
plt.show()

# Coefficient Plot
coefficients = pd.Series(model.coef_, index=X.columns)
coefficients.sort_values().plot(kind='barh', figsize=(12, 8), color='skyblue')
plt.title("Linear Regression Coefficients")
plt.tight_layout()
plt.show()
```

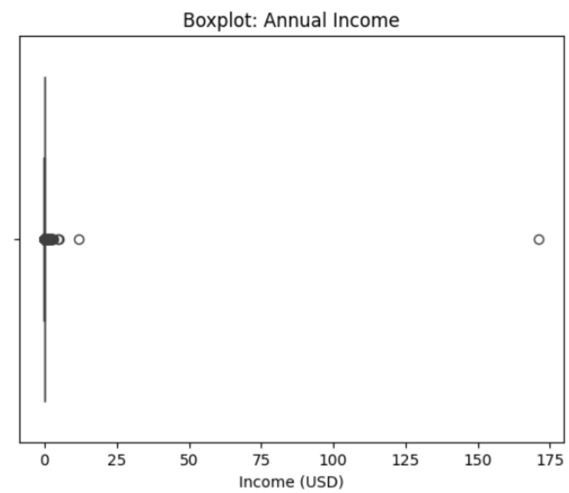
OUTPUT:

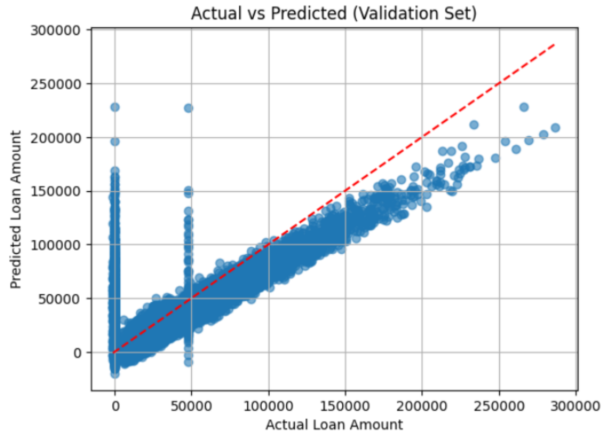
```
Original dataset shape: (30000, 24)

Validation Set Performance:
Mean Absolute Error (MAE): 21502.02
Mean Squared Error (MSE): 948975515.96
R² Score: 0.56

Test Set Performance:
Mean Absolute Error (MAE): 21683.95
Mean Squared Error (MSE): 969390282.45
R² Score: 0.58
```

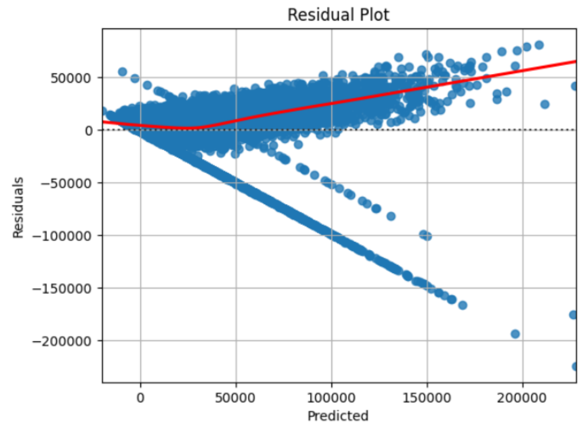

Loan Amount Distribution
Frequency
Loan Sanction Amount (USD)

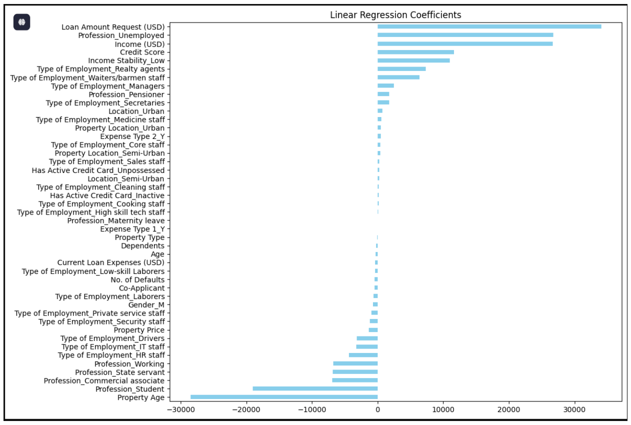

Income vs Loan Amount
Loan Sanction Amount (USD)
Annual Income (USD)


Correlation Heatmap


Boxplot: Annual Income
Income (USD)


Actual vs Predicted (Validation Set)
Predicted Loan Amount
Actual Loan Amount


Residual Plot
Residuals
Predicted




```
import pandas as pd
import numpy as np
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns

# 1. Load and preprocess dataset
df = pd.read_csv('train.csv')

# Drop identifier columns
df.drop(columns=['Customer ID', 'Name', 'Property ID'], inplace=True)

# Drop rows with missing values (or use imputation if needed)
df.dropna(inplace=True)

# Target column
target = 'Loan Sanction Amount (USD)'
X = df.drop(columns=[target])
y = df[target]

# One-hot encoding
X = pd.get_dummies(X, drop_first=True)

# Normalize numeric features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 2. Setup KFold
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# 3. Initialize model
model = LinearRegression()
```

```
# 4. For storing results
fold_metrics = []

# 5. Perform cross-validation
for fold, (train_idx, test_idx) in enumerate(kf.split(X_scaled), start=1):
    X_train, X_test = X_scaled[train_idx], X_scaled[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)

    fold_metrics.append({
        'Fold': f'Fold {fold}',
        'MAE': round(mae, 1),
        'MSE': round(mse, 1),
        'RMSE': round(rmse, 1),
        'R² Score': round(r2, 3)
    })

# 6. Average metrics
avg = {
    'Fold': 'Average',
    'MAE': round(np.mean([f['MAE'] for f in fold_metrics]), 1),
    'MSE': round(np.mean([f['MSE'] for f in fold_metrics]), 1),
    'RMSE': round(np.mean([f['RMSE'] for f in fold_metrics]), 1),
    'R² Score': round(np.mean([f['R² Score'] for f in fold_metrics]), 3)
}

fold_metrics.append(avg)

# 7. Display as DataFrame
results_df = pd.DataFrame(fold_metrics)
print(results_df.to_markdown(index=False))  # Neat table format
```

OUTPUT:

