Principal Component Analysis (PCA) on Classification and Regression Tasks

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Aim

To apply Principal Component Analysis (PCA) on both classification and regression datasets, reduce dimensionality while retaining 95% of variance, and train multiple models to evaluate the impact of PCA on performance.

Libraries Used

- Pandas, Numpy
- Matplotlib, Seaborn
- Scikit-learn (PCA, classifiers, regressors, metrics)
- XGBoost

Datasets

Classification: Spambase

- Predict spam emails (1) vs ham (0)
- Features: 57 continuous attributes
- Target: ‘class‘

Regression: Loan Sanction Amount

- Predict sanctioned loan amount
- Features: Customer and property details
- Target: ‘Loan Sanction Amount (USD)‘

Methodology

Preprocessing

- Handle missing values: median (numeric), mode (categorical)
- Encode categorical columns with LabelEncoder

- Standardize all features

PCA

- Applied PCA retaining 95% variance
- Transformed features for all models

Model Training

Classification

- Gaussian Naive Bayes, KNN, Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, SVM

Regression

- Linear, Ridge, Lasso, ElasticNet, Decision Tree, Random Forest, Gradient Boosting, KNN, SVR

Evaluation Metrics

Classification

- Accuracy, Precision, Recall, F1-score
- Confusion Matrix

Regression

- MAE, MSE, R^2
- Actual vs Predicted scatter plots
- Residual distribution

Code and Results

##1. Load Dataset

[6]:
```
import kagglehub

# Download latest version
path = kagglehub.dataset_download("somesh24/spambase")

print("Path to dataset files:", path)
```

```
Using Colab cache for faster access to the 'spambase' dataset.
Path to dataset files: /kaggle/input/spambase
```

[7]:
```
import os
```

```python
# List all files in the dataset folder
print(os.listdir(path))
```

```
['spambase_csv.csv']
```

[8]:
```python
import pandas as pd

df = pd.read_csv(os.path.join(path, 'spambase_csv.csv'))  # adjust name if needed
print(df.head())
```

```
   word_freq_make  word_freq_address  word_freq_all  word_freq_3d  \
0            0.00               0.64           0.64           0.0
1            0.21               0.28           0.50           0.0
2            0.06               0.00           0.71           0.0
3            0.00               0.00           0.00           0.0
4            0.00               0.00           0.00           0.0

   word_freq_our  word_freq_over  word_freq_remove  word_freq_internet  \
0           0.32            0.00              0.00                0.00
1           0.14            0.28              0.21                0.07
2           1.23            0.19              0.19                0.12
3           0.63            0.00              0.31                0.63
4           0.63            0.00              0.31                0.63

   word_freq_order  word_freq_mail  ...  char_freq_%3B  char_freq_%28  \
0             0.00            0.00  ...           0.00          0.000
1             0.00            0.44  ...           0.00          0.132
2             0.64            0.25  ...           0.01          0.143
3             0.31            0.63  ...           0.00          0.137
4             0.31            0.63  ...           0.00          0.135

   char_freq_%5B  char_freq_%21  char_freq_%24  char_freq_%23  \
0            0.0          0.778          0.000          0.000
1            0.0          0.372          0.180          0.048
2            0.0          0.276          0.184          0.010
3            0.0          0.137          0.000          0.000
4            0.0          0.135          0.000          0.000

   capital_run_length_average  capital_run_length_longest  \
0                       3.756                          61
1                       5.114                         101
2                       9.821                         485
3                       3.537                          40
4                       3.537                          40

   capital_run_length_total  class
0                       278      1
1                      1028      1
```

```
2                         2259      1
3                          191      1
4                          191      1

[5 rows x 58 columns]
```

