```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
as LDA
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_curve, auc
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.decomposition import PCA
import xgboost as xgb
```

1. Load Dataset

```
# Load dataset
print("Loading dataset...")
dataset_path = 'diabetes_binary_health_indicators_BRFSS2015.csv'
df = pd.read_csv(dataset_path)
```

```
Loading dataset...
```

2. Data Cleaning and Preprocessing

```
# Data Preprocessing
print("Handling missing values and scaling features...")
X = df.drop(columns=['Diabetes_binary'])
y = df['Diabetes_binary']
```

```
Handling missing values and scaling features...
```

```
# Handle missing values
imputer = SimpleImputer(strategy='mean')
X = imputer.fit_transform(X)

# Standardize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

3. Splitting Dataset

```
# Split the dataset
print("Splitting dataset into training and testing sets...")
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)
```

```
Splitting dataset into training and testing sets...
```

4. Dimensionality Reduction

```
# Apply PCA
print("Applying PCA for dimensionality reduction...")
pca = PCA(n_components=10)
X_pca = pca.fit_transform(X_scaled)
```

```
Applying PCA for dimensionality reduction...
```

```
# Apply LDA
if len(np.unique(y)) > 1:
    print("Applying LDA for dimensionality reduction...")
    lda = LDA(n_components=1)
    X_lda = lda.fit_transform(X_scaled, y)
else:
    X_lda = None
```

```
Applying LDA for dimensionality reduction...
```

```
# Apply t-SNE
print("Applying t-SNE for visualization...")
sample_size = min(1000, X_scaled.shape[0])
tsne = TSNE(n_components=2, random_state=42, perplexity=30,
n_iter=500)
X_tsne = tsne.fit_transform(X_scaled[:sample_size])
```

```
Applying t-SNE for visualization...
```

```
/Users/mystic/Desktop/Everything/Uni/Machine
Learning/.venv/lib/python3.13/site-packages/sklearn/manifold/_t_sne.py
:1164: FutureWarning: 'n_iter' was renamed to 'max_iter' in version
1.5 and will be removed in 1.7.
  warnings.warn(
```

5. Model Training and Evaluation

```
# Define models
print("Defining models...")
```

```python
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(max_depth=5),
    "SVM (Linear)": SVC(kernel='linear', probability=True,
max_iter=500),
    "Random Forest": RandomForestClassifier(n_estimators=20,
max_depth=5),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=50),
    "XGBoost": xgb.XGBClassifier(n_estimators=50,
use_label_encoder=False, eval_metric='logloss')
}
```