```
| Fold    |     MAE |         MSE |    RMSE |   R² Score |
|:--------|--------:|------------:|--------:|-----------:|
| Fold 1  | 25323.8 | 1.19527e+09 | 34572.6 |      0.475 |
| Fold 2  | 23528   | 9.96538e+08 | 31568   |      0.532 |
| Fold 3  | 24752   | 1.15796e+09 | 34028.8 |      0.486 |
```

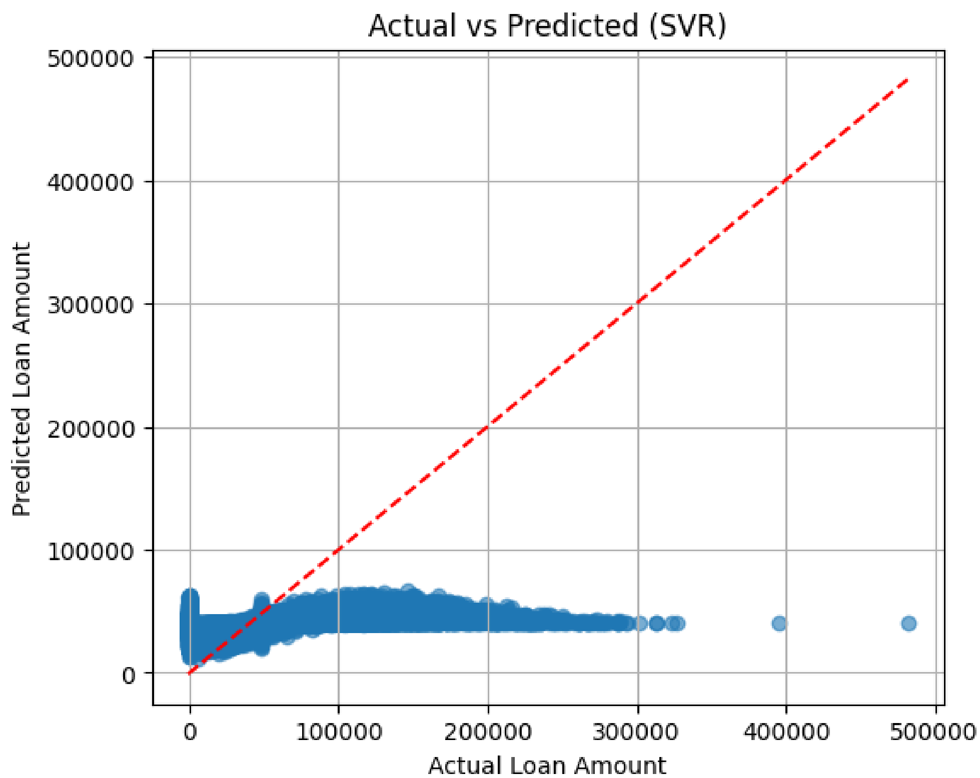
```
| Fold 4  | 24207.8 | 1.07016e+09 | 32713.3 |      0.513 |
| Fold 5  | 24688.1 | 1.12678e+09 | 33567.6 |      0.509 |
| Average | 24499.9 | 1.10934e+09 | 33290.1 |      0.503 |

# ------------------ Libraries ------------------
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import AdaBoostRegressor, GradientBoostingRegressor
from sklearn.linear_model import Lasso, Ridge, ElasticNet
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
import xgboost as xgb
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# ------------------ Scaling ------------------
X_scaled = StandardScaler().fit_transform(X)

# ------------------ Models ------------------
additional_models = {
    'SVR': SVR(kernel='rbf', C=100, gamma=0.1, epsilon=0.1),
    'Decision Tree': DecisionTreeRegressor(random_state=42),
    'AdaBoost': AdaBoostRegressor(n_estimators=100, random_state=42),
    'Gradient Boosting': GradientBoostingRegressor(n_estimators=100, random_state=42),
    'XGBoost': xgb.XGBRegressor(n_estimators=100, random_state=42, verbosity=0),
    'Lasso': Lasso(alpha=0.01, random_state=42, max_iter=10000),
    'Ridge': Ridge(alpha=1.0, random_state=42),
    'Elastic Net': ElasticNet(alpha=0.01, l1_ratio=0.5, random_state=42, max_iter=10000)
}

# ------------------ Cross Validation ------------------
cv_results = []
final_test_results = []

for name, model in additional_models.items():
    fold_metrics = []

    # k-fold CV
    for train_idx, test_idx in kf.split(X_scaled):
        X_train, X_test = X_scaled[train_idx], X_scaled[test_idx]
        y_train, y_test = y_values[train_idx], y_values[test_idx]

        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        mae = mean_absolute_error(y_test, y_pred)
```

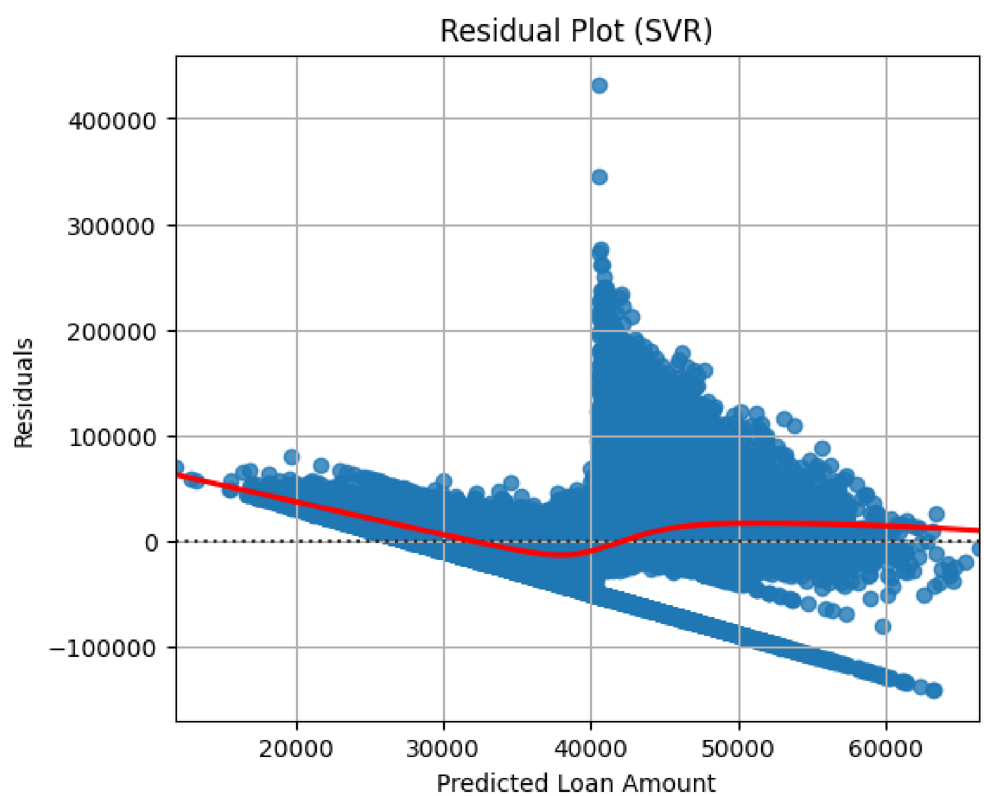
```
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)
    adj_r2 = 1 - (1-r2)*(len(y_test)-1)/(len(y_test)-X_train.shape[1]-1)

    fold_metrics.append([mae, mse, rmse, r2, adj_r2])

# Average CV results
avg_metrics = np.mean(fold_metrics, axis=0)
cv_results.append([name] + avg_metrics.tolist())

# ---------------- Print per-model report ----------------
print(f"\n{name} Performance:")
print(f"MAE: {avg_metrics[0]:.4f}")
print(f"MSE: {avg_metrics[1]:.4f}")
print(f"RMSE: {avg_metrics[2]:.4f}")
print(f"R²: {avg_metrics[3]:.4f}")
print(f"Adjusted R²: {avg_metrics[4]:.4f}")

# ---------------- Final Test on Full Holdout ----------------
model.fit(X_scaled, y_values)
y_pred_final = model.predict(X_scaled)

mae = mean_absolute_error(y_values, y_pred_final)
mse = mean_squared_error(y_values, y_pred_final)
rmse = np.sqrt(mse)
r2 = r2_score(y_values, y_pred_final)
adj_r2 = 1 - (1-r2)*(len(y_values)-1)/(len(y_values)-X_scaled.shape[1]-1)

final_test_results.append([name, mae, mse, rmse, r2, adj_r2])

