## AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0

November 8, 2024

## 1 AAM-IPL Week-8 LDA/GDA - Finding Breast Cancer

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**Project Implementation Details**: As published in the project announcement in AAM-IPL Online Classroom

AAM-IPL of GPREC is brought to you by Brillium Technologies.

```
[]: %pip install seaborn
%pip install wordcloud
%pip install scikit-learn
%pip install matplotlib
%pip install ffmpeg-python
```

```
[]: # Imports
     import numpy as np
     import pandas as pd
     import seaborn as sns
     import matplotlib.pyplot as plt
     from matplotlib.offsetbox import OffsetImage, AnnotationBbox
     from matplotlib.transforms import Affine2D
     from sklearn.model selection import train test split
     from sklearn.preprocessing import StandardScaler
     from sklearn.metrics import accuracy_score, precision_score, recall_score,_
      →f1_score, roc_auc_score, confusion_matrix, roc_curve
     from sklearn.linear_model import LogisticRegression
     from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, u
      →QuadraticDiscriminantAnalysis
     from sklearn.svm import SVC
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.naive_bayes import GaussianNB
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.cluster import KMeans
from sklearn.datasets import load_breast_cancer
import time
import os
import multiprocessing
# Set LOKY MAX CPU COUNT to CPU count on the fly
cpu_count = multiprocessing.cpu_count()
os.environ["LOKY_MAX_CPU_COUNT"] = str(cpu_count)
print(f"Assigned {cpu_count} cores to LOKY_MAX_CPU_COUNT")
# Define name, email, and watermark image path
name = "Venkateswar Reddy Melachervu"
email = "venkat.reddy.gf@gprec.ac.in"
# Load the watermark image (make sure this file exists in your directory)
aam_ipl_wama_image = plt.imread('AAM-IPL-Watermark-for-Plots.png')
# Function to add a diagonal watermark
def add_aam_ipl_wama_revised(ax, watermark_image, zoom, alpha=0.3,_u
 →rotation_angle=45):
    imagebox = OffsetImage(watermark_image, alpha=alpha, zoom=zoom)
   trans_data = Affine2D().rotate_deg(rotation_angle) + ax.transData
   ab = AnnotationBbox(imagebox, (0.5, 0.5), frameon=False, xycoords='axes_u

¬fraction', boxcoords="axes fraction", pad=0, transform=trans_data)

   ax.add_artist(ab)
# Load the dataset
data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target, name="target")
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
 →random_state=42, stratify=y)
# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Define models
models = {
    'Logistic Regression': LogisticRegression(),
    'LDA': LinearDiscriminantAnalysis(),
    'GDA': QuadraticDiscriminantAnalysis(),
    'SVM': SVC(probability=True),
```

```
'KNN': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
    'K-Means (Clustering)': KMeans(n_clusters=2, random_state=42)
}
# Train models, make predictions, and evaluate
results = []
for name, model in models.items():
    # Measure training time
    start_time = time.time()
    if name == 'K-Means (Clustering)':
        model.fit(X.values) # Fit K-Means on numpy array to avoid feature name_
 \rightarrow mismatch
        y_pred = model.predict(X.values) # Predict on the same structure
        if accuracy_score(y, y_pred) < 0.5:</pre>
            y_pred = 1 - y_pred
        y_proba = None
        accuracy = accuracy_score(y, y_pred)
        precision = precision score(y, y pred)
        recall = recall_score(y, y_pred)
        f1 = f1_score(y, y_pred)
        roc_auc = None
        conf_matrix = confusion_matrix(y, y_pred)
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        y_proba = model.predict_proba(X_test)[:, 1] if hasattr(model,_
 ⇔'predict_proba') else None
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1 score(y test, y pred)