[9]:
```
print(df.shape)
print(df.dtypes)
```

```
(4601, 58)
word_freq_make                float64
word_freq_address             float64
word_freq_all                 float64
word_freq_3d                  float64
word_freq_our                 float64
word_freq_over                float64
word_freq_remove              float64
word_freq_internet            float64
word_freq_order               float64
word_freq_mail                float64
word_freq_receive             float64
word_freq_will                float64
word_freq_people              float64
word_freq_report              float64
word_freq_addresses           float64
word_freq_free                float64
word_freq_business            float64
word_freq_email               float64
word_freq_you                 float64
word_freq_credit              float64
word_freq_your                float64
word_freq_font                float64
word_freq_000                 float64
word_freq_money               float64
word_freq_hp                  float64
word_freq_hpl                 float64
word_freq_george              float64
word_freq_650                 float64
word_freq_lab                 float64
word_freq_labs                float64
word_freq_telnet              float64
word_freq_857                 float64
word_freq_data                float64
word_freq_415                 float64
word_freq_85                  float64
word_freq_technology          float64
word_freq_1999                float64
word_freq_parts               float64
```

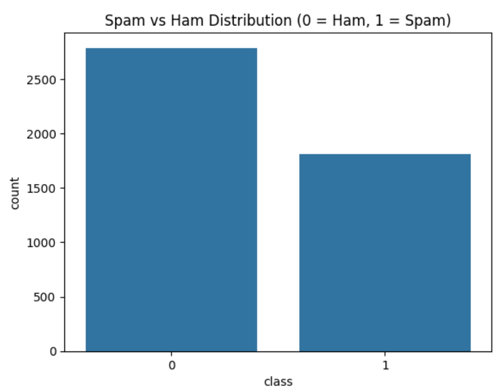
```
word_freq_pm                  float64
word_freq_direct              float64
word_freq_cs                  float64
word_freq_meeting             float64
word_freq_original            float64
word_freq_project             float64
word_freq_re                  float64
word_freq_edu                 float64
word_freq_table               float64
word_freq_conference          float64
char_freq_%3B                 float64
char_freq_%28                 float64
char_freq_%5B                 float64
char_freq_%21                 float64
char_freq_%24                 float64
char_freq_%23                 float64
capital_run_length_average    float64
capital_run_length_longest      int64
capital_run_length_total        int64
class                           int64
dtype: object
```

[10]:

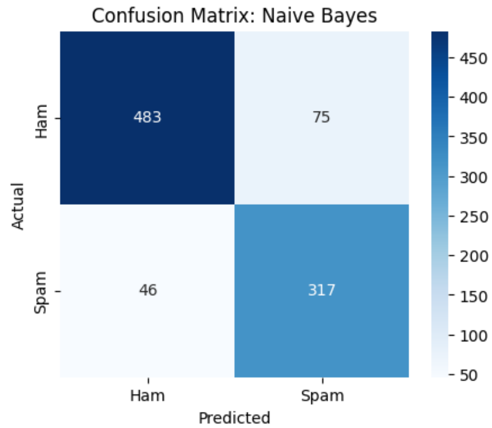
```
## 1. Imports
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, confusion_matrix, classification_report

# Classifiers
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC

# Visualization
import seaborn as sns
import matplotlib.pyplot as plt

# Features and Labels
X = df.drop('class', axis=1)
y = df['class']
```

```python
# Check class distribution
sns.countplot(x=y)
plt.title("Spam vs Ham Distribution (0 = Ham, 1 = Spam)")
plt.show()

# Check missing values
print("Missing values:", X.isnull().sum().sum())

## 3. Scale Features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

## 4. Apply PCA
pca = PCA(n_components=0.45)  # retain 95% variance
X_pca = pca.fit_transform(X_scaled)

## 5. Split Dataset
X_train, X_test, y_train, y_test = train_test_split(
    X_pca, y, test_size=0.2, stratify=y, random_state=42
)

## 6. Define Classifiers
classifiers = {
    "Naive Bayes": GaussianNB(),
    "K-Nearest Neighbors": KNeighborsClassifier(n_neighbors=5),
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100,␣
↪random_state=42),
    "SVM": SVC(kernel='rbf', probability=True)
}

## 7. Train, Evaluate, and Plot Confusion Matrices
results = []

for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    results.append([name, acc, prec, rec, f1])
```