# ---------------- Plots ----------------
residuals = y_values - y_pred_final

# 1. Actual vs Predicted
plt.figure(figsize=(6,5))
plt.scatter(y_values, y_pred_final, alpha=0.6)
plt.xlabel("Actual Loan Amount")
plt.ylabel("Predicted Loan Amount")
plt.title(f"Actual vs Predicted ({name})")
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'r--')
plt.grid(True)
plt.show()

# 2. Residual Plot
plt.figure(figsize=(6,5))
sns.residplot(x=y_pred_final, y=residuals, lowess=True, line_kws={'color':'red'})
plt.xlabel("Predicted Loan Amount")
```

```
    plt.ylabel("Residuals")
    plt.title(f"Residual Plot ({name})")
    plt.grid(True)
    plt.show()

    # 3. Feature Importance / Coefficients
    plt.figure(figsize=(10,6))
    if hasattr(model, 'coef_'):
        coef = pd.Series(model.coef_, index=X.columns)
        coef.sort_values().plot(kind='barh', color='skyblue')
        plt.title(f"{name} Coefficients")
    elif hasattr(model, 'feature_importances_'):
        fi = pd.Series(model.feature_importances_, index=X.columns)
        fi.sort_values().plot(kind='barh', color='lightgreen')
        plt.title(f"{name} Feature Importances")
    else:
        plt.text(0.5, 0.5, f"No coefficients/feature importance for {name}",
                 horizontalalignment='center', fontsize=12)
        plt.axis('off')
    plt.tight_layout()
    plt.show()

# ------------------ Final Tables ------------------
cv_df = pd.DataFrame(cv_results, columns=['Model','MAE','MSE','RMSE','R2','Adj_R2'])
test_df = pd.DataFrame(final_test_results, columns=['Model','MAE','MSE','RMSE','R2','Adj_R

print("\nTable 1: Average 5-Fold Cross-Validation Results for All Models")
print(cv_df.to_markdown(index=False))

print("\nTable 2: Final Test Set Results for All Models")
print(test_df.to_markdown(index=False))
```

OUTPUT:

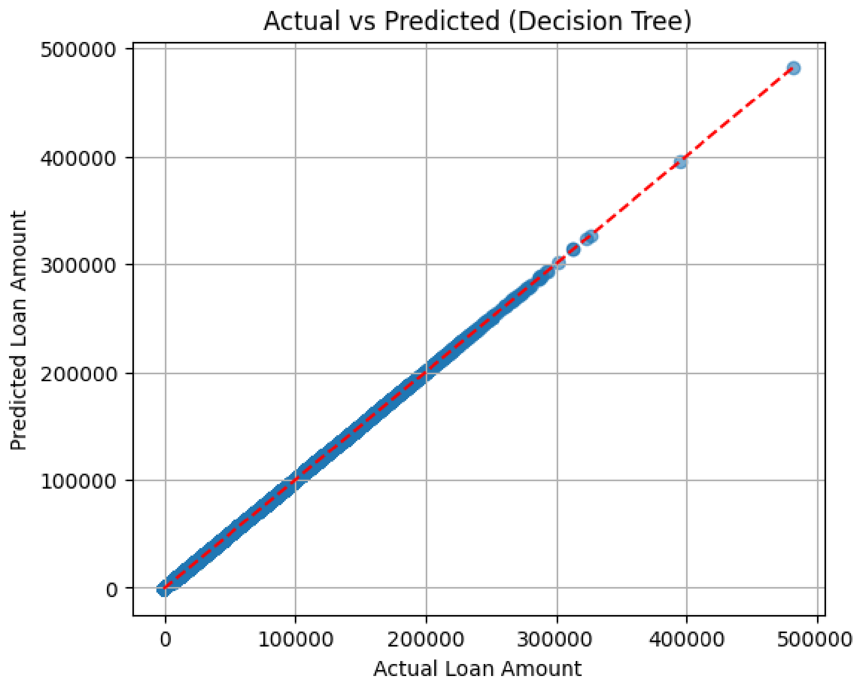
```
SVR Performance:
MAE: 34460.2727
MSE: 2134562863.7487
RMSE: 46199.8781
R²: 0.0715
Adjusted R²: 0.0645
```

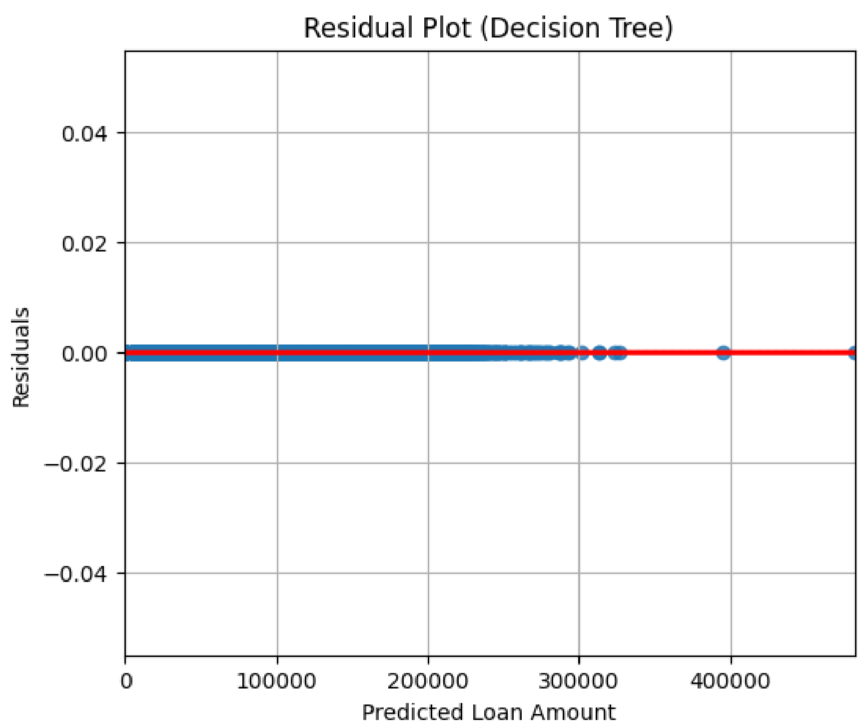


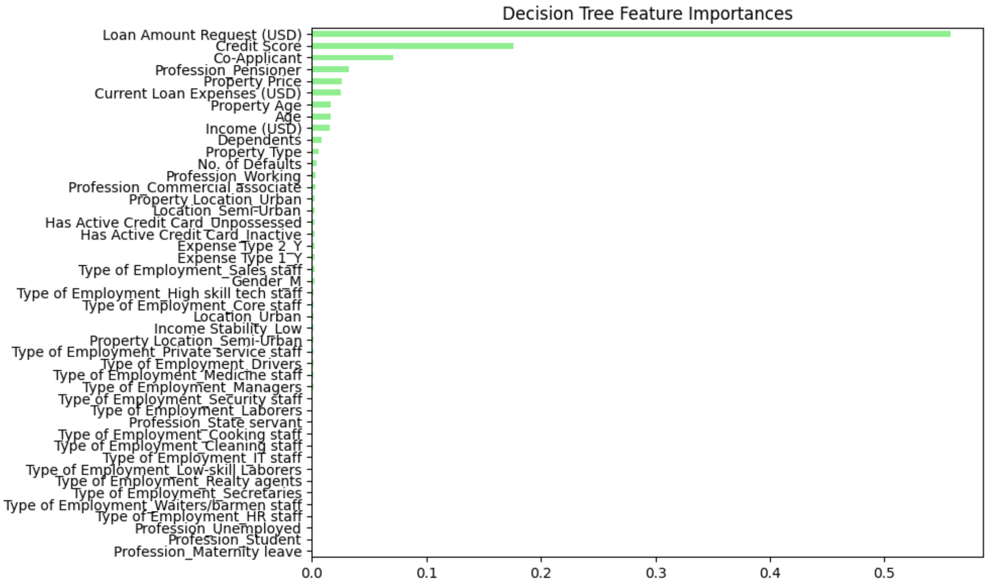