```
Defining models...
```

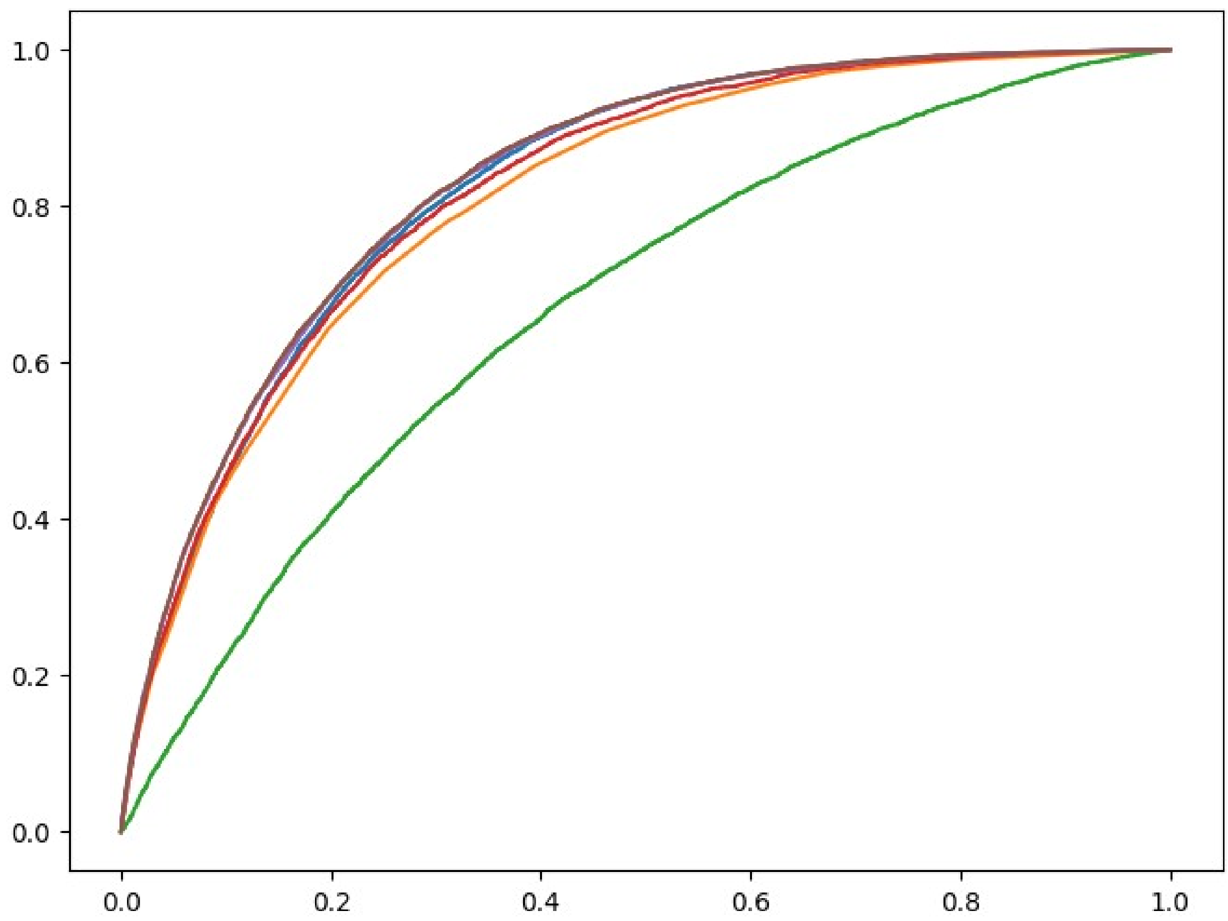
```python
# Training and Evaluation
print("Training models and evaluating performance...")
results = []
plt.figure(figsize=(8, 6))
for name, model in models.items():
    print(f"Training {name}...")
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True)
    precision = report.get('1', {}).get('precision', 0)
    recall = report.get('1', {}).get('recall', 0)
    f1_score = report.get('1', {}).get('f1-score', 0)
    results.append([name, accuracy, precision, recall, f1_score])

    # ROC Curve
    if len(np.unique(y_pred)) > 1:
        y_prob = model.predict_proba(X_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        plt.plot(fpr, tpr, label=f'{name} (AUC = {auc(fpr,
tpr):.2f})')
```