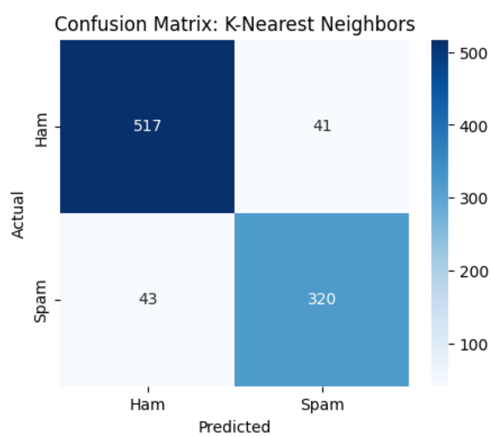
```
    print(f"----- {name} -----")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Ham',␣
↪'Spam'], yticklabels=['Ham', 'Spam'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix: {name}')
    plt.show()

## 8. Summary Table
results_df = pd.DataFrame(results, columns=['Classifier', 'Accuracy',␣
↪'Precision', 'Recall', 'F1-score'])
print("\nSummary of Classifier Performance:\n")
print(results_df.sort_values(by='F1-score', ascending=False))
```




```
Missing values: 0
----- Naive Bayes -----
              precision    recall  f1-score   support

           0       0.41      0.87      0.89       558
           1       0.81      0.87      0.84       363

    accuracy                           0.87       921
   macro avg       0.86      0.87      0.86       921
weighted avg       0.87      0.87      0.87       921
```

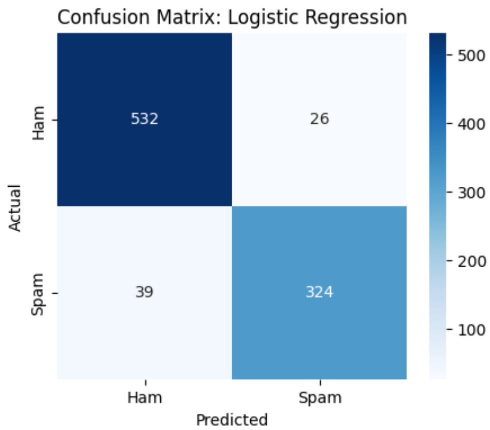



```
----- K-Nearest Neighbors -----
              precision    recall  f1-score   support

           0       0.42      0.43      0.42       558
           1       0.89      0.88      0.88       363

    accuracy                           0.41       921
   macro avg       0.40      0.40      0.40       921
weighted avg       0.41      0.41      0.41       921
```

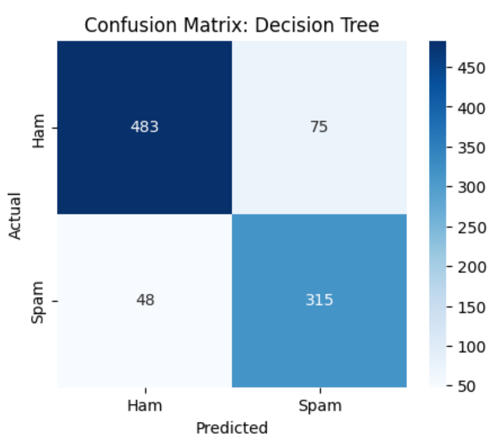



```
----- Logistic Regression -----
              precision    recall  f1-score   support

           0       0.43      0.45      0.44       558
           1       0.43      0.89      0.41       363
```

```
    accuracy                           0.43       921
   macro avg       0.43      0.42      0.43       921
weighted avg       0.43      0.43      0.43       921
```

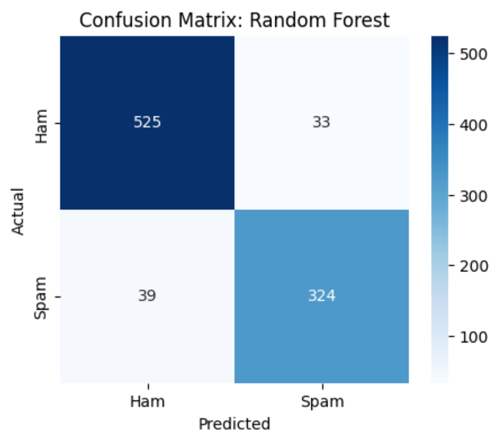



```
----- Decision Tree -----
              precision    recall  f1-score   support

           0       0.41      0.87      0.89       558
           1       0.81      0.87      0.84       363

    accuracy                           0.87       921
   macro avg       0.86      0.87      0.86       921
weighted avg       0.87      0.87      0.87       921
```