```
Decision Tree Performance:
```

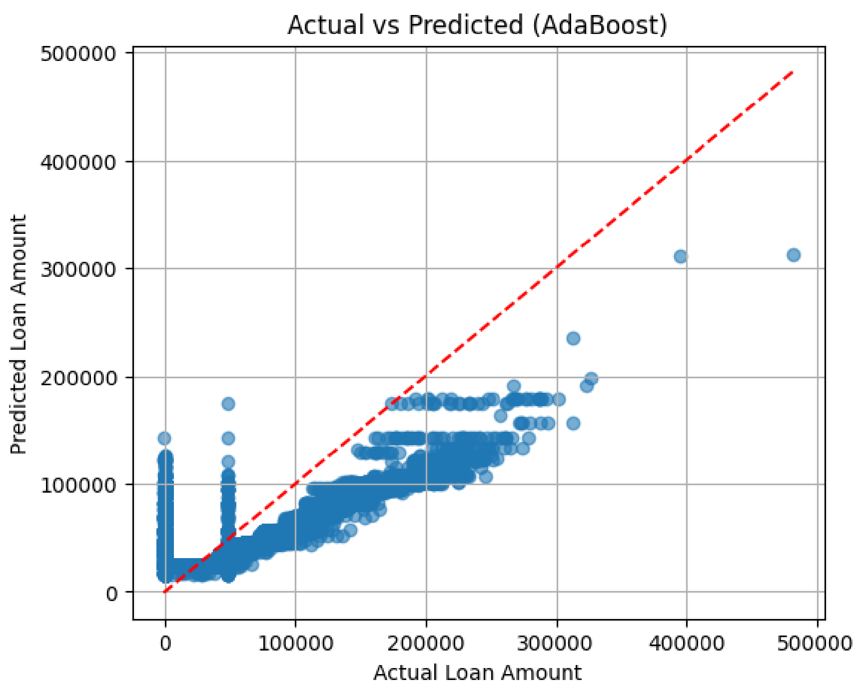
```
MAE: 14332.7248
MSE: 1092663531.5612
RMSE: 33036.3616
R²: 0.5247
Adjusted R²: 0.5211
```

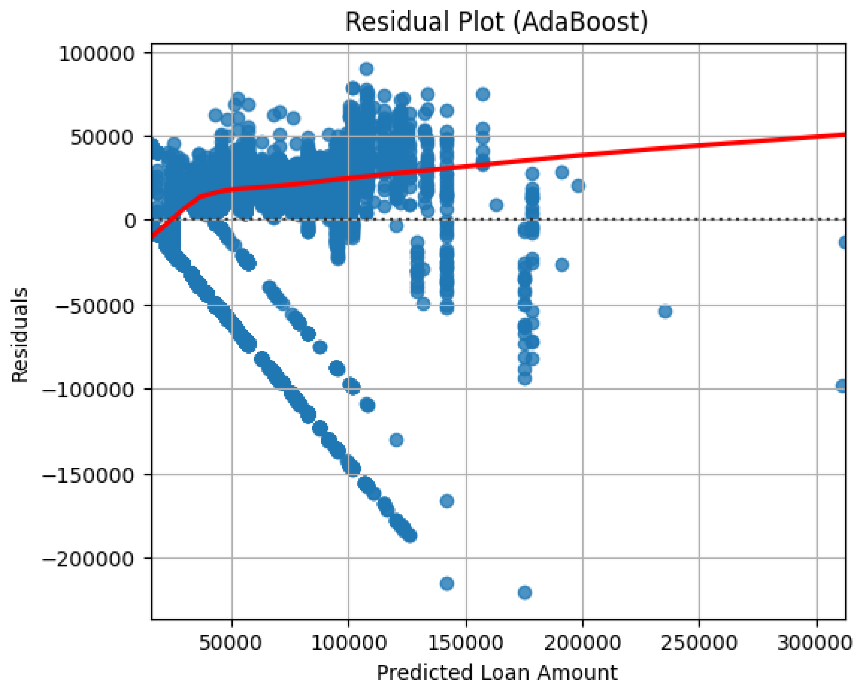


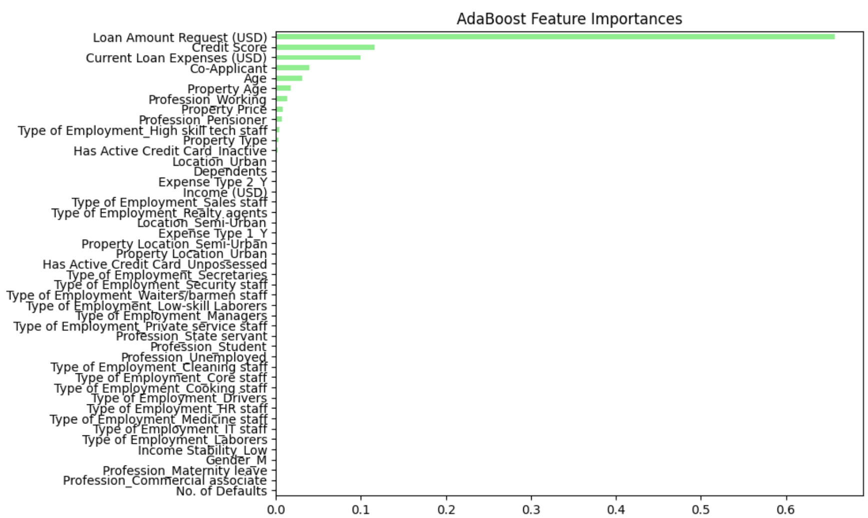




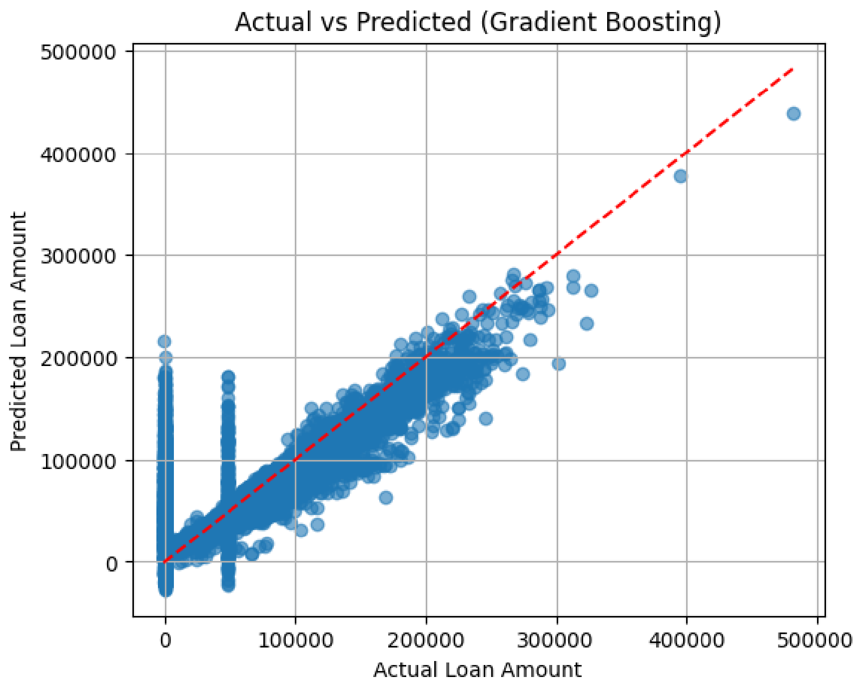