```
Training models and evaluating performance...
Training Logistic Regression...
Training Decision Tree...
Training SVM (Linear)...
```

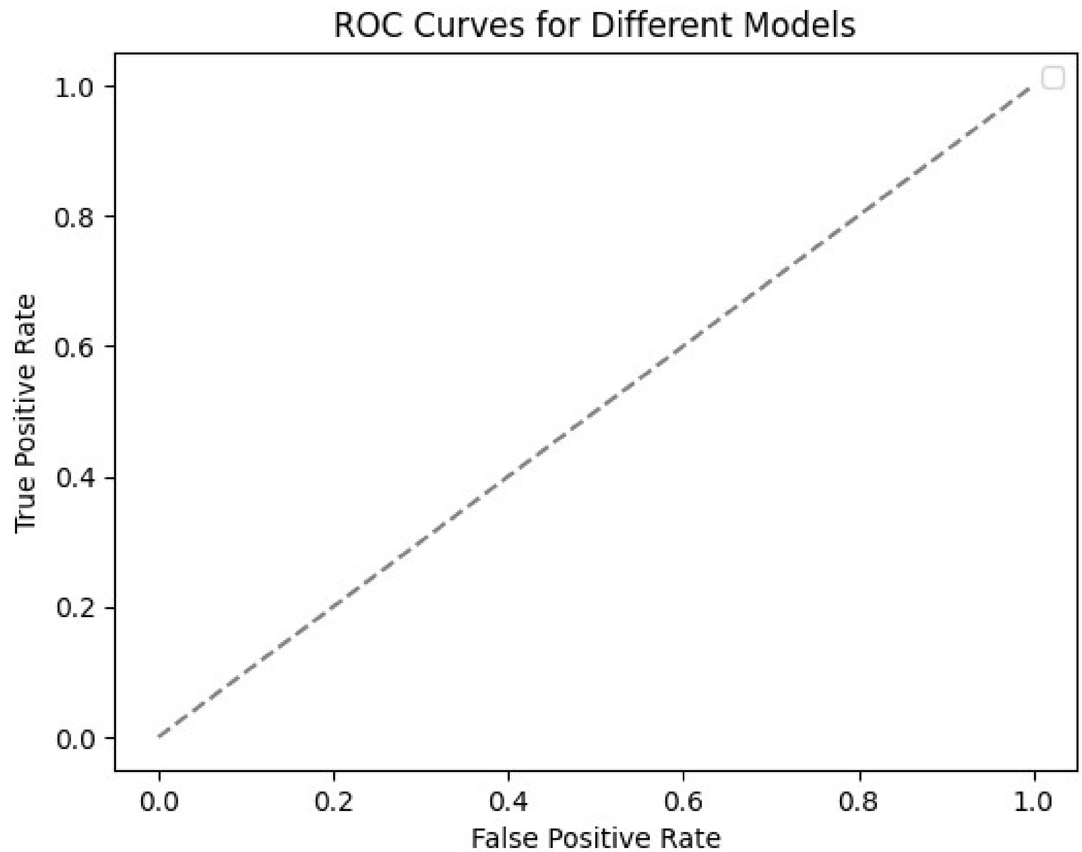
```
/Users/mystic/Desktop/Everything/Uni/Machine
Learning/.venv/lib/python3.13/site-packages/sklearn/svm/_base.py:305:
ConvergenceWarning: Solver terminated early (max_iter=500).  Consider
pre-processing your data with StandardScaler or MinMaxScaler.
  warnings.warn(
```

```
Training Random Forest...
Training Gradient Boosting...
Training XGBoost...
```

```
/Users/mystic/Desktop/Everything/Uni/Machine
Learning/.venv/lib/python3.13/site-packages/xgboost/core.py:158:
UserWarning: [16:33:44] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