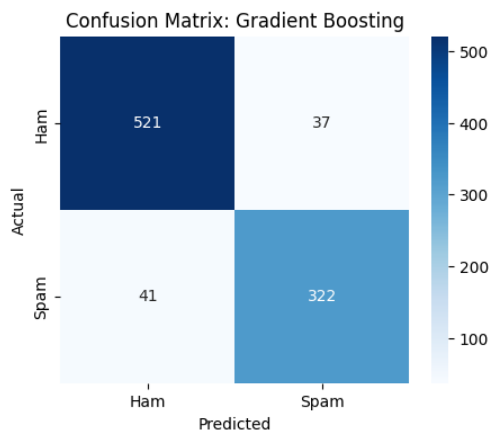

```
----- Random Forest -----
```

	precision	recall	f1-score	support
0	0.43	0.44	0.44	558
1	0.41	0.89	0.40	363
accuracy			0.42	921
macro avg	0.42	0.42	0.42	921
weighted avg	0.42	0.42	0.42	921

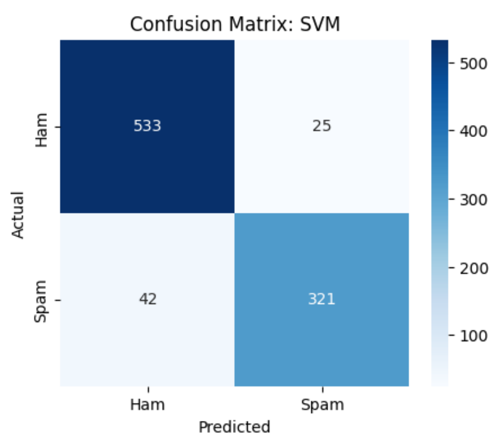


----- Gradient Boosting -----

	precision	recall	f1-score	support
0	0.43	0.43	0.43	558
1	0.40	0.89	0.89	363
accuracy			0.42	921
macro avg	0.41	0.41	0.41	921
weighted avg	0.42	0.42	0.42	921




```
----- SVM -----
              precision    recall  f1-score   support

           0       0.43      0.46      0.44       558
           1       0.43      0.88      0.41       363

    accuracy                           0.43       921
   macro avg       0.43      0.42      0.42       921
weighted avg       0.43      0.43      0.43       921
```




```
Summary of Classifier Performance:

            Classifier  Accuracy  Precision    Recall  F1-score
2  Logistic Regression  0.429425   0.425714  0.892562  0.408836
6                  SVM  0.427253   0.427746  0.884298  0.405501
```

```
4        Random Forest  0.421824   0.407563  0.892562  0.400000
5    Gradient Boosting  0.415309   0.896936  0.887052  0.891967
1  K-Nearest Neighbors  0.408795   0.886427  0.881543  0.883978
0          Naive Bayes  0.868621   0.808673  0.873278  0.839735
3        Decision Tree  0.866450   0.807692  0.867769  0.836653
```

[12]:

```
train_path = '/content/drive/MyDrive/Docs/archive/train.csv'
df = pd.read_csv(train_path)
```

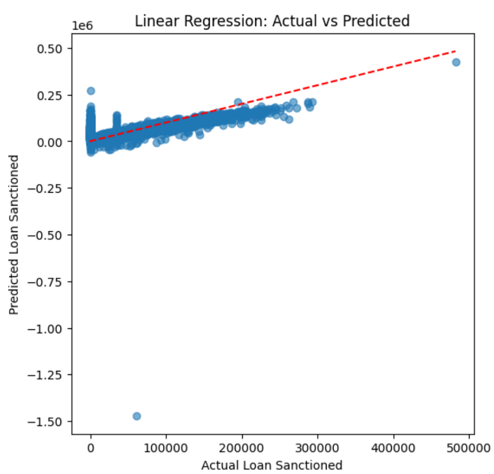
[14]:

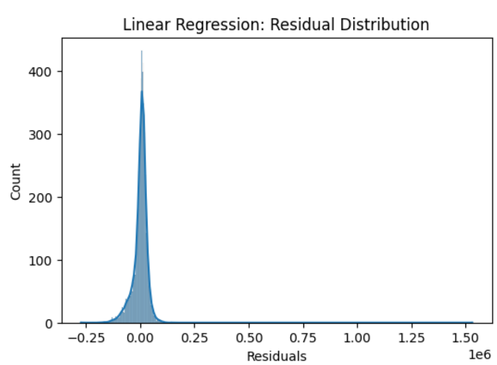
```
## 1. Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Regression models
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR


## 3. Handle missing values
for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = df[col].fillna(df[col].mode()[0])
    else:
        df[col] = df[col].fillna(df[col].median())

## 4. Encode categorical columns
label_encoders = {}
for col in df.select_dtypes(include='object').columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

## 5. Feature / Target split
target = 'Loan Sanction Amount (USD)'
X = df.drop(columns=[target])
y = df[target]
```

```python
## 6. Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

## 7. Apply PCA
pca = PCA(n_components=0.45)  # retain 95% variance
X_pca = pca.fit_transform(X_scaled)

## 8. Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_pca, y, test_size=0.2, random_state=42
)

## 9. Define regression models
regressors = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(),
    "Lasso Regression": Lasso(),
    "ElasticNet": ElasticNet(),
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100,␣
 ↪random_state=42),
    "KNN Regressor": KNeighborsRegressor(),
    "SVR": SVR()
}

## 10. Train, evaluate, and visualize
results = []

for name, model in regressors.items():
    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)
    r2 = r2_score(y_test, y_pred)

    results.append([name, mae, mse, r2])

    print(f"----- {name} -----")
    print(f"MAE: {mae:.2f}, MSE: {mse:.2f}, R²: {r2:.4f}")

    # Plot Actual vs Predicted
    plt.figure(figsize=(6,6))
    plt.scatter(y_test, y_pred, alpha=0.6)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
```

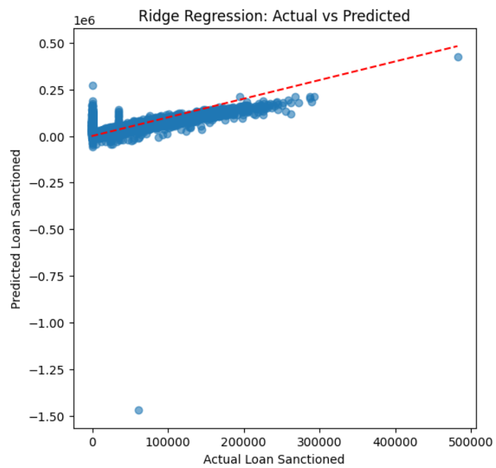
```
    plt.xlabel("Actual Loan Sanctioned")
    plt.ylabel("Predicted Loan Sanctioned")
    plt.title(f"{name}: Actual vs Predicted")
    plt.show()

    # Optional: Residual plot
    residuals = y_test - y_pred
    plt.figure(figsize=(6,4))
    sns.histplot(residuals, kde=True)
    plt.title(f"{name}: Residual Distribution")
    plt.xlabel("Residuals")
    plt.show()

## 11. Summary table
results_df = pd.DataFrame(results, columns=['Regressor', 'MAE', 'MSE', 'R²'])
print("\nSummary of Regressor Performance:\n")
print(results_df.sort_values(by='R²', ascending=False))
```