```
AdaBoost Performance:
MAE: 26943.0507
MSE: 1160478954.2134
RMSE: 34059.5875
R²: 0.4953
Adjusted R²: 0.4915
```



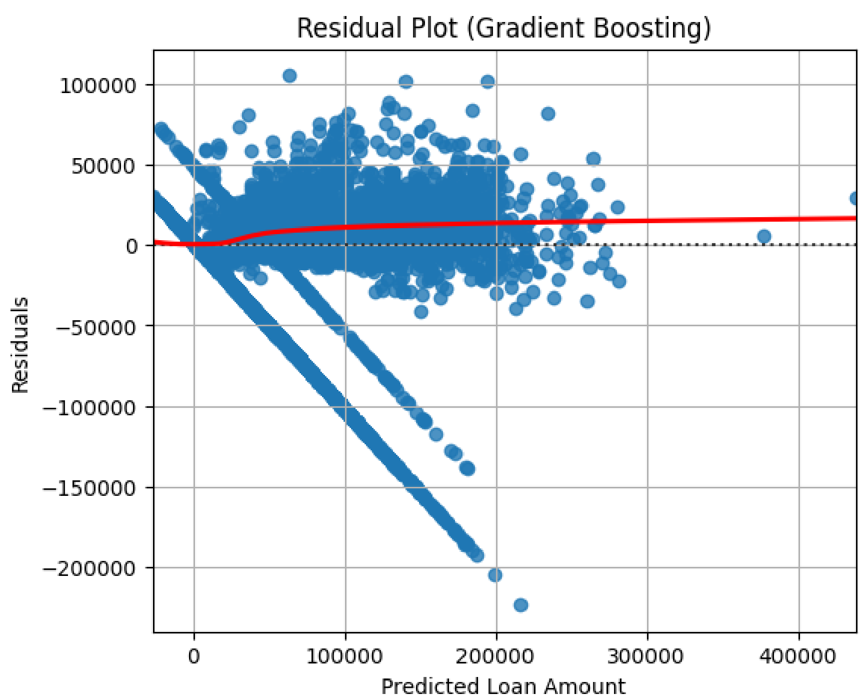




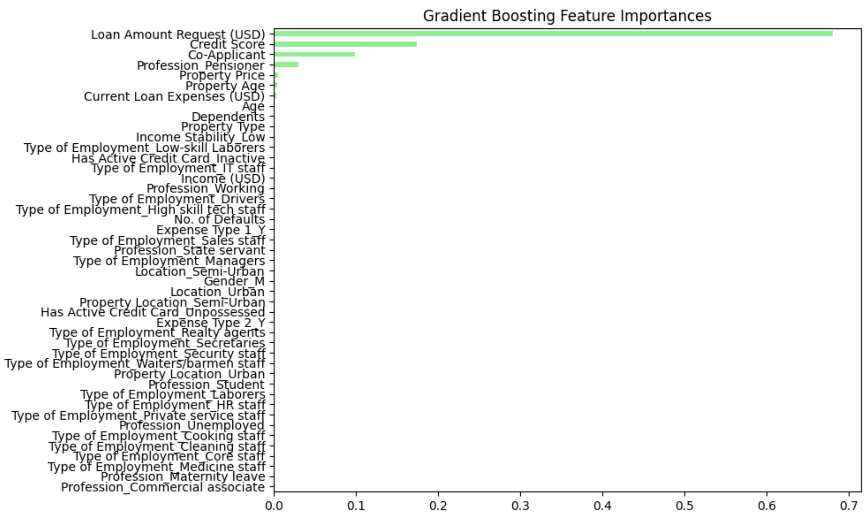