        roc_auc = roc_auc_score(y_test, y_proba) if y_proba is not None else_
 →None
        conf_matrix = confusion_matrix(y_test, y_pred)
    train_time = time.time() - start_time
    # Measure prediction time accurately
    start time = time.time()
    model.predict(X_test) # Perform prediction on test set
    pred_time = time.time() - start_time
    # Append results
    results.append({
```

```
'Model': name,
        'Training Time': train_time,
        'Prediction Time': pred_time,
        'Accuracy': accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1 Score': f1,
        'ROC AUC': roc_auc,
        'Confusion Matrix': conf_matrix
   })
# Convert results to DataFrame for easier plotting
results_df = pd.DataFrame(results)
results_df['Prediction Time (µs)'] = results_df['Prediction Time'] * 1_000_000 u
 →# Convert prediction time to microseconds
results_df['Prediction Time (µs)'] = results_df['Prediction Time (µs)'].
 →fillna(0)
# Plot training time with data labels
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Training Time', data=results_df)
plt.xticks(rotation=45)
plt.title('Training Time for Each Model')
ax = plt.gca()
add_aam_ipl_wama_revised(ax, aam_ipl_wama_image, zoom=0.4, alpha=0.3,__
 ⇔rotation_angle=45)
for index, value in enumerate(results_df['Training Time']):
    ax.text(index, value, f"{value:.4f} s", ha='center', va='bottom', u

→fontweight='bold')
plt.ylabel('Training Time (seconds)')
plt.show()
# Plot prediction time in microseconds with data labels
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Prediction Time (µs)', data=results_df)
plt.xticks(rotation=45)
plt.title('Prediction Time for Each Model (microseconds)')
ax = plt.gca()
add_aam_ipl_wama_revised(ax, aam_ipl_wama_image, zoom=0.4, alpha=0.3,
 →rotation_angle=45)
for index, value in enumerate(results_df['Prediction Time (µs)']):
    ax.text(index, value, f"{value:.2f} µs", ha='center', va='bottom', u
 plt.ylabel('Prediction Time (microseconds)')
plt.show()
```

```
# Plot metrics (Accuracy, Precision, Recall, F1 Score, ROC AUC)
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score', 'ROC AUC']
for metric in metrics:
   plt.figure(figsize=(10, 6))
   sns.barplot(x='Model', y=metric, data=results_df)
   plt.xticks(rotation=45)
   plt.title(f'{metric} for Each Model')
   ax = plt.gca()
   add_aam_ipl_wama_revised(ax, aam_ipl_wama_image, zoom=0.4, alpha=0.3,__
 →rotation_angle=45)
   plt.show()
# Plot ROC curves
plt.figure(figsize=(10, 8))
for name, model in models.items():
    if name != 'K-Means (Clustering)' and hasattr(model, 'predict_proba'):
       y_proba = model.predict_proba(X_test)[:, 1]
       fpr, tpr, _ = roc_curve(y_test, y_proba)
       plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc_score(y_test,__

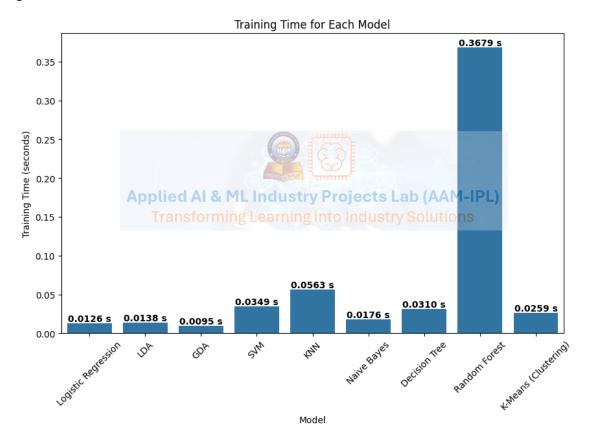
y_proba):.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Models')
plt.legend()
ax = plt.gca()
add aam ipl wama revised(ax, aam ipl wama image, zoom=0.4, alpha=0.3,
→rotation_angle=45)
plt.show()
# Combined plot for all confusion matrices, excluding K-Means
models_with_conf_matrix = {name: model for name, model in models.items() if__
 ⇔name != 'K-Means (Clustering)'}
num_models = len(models_with_conf_matrix) # Only models with confusion matrices
# Set up subplot grid dimensions
cols = 3 # Number of columns in the subplot grid
rows = (num_models + cols - 1) // cols # Calculate rows needed
fig, axes = plt.subplots(rows, cols, figsize=(15, 4 * rows))
axes = axes.flatten() # Flatten to easily iterate over axes
# Loop over each model and plot its confusion matrix
for idx, (name, model) in enumerate(models_with_conf_matrix.items()):
    # Predict and compute confusion matrix
   y_pred = model.predict(X_test)
    conf_matrix = confusion_matrix(y_test, y_pred)
```