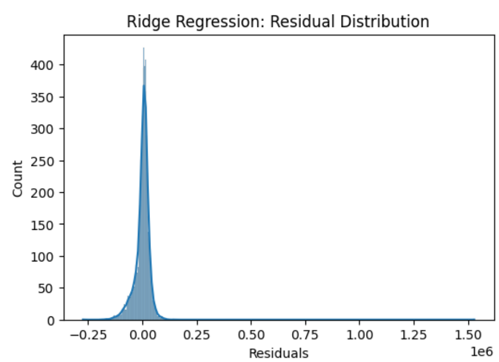
```
----- Linear Regression -----
MAE: 23003.81, MSE: 1440613278.75, R²: 0.3738
```



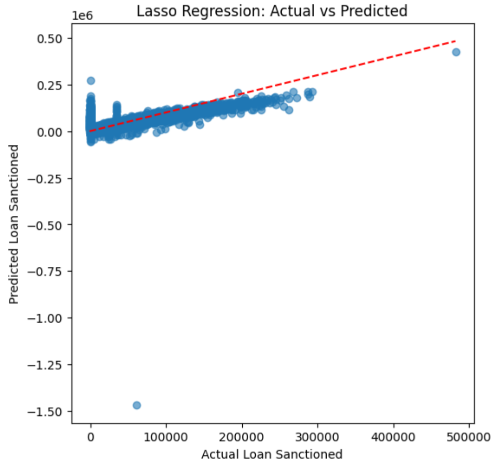


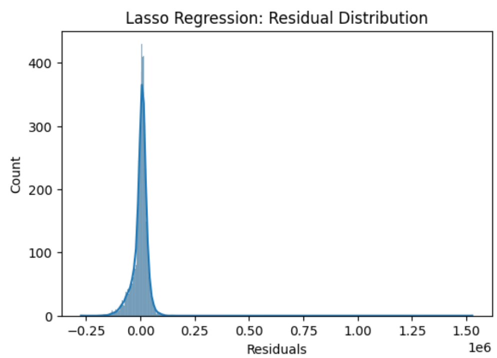
```
----- Ridge Regression -----
MAE: 23003.58, MSE: 1439755573.62, R²: 0.3742
```



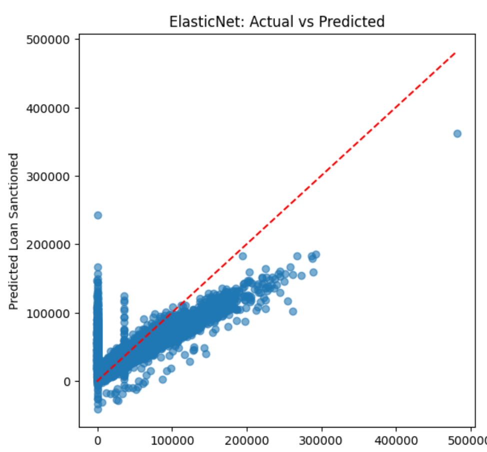


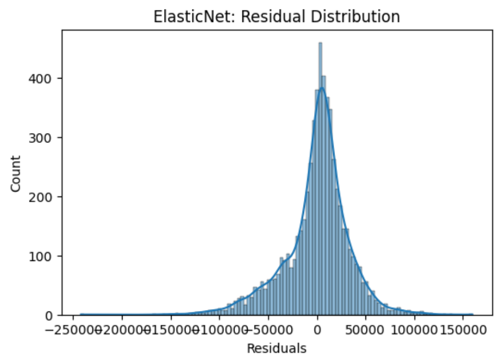

```
----- Lasso Regression -----
MAE: 23003.24, MSE: 1438717324.30, R²: 0.3746
```