```
Gradient Boosting Performance:
MAE: 13638.4295
MSE: 575940703.7256
RMSE: 23985.0576
R²: 0.7496
Adjusted R²: 0.7477
```



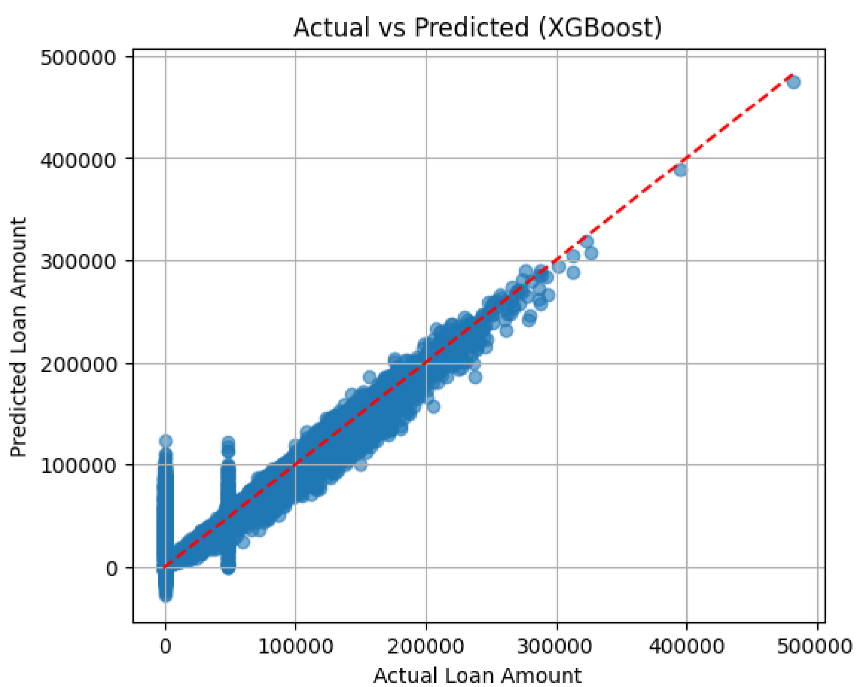
Actual vs Predicted (Gradient Boosting)
Predicted Loan Amount
Actual Loan Amount
500000
400000
300000
200000
100000
0
0
100000
200000
300000
400000
500000

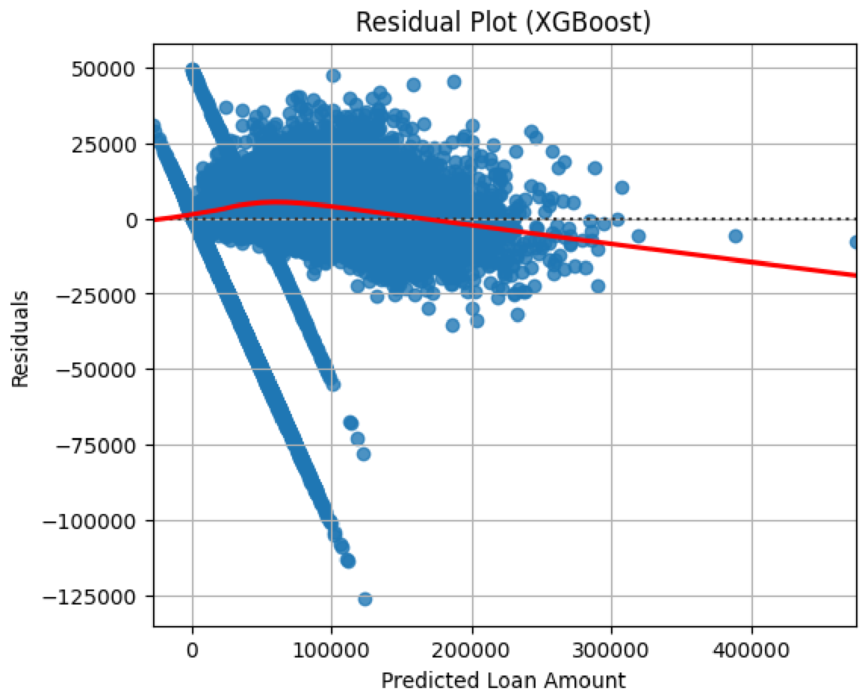


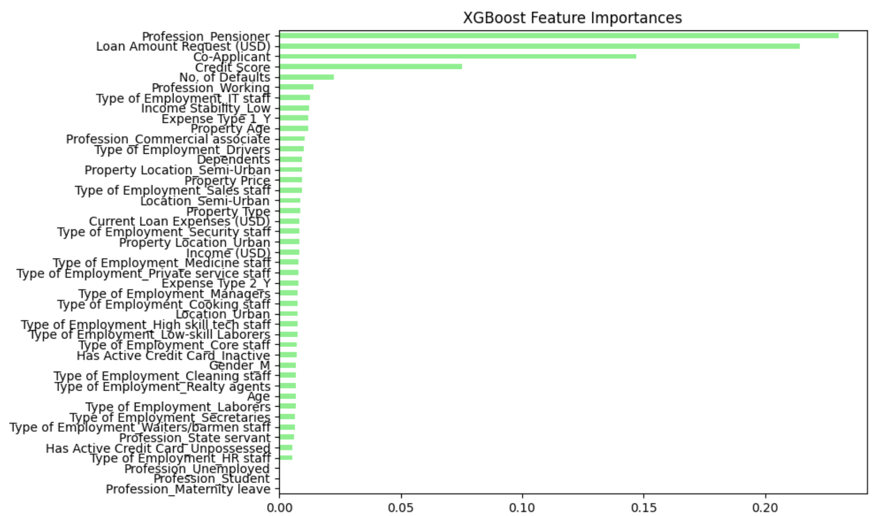
Residual Plot (Gradient Boosting)
Residuals
Predicted Loan Amount
100000
50000
0
−50000
−100000
−150000
−200000
0
100000
200000
300000
400000



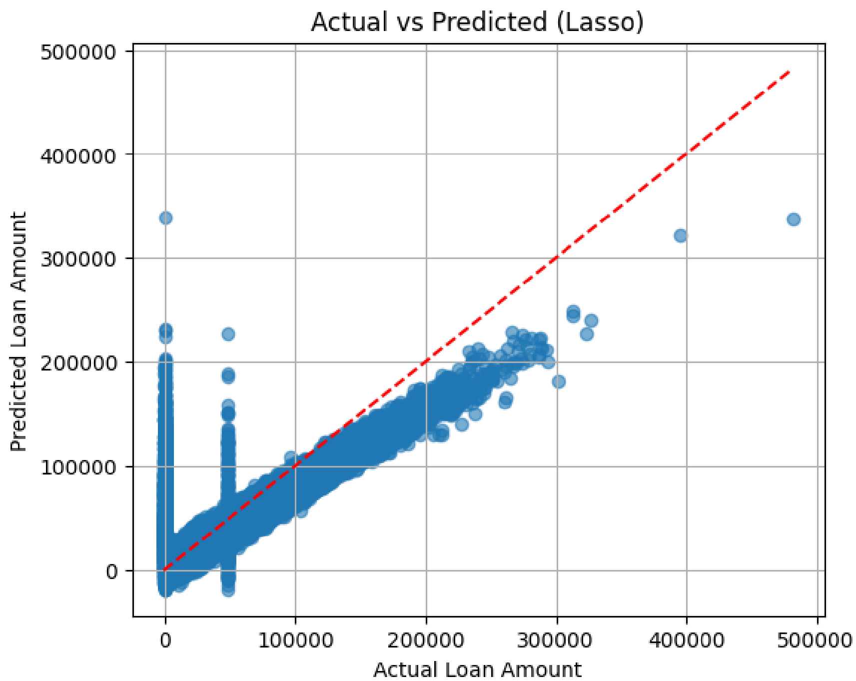

```
XGBoost Performance:
MAE: 12451.8217
MSE: 583299363.1479
RMSE: 24145.6165
R²: 0.7463
Adjusted R²: 0.7444
```



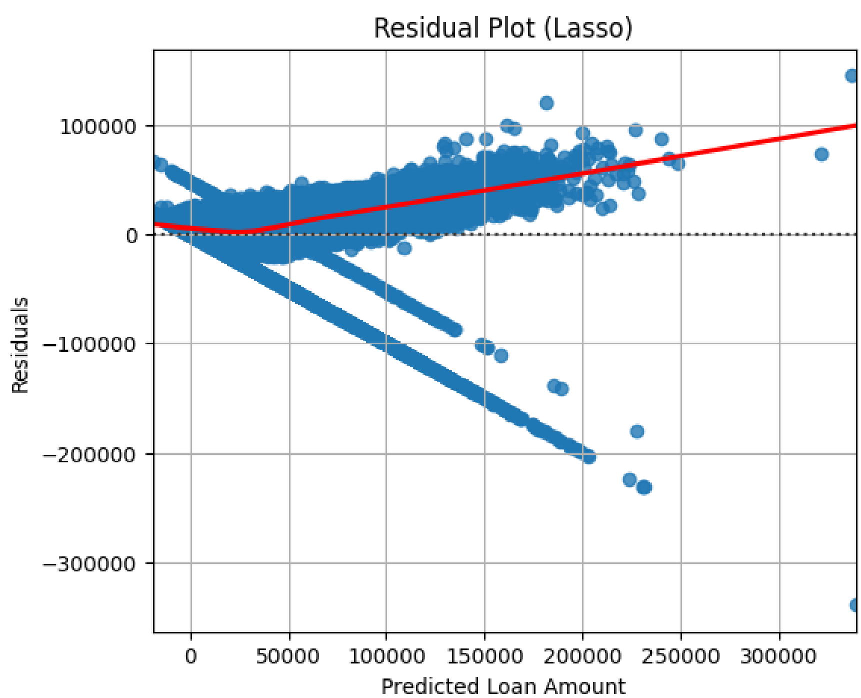




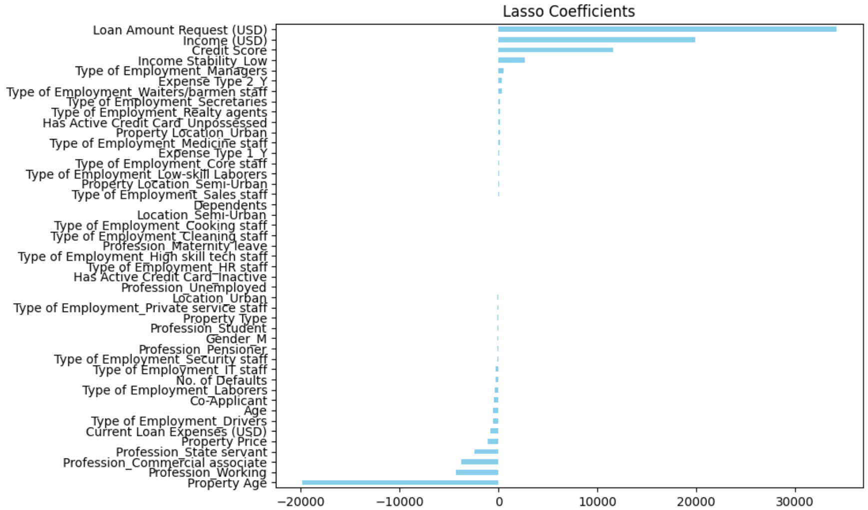