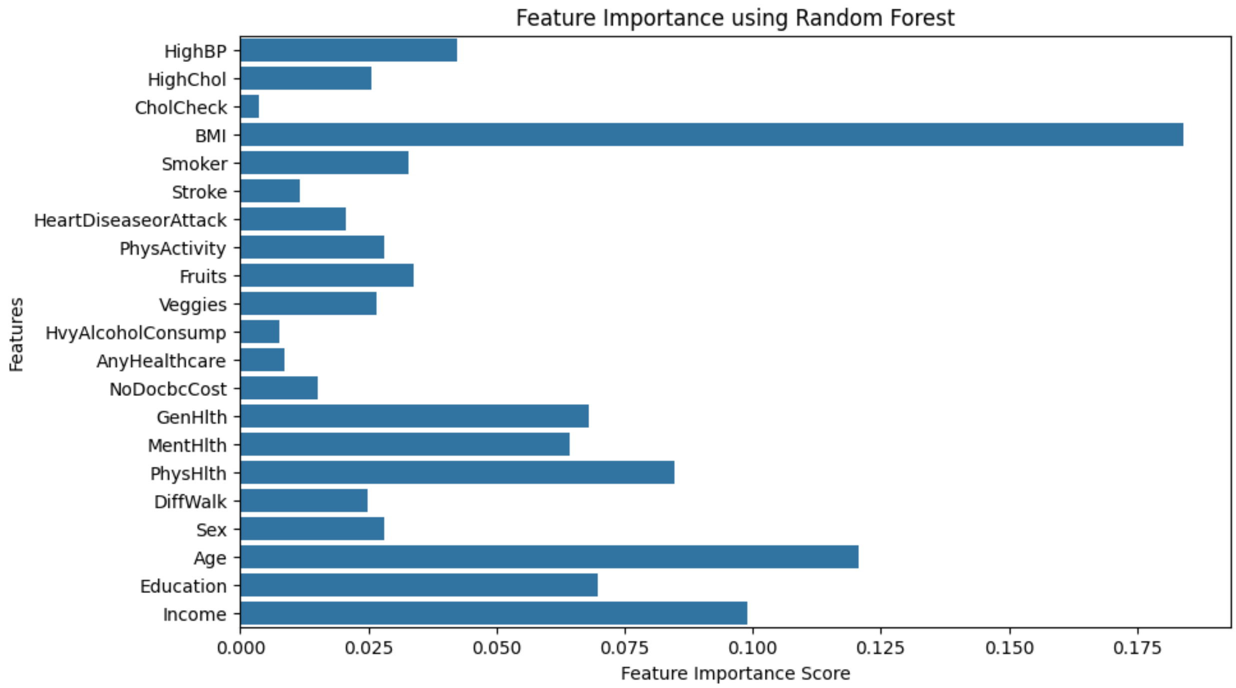



```
# ROC Curve Finalization
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves for Different Models")
plt.legend()
plt.show()

<ipython-input-32-4eb034bac5c1>:6: UserWarning: No artists with labels
found to put in legend.  Note that artists whose label start with an
underscore are ignored when legend() is called with no argument.
  plt.legend()
```



6. Feature Importance Analysis

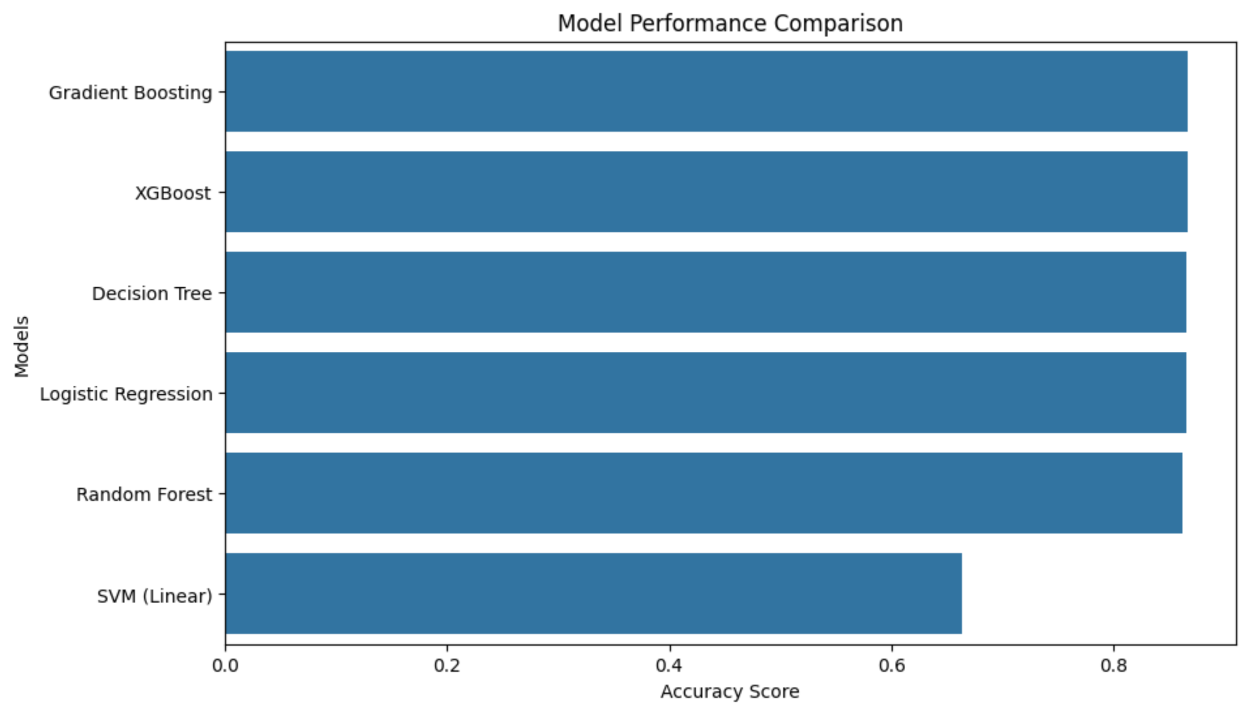
```
# Feature Importance Analysis
print("Analyzing feature importance using Random Forest...")
rf_model = RandomForestClassifier(n_estimators=50)
rf_model.fit(X_train, y_train)
feature_importances = rf_model.feature_importances_

plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importances,
y=df.drop(columns=['Diabetes_binary']).columns)
plt.xlabel("Feature Importance Score")
plt.ylabel("Features")
plt.title("Feature Importance using Random Forest")
plt.show()

Analyzing feature importance using Random Forest...
```