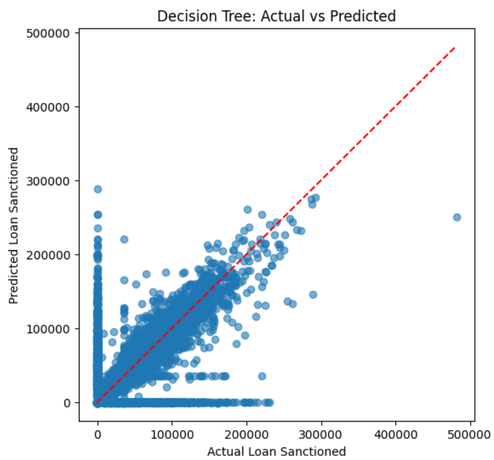


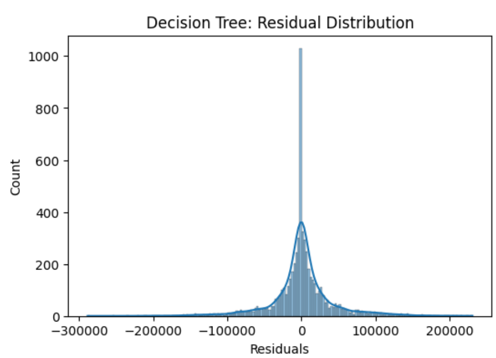

```
----- ElasticNet -----
MAE: 23630.71, MSE: 1094052374.99, R²: 0.5244
```



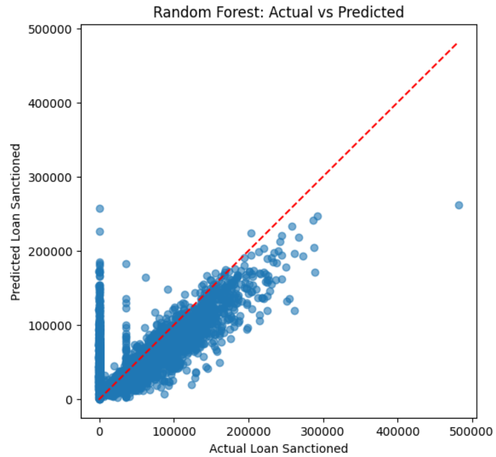


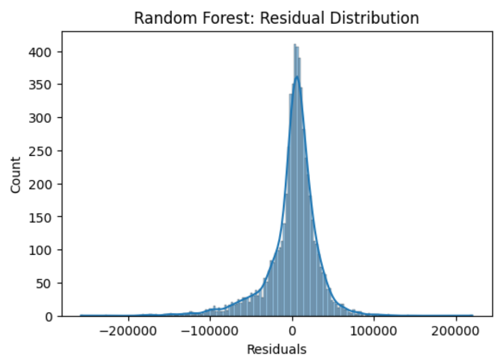

```
----- Decision Tree -----
MAE: 25996.73, MSE: 1892481443.98, R²: 0.1774
```



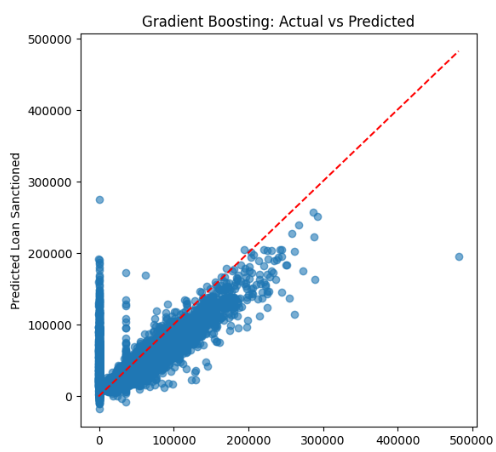


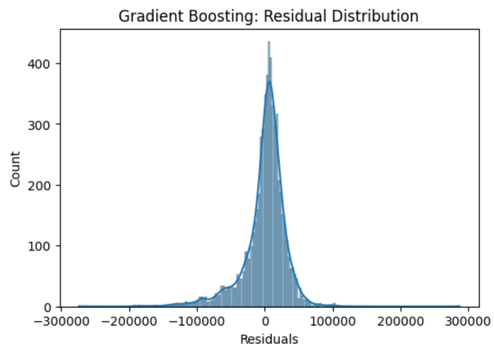

```
----- Random Forest -----
MAE: 21127.23, MSE: 1003895771.62, R²: 0.5636
```