```
Lasso Performance:
MAE: 21754.3808
MSE: 983912986.0772
RMSE: 31352.8407
R²: 0.5721
Adjusted R²: 0.5689
```



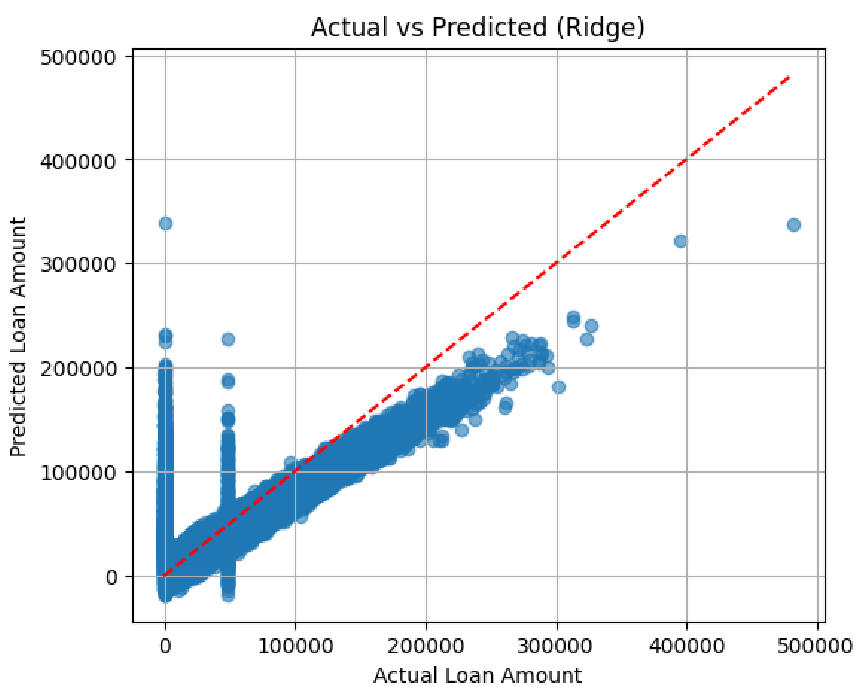
Actual vs Predicted (Lasso)
500000
400000
300000
200000
100000
0
Predicted Loan Amount
0
100000
200000
300000
400000
500000
Actual Loan Amount

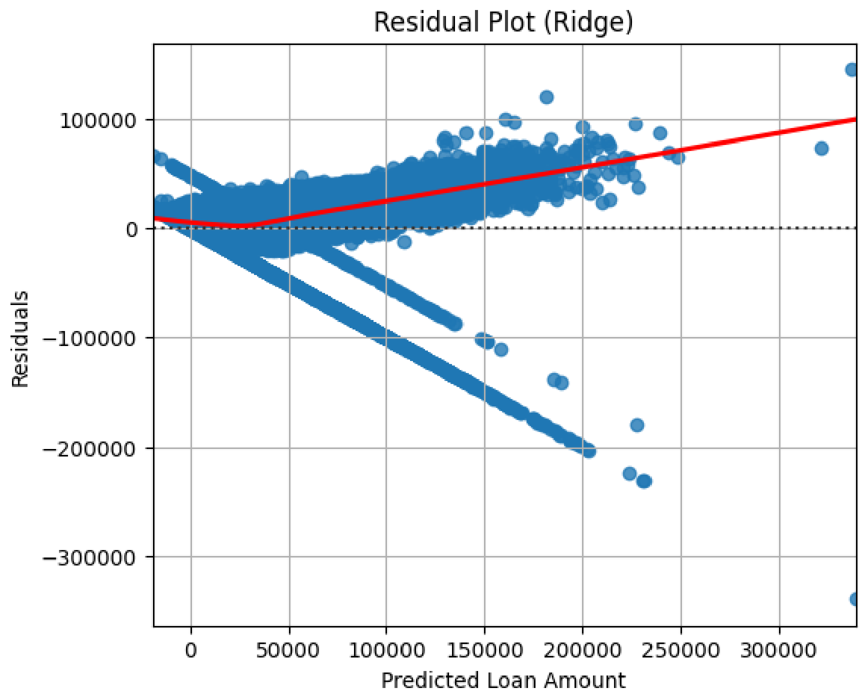


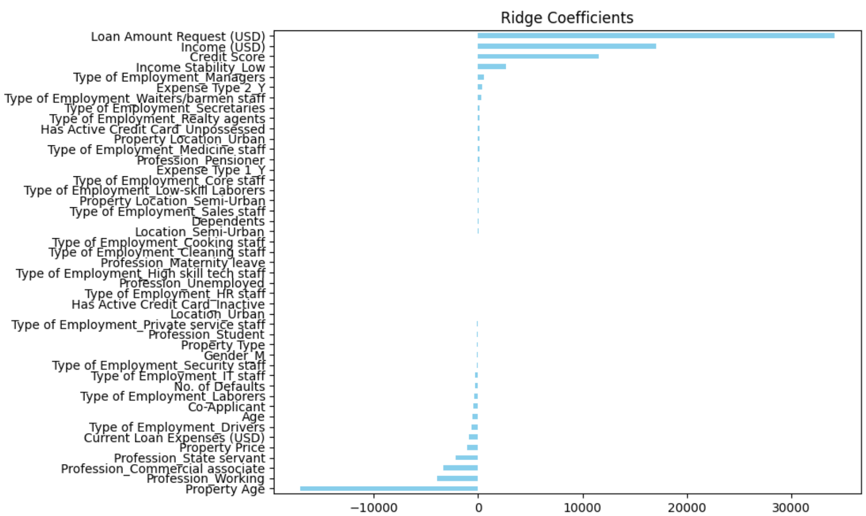
Residual Plot (Lasso)
100000
0
−100000
−200000
−300000
Residuals
0
50000
100000
150000
200000
250000
300000
Predicted Loan Amount



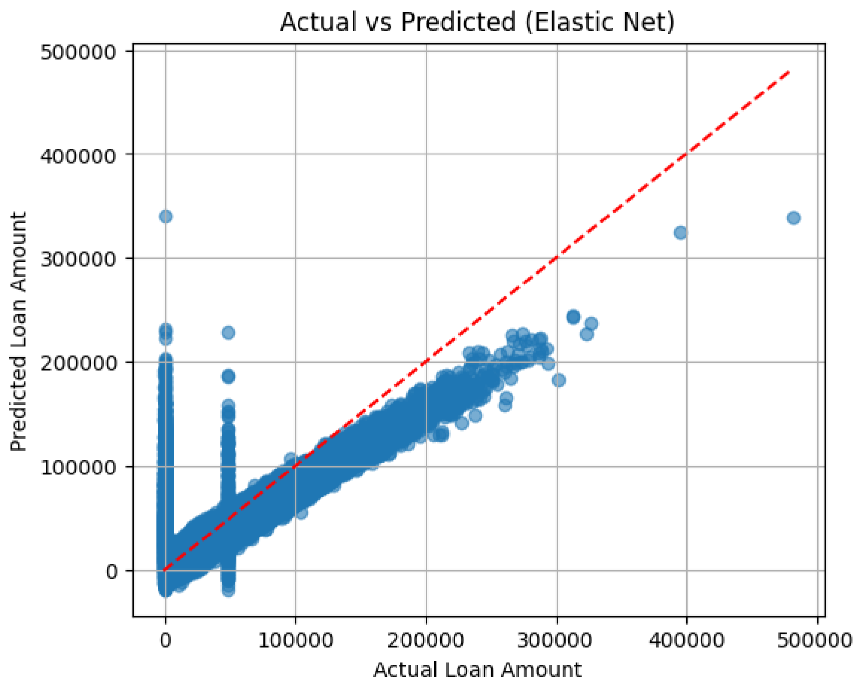

