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

Experiment 7: *Ensemble Learning – Bagging and Boosting Methods*

Aim

To investigate the performance of ensemble machine learning techniques, specifically Bagging and Boosting, and to compare their prediction accuracy and generalization ability against single classifiers such as Decision Tree and Logistic Regression. The experiment involves model training, tuning, and evaluation on a common dataset.

Libraries Used

- NumPy
- Pandas
- Matplotlib
- Scikit-learn
- XGBoost

Objective

To study how ensemble approaches like Bagging (Random Forest) and Boosting (AdaBoost, Gradient Boosting, and XGBoost) improve model accuracy, reduce overfitting, and enhance robustness compared to individual base learners through hyperparameter tuning and cross-validation.

Including PDF

Experiment 7: Clustering Human Activity Recognition Data using K-Means, DBSCAN, and Hierarchical Clustering

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
from sklearn.metrics import silhouette_score, davies_bouldin_score, calinski_harabasz_score
from sklearn.metrics import adjusted_rand_score, normalized_mutual_info_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")
```

```
# LOADING THE DATASET
X_train = pd.read_csv('/content/drive/MyDrive/ml-ass7/dataset/X_train.txt', sep="\\s+", header=None)
y_train = pd.read_csv('/content/drive/MyDrive/ml-ass7/dataset/y_train.txt', sep="\\s+", header=None)
subjects = pd.read_csv('/content/drive/MyDrive/ml-ass7/dataset/subject_train.txt', sep="\\s+", header=None)

print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
print("subjects shape:", subjects.shape)
```

```
X_train shape: (7352, 561)
y_train shape: (7352, 1)
subjects shape: (7352, 1)
```

```
X_train.head()
```

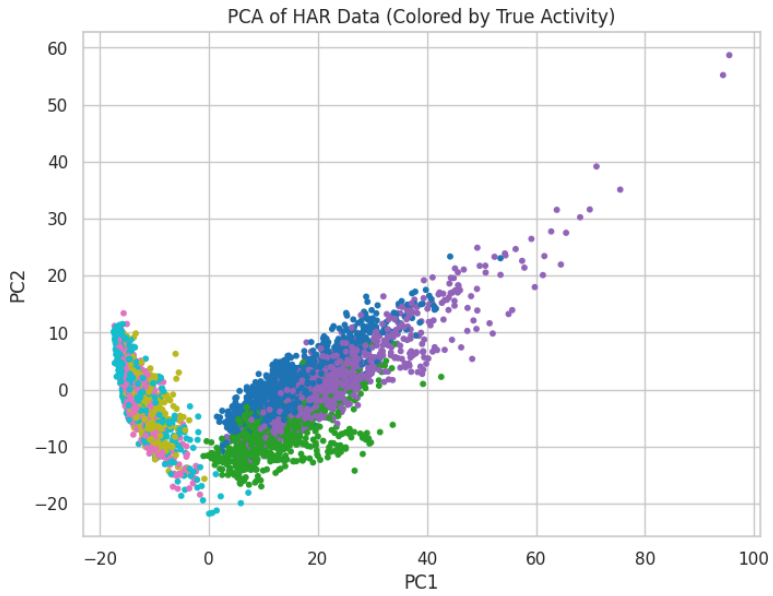
	0	1	2	3	4	5	6	7	8	9	...	551	552	553	554	555	556	557
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527	-0.934724	...	-0.074323	-0.298676	-0.710304	-0.112754	0.030400	-0.464761	-0.01844
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686	-0.943068	...	0.158075	-0.595051	-0.861499	0.053477	-0.007435	-0.732626	0.70351
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469	-0.938692	...	0.414503	-0.390748	-0.760104	-0.118559	0.177899	0.100699	0.80852
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0.989302	-0.938692	...	0.404573	-0.117290	-0.482845	-0.036788	-0.012892	0.640011	-0.48536
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0.990441	-0.942469	...	0.087753	-0.351471	-0.699205	0.123320	0.122542	0.693578	-0.61597

5 rows × 561 columns