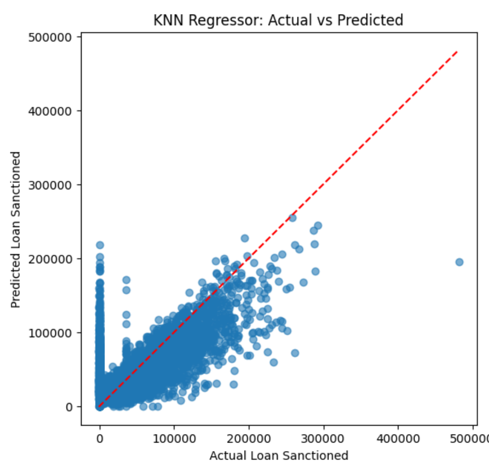


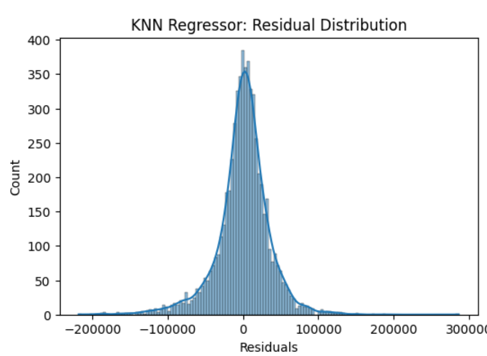

```
----- Gradient Boosting -----
MAE: 21386.51, MSE: 999942997.28, R²: 0.5653
```



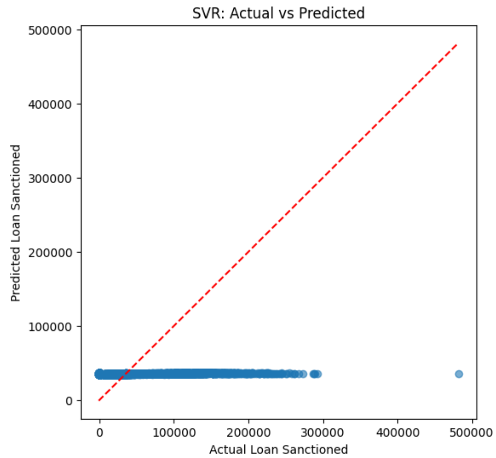


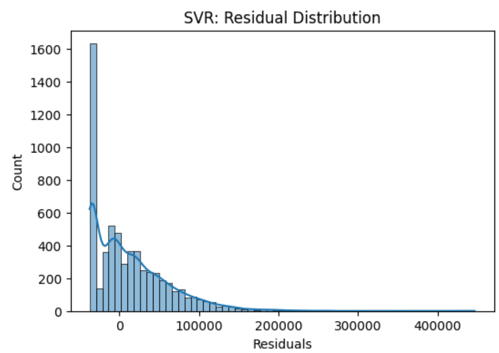
----- KNN Regressor -----
MAE: 24686.28, MSE: 1263139460.13, R²: 0.4509





----- SVR -----
MAE: 36381.87, MSE: 2415185767.48, R²: -0.0498






```
Summary of Regressor Performance:

           Regressor           MAE           MSE        R²
6  Gradient Boosting  21386.509227  9.999430e+08  0.565348
5      Random Forest  21127.234983  1.003896e+09  0.563630
3         ElasticNet  23630.705591  1.094052e+09  0.524441
7      KNN Regressor  24686.278935  1.263139e+09  0.450942
2   Lasso Regression  23003.244532  1.438717e+09  0.374623
1   Ridge Regression  23003.577878  1.439756e+09  0.374171
0  Linear Regression  23003.811776  1.440613e+09  0.373799
4      Decision Tree  25996.732272  1.892481e+09  0.177382
8                SVR  36381.868893  2.415186e+09 -0.049826
```

Learning Outcomes

- Implemented PCA for dimensionality reduction in classification and regression
- Trained multiple models and evaluated their performance after PCA transformation

- Learned preprocessing techniques including scaling and encoding
- Visualized confusion matrices, actual vs predicted plots, and residual distributions
- Compared performance across multiple models and understood the effect of PCA