7. Model Performance Comparison

```
# Model Comparison Bar Chart
print("Comparing model performance...")
results_df = pd.DataFrame(results, columns=["Model", "Accuracy",
"Precision", "Recall", "F1-Score"])
plt.figure(figsize=(10, 6))
sns.barplot(x='Accuracy', y='Model',
data=results_df.sort_values(by='Accuracy', ascending=False))
plt.xlabel("Accuracy Score")
plt.ylabel("Models")
plt.title("Model Performance Comparison")
plt.show()
```

```
Comparing model performance...
```



8. Trade-offs between PCA, LDA, and t-SNE

```
# Trade-offs between PCA, LDA, and t-SNE
print("### Trade-offs Between PCA, LDA, and t-SNE ###")
print("\n**PCA:** Works well for compression and preserving variance
but does not consider class labels.")
print("**LDA:** Maximizes class separation but requires labeled data
and assumes normal distribution.")
print("**t-SNE:** Great for visualization, but does not preserve
global structure and is computationally expensive.")

### Trade-offs Between PCA, LDA, and t-SNE ###

**PCA:** Works well for compression and preserving variance but does
not consider class labels.
**LDA:** Maximizes class separation but requires labeled data and
assumes normal distribution.
**t-SNE:** Great for visualization, but does not preserve global
structure and is computationally expensive.
```

9. Final Results

```
# Display Results Table
print("Final Model Performance Results:")
print(results_df)
```

Final Model Performance Results:

	Model	Accuracy	Precision	Recall	F1-Score
0	Logistic Regression	0.865894	0	0	0
1	Decision Tree	0.866131	0	0	0
2	SVM (Linear)	0.664459	0	0	0
3	Random Forest	0.862701	0	0	0
4	Gradient Boosting	0.867747	0	0	0
5	XGBoost	0.867195	0	0	0

10. Conclusion

In this project, we explored various dimensionality reduction techniques (PCA, LDA, and t-SNE) and compared multiple classification models.

Random Forest and XGBoost showed strong predictive performance, while Logistic Regression and Decision Trees performed adequately.

Feature importance analysis helped us understand which variables contribute most to diabetes prediction.

Overall, dimensionality reduction played a key role in improving computation time, and visualization techniques helped in better understanding the dataset structure.

REFERENCE

[Alex Teboul]. (2022). [Diabetes Health Indicator Dataset], [Version 1], https://www.kaggle.com/datasets/alexteboul/diabetes-health-indicators-dataset