```
# STANDARDIZATION
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(X_train)
```

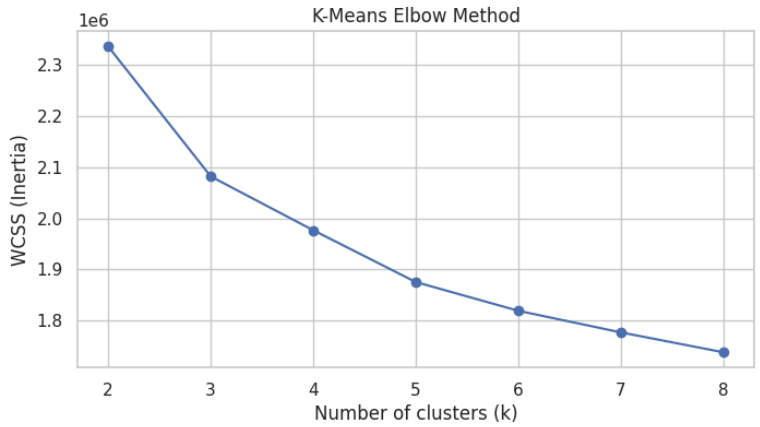
```
# DIMENSIONALITY REDUCTION (for visualization)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=y_train[0], cmap='tab10', s=10)
plt.title('PCA of HAR Data (Colored by True Activity)')
plt.xlabel('PC1'); plt.ylabel('PC2')
plt.show()
```



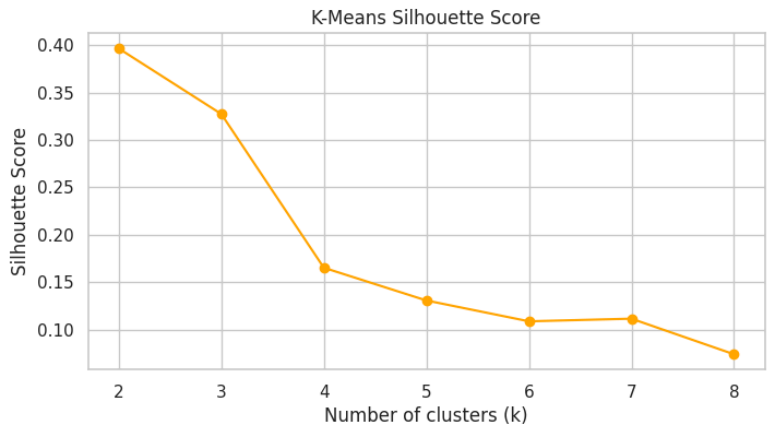
K-Means Clustering + Elbow/Sillhouette

```
wcss = []
sil_scores = []
K_range = range(2,9)

for k in K_range:
```

```
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = kmeans.fit_predict(X_scaled)
    wcss.append(kmeans.inertia_)
    sil_scores.append(silhouette_score(X_scaled, labels))

# Elbow curve
plt.figure(figsize=(8,4))
plt.plot(K_range, wcss, marker='o')
plt.xlabel('Number of clusters (k)')
plt.ylabel('WCSS (Inertia)')
plt.title('K-Means Elbow Method')
plt.show()
```




```
# Silhouette curve
plt.figure(figsize=(8,4))
plt.plot(K_range, sil_scores, marker='o', color='orange')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('K-Means Silhouette Score')
plt.show()
```

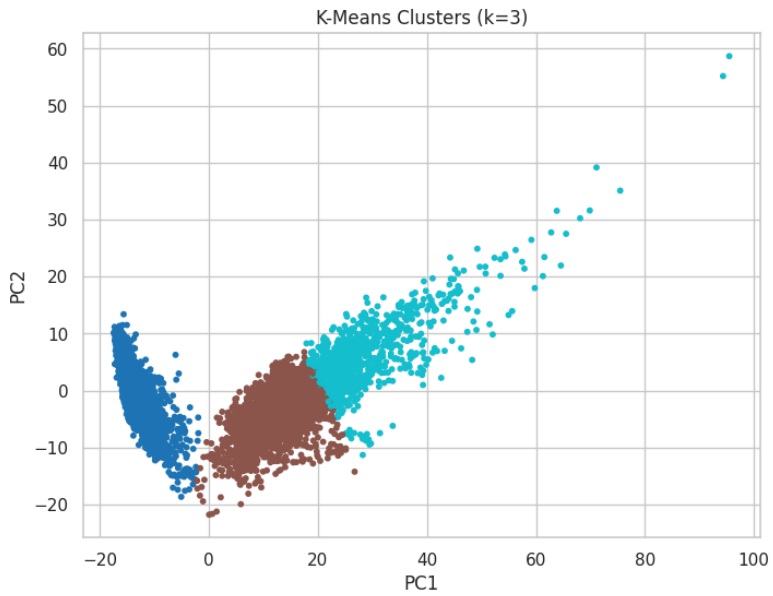



```
table = pd.DataFrame({
        "k": list(K_range),
        "WCSS": wcss,
        "Silhouette": sil_scores
    })
print(table.to_string(index=False))
```