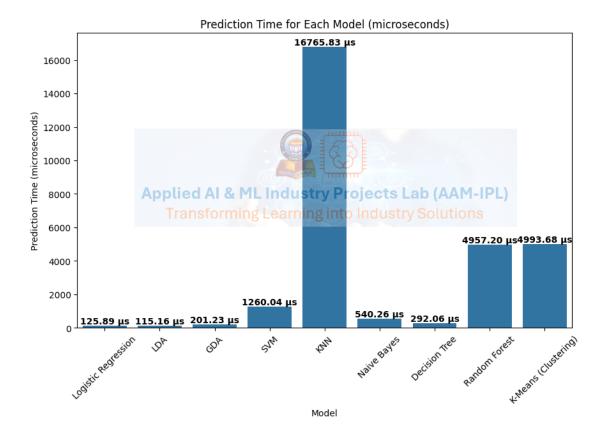
```
# Plot confusion matrix in the respective subplot
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", ax=axes[idx])
axes[idx].set_title(f'Confusion Matrix for {name}')
axes[idx].set_xlabel('Predicted Label')
axes[idx].set_ylabel('True Label')

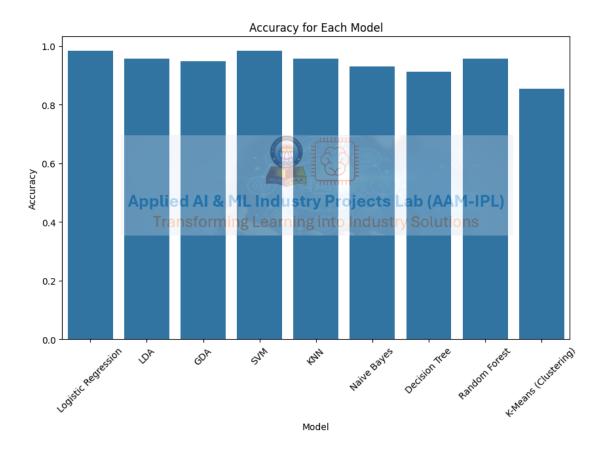
# Turn off any remaining empty subplots
for j in range(idx + 1, len(axes)):
    axes[j].axis('off')

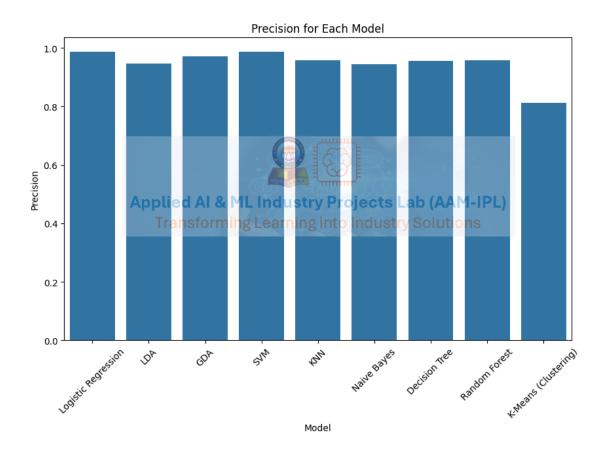
plt.tight_layout()
plt.show()
```