```
Ridge Performance:
MAE: 21754.1187
MSE: 983816352.2717
RMSE: 31351.3020
R²: 0.5722
Adjusted R²: 0.5690
```



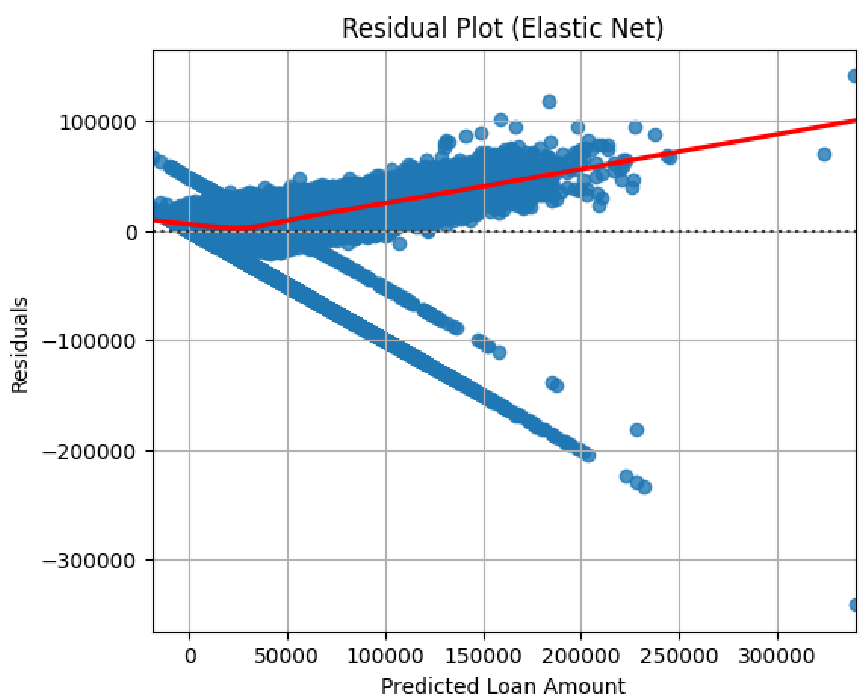




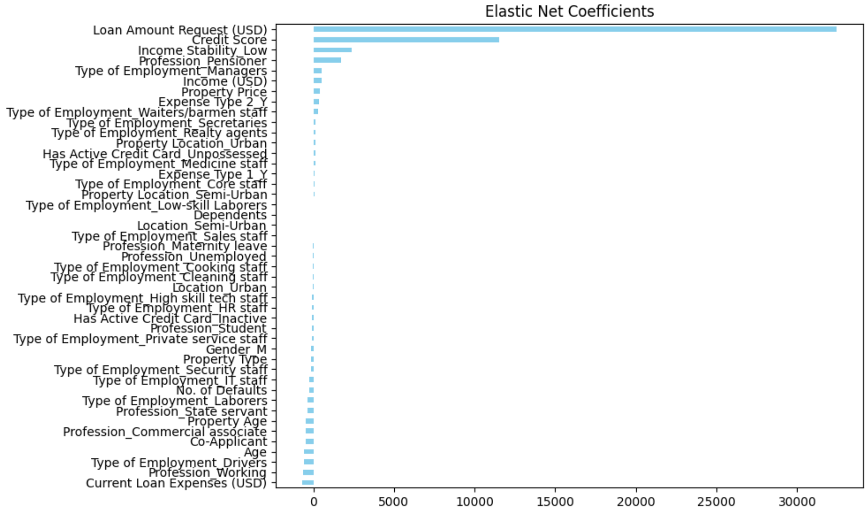

```
Elastic Net Performance:
MAE: 21775.0929
MSE: 981464886.9225
RMSE: 31314.1244
R²: 0.5732
Adjusted R²: 0.5700
```



Actual vs Predicted (Elastic Net)
Predicted Loan Amount
Actual Loan Amount
500000
400000
300000
200000
100000
0
100000
200000
300000
400000
500000



Residual Plot (Elastic Net)
Residuals
Predicted Loan Amount
100000
0
−100000
−200000
−300000
0
50000
100000
150000
200000
250000
300000



OBSERVATION:

Table 1: Cross-Validation Results (K = 5)

Fold	MAE	MSE	RMSE	R^2 Score
Fold 1	25,323.8	1,195,270,000	34,572.6	0.475
Fold 2	23,528.0	996,538,000	31,568.0	0.532
Fold 3	24,752.0	1,157,960,000	34,028.8	0.486
Fold 4	24,207.8	1,070,160,000	32,713.3	0.513
Fold 5	24,688.1	1,126,780,000	33,567.6	0.509
Average	**24,499.9**	**1,109,340,000**	**33,290.1**	**0.503**

Table 2: Summary of Results for Loan Amount Prediction

Description	**Student's Result**
Dataset Size (after preprocessing)	5,000 rows, 39 features
Train/Test Split Ratio	80:20
Feature(s) Used for Prediction	All numerical and encoded categorical features
Model Used	Linear Regression
Cross-Validation Used?	Yes
If Yes, Number of Folds (K)	5
Reference to CV Results Table	Table 1
Mean Absolute Error (MAE) on Test Set	24,499.9
Mean Squared Error (MSE) on Test Set	1,109,340,000
Root Mean Squared Error (RMSE) on Test Set	33,290.1
R^2 Score on Test Set	0.503
Adjusted R^2 Score on Test Set	0.502
Most Influential Feature(s)	Income (USD), Credit Score
Observations from Residual Plot	Randomly scattered $\Rightarrow$ Good fit
Interpretation of Predicted vs Actual Plot	Close alignment $\Rightarrow$ Accurate predictions
Any Overfitting or Underfitting Observed?	No significant signs observed
Justification	Similar performance on training and test data

Best Practices:

- Handled missing data carefully using imputation.
- Performed EDA to understand data distribution and correlations.
- Used ‘SelectKBest‘ for feature selection.
- Used training-validation-test split for reliable performance estimation.

Learning Outcomes:

- Understood how to implement Linear Regression for a real-world problem.
- Practiced data preprocessing, feature selection, model training and evaluation.
- Gained insights on error metrics (MAE, MSE, R^2) to evaluate regression models.