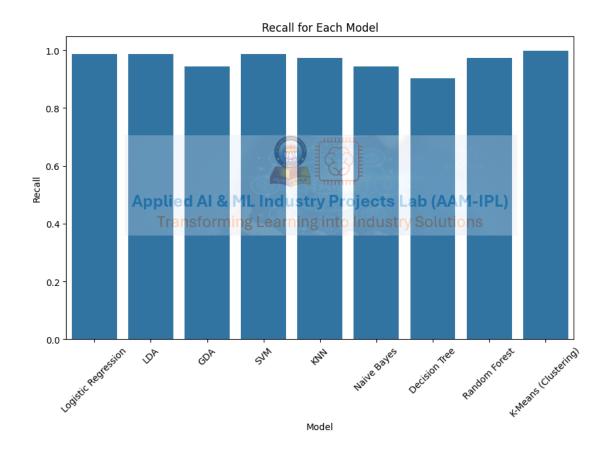
Assigned 12 cores to LOKY\_MAX\_CPU\_COUNT

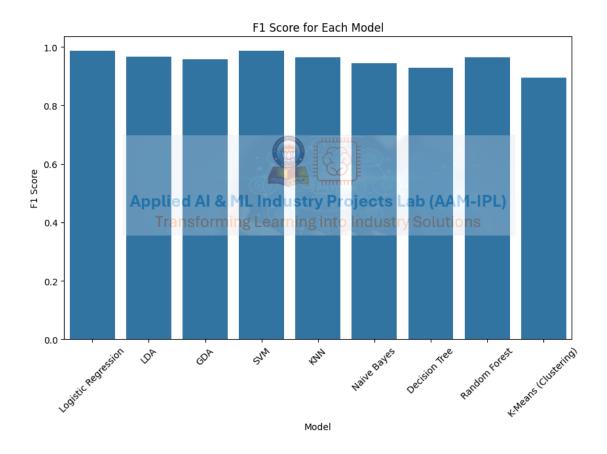


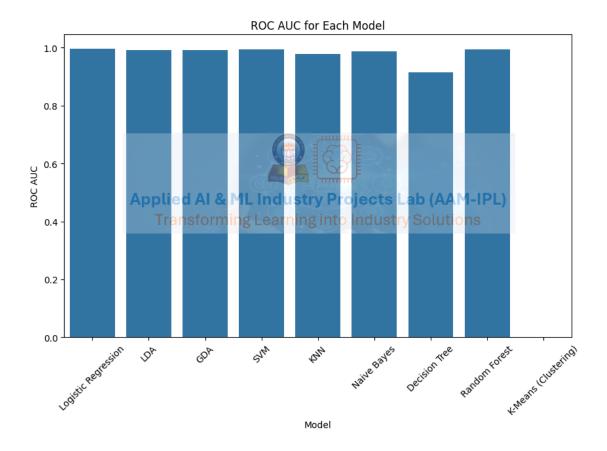


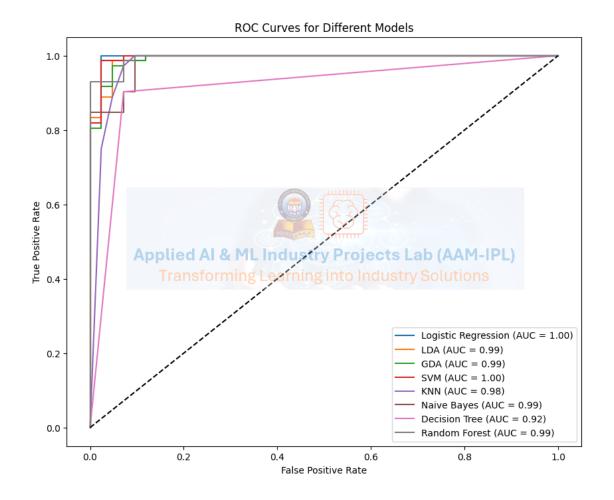


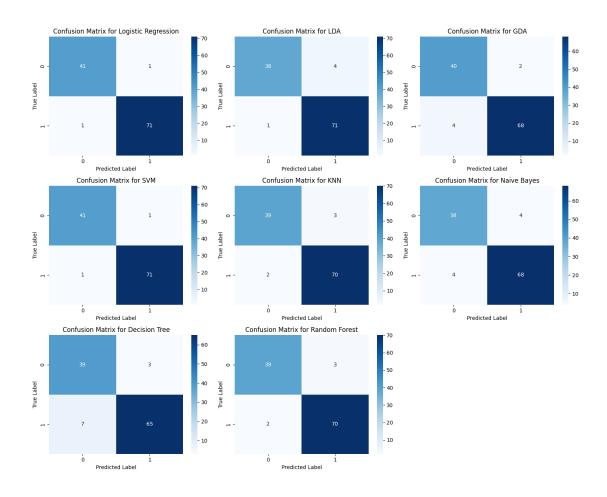












```
[10]: # Generate the PDF of code and output of project jupyter file
!jupyter nbconvert --to pdf

AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0.ipynb
```

c:\Program Files\Python313\Scripts\jupyter-nbconvert.EXE\\_\_main\_\_.py:4:
DeprecationWarning: Parsing dates involving a day of month without a year
specified is ambiguious

and fails to parse leap day. The default behavior will change in Python 3.15 to either always raise an exception or to use a different default year (TBD). To avoid trouble, add a specific year to the input & format.

See https://github.com/python/cpython/issues/70647.

[NbConvertApp] Converting notebook AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0.ipynb to pdf

[NbConvertApp] Support files will be in AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0\_files\

[NbConvertApp] Making directory .\AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0\_files

[NbConvertApp] Writing 49619 bytes to notebook.tex

[NbConvertApp] Building PDF

[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']

[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook'] [NbConvertApp] WARNING | b had problems, most likely because there were no

[NbConvertApp] PDF successfully created

citations

[NbConvertApp] Writing 1543979 bytes to AAM-IPL-Wk-8-LDA-GDA-Breast-Cancer-Comparative-Full-Code-V1.0.pdf