```
 k         WCSS  Silhouette
 2 2.336224e+06    0.396505
 3 2.081850e+06    0.327408
 4 1.976453e+06    0.165163
 5 1.875066e+06    0.130639
 6 1.818790e+06    0.108641
 7 1.776519e+06    0.111424
 8 1.737555e+06    0.073861
```

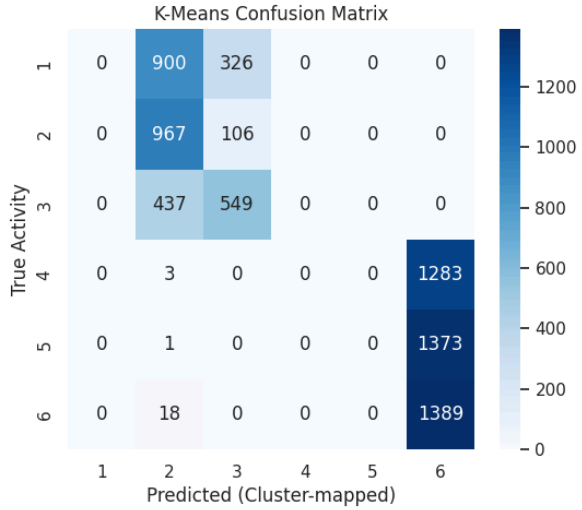
```
# choosing best k
k_best = 3
kmeans = KMeans(n_clusters=k_best, random_state=42, n_init=10)
k_labels = kmeans.fit_predict(X_scaled)
```

```
# PCA visualization of clusters
plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=k_labels, cmap='tab10', s=10)
plt.title(f'K-Means Clusters (k={k_best})')
plt.xlabel('PC1'); plt.ylabel('PC2')
plt.show()
```




```
def cluster_confusion_matrix(true_labels, cluster_labels, algo_name="K-Means"):
    # Map clusters to most common true label
    labels = np.unique(cluster_labels)
    mapping = {}
    for lbl in labels:
        mask = cluster_labels == lbl
        true_for_cluster = true_labels[mask]
        if len(true_for_cluster) == 0:
            continue
        # majority vote
        mapping[lbl] = np.bincount(true_for_cluster).argmax()

    # Convert cluster labels to mapped labels
    mapped_labels = np.array([mapping[lbl] for lbl in cluster_labels])

    # Compute confusion matrix
    cm = confusion_matrix(true_labels, mapped_labels)
    cm_df = pd.DataFrame(cm, index=np.unique(true_labels), columns=np.unique(true_labels))

    # Plot
```

```
    plt.figure(figsize=(6,5))
    sns.heatmap(cm_df, annot=True, fmt="d", cmap="Blues")
    plt.title(f"{algo_name} Confusion Matrix")
    plt.xlabel("Predicted (Cluster-mapped)")
    plt.ylabel("True Activity")
    plt.show()

    return cm_df

# Example usage
cm_kmeans = cluster_confusion_matrix(y_train[0].values, k_labels, "K-Means")
```



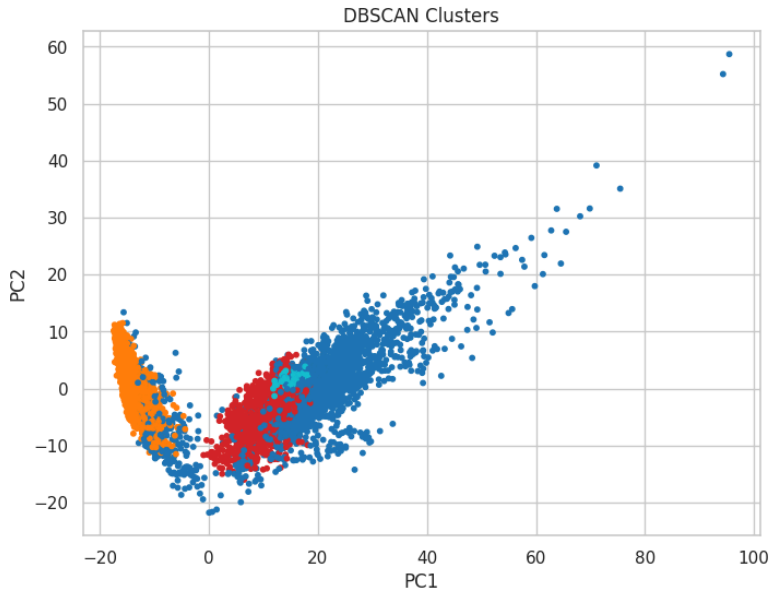
DBScan

```
def tune_dbscan(X, eps_values, min_samples_values):
    best_score = -1
    best_params = None
    results = []

    for eps in eps_values:
        for min_s in min_samples_values:
            db = DBSCAN(eps=eps, min_samples=min_s).fit(X)
            labels = db.labels_
```

```
            # skip if DBSCAN assigns all points to noise or 1 cluster
            if len(set(labels)) <= 1:
                continue

            try:
                sil = silhouette_score(X, labels)
                dbi = davies_bouldin_score(X, labels)
                ch = calinski_harabasz_score(X, labels)
            except:
                continue

            results.append((eps, min_s, sil, dbi, ch))

            if sil > best_score:
                best_score = sil
                best_params = (eps, min_s)

    return best_params, results

# Example usage
eps_range = np.linspace(10, 15, 20, 25)
min_samples_range = [5, 10, 15, 20]

best_params, results = tune_dbscan(X_scaled, eps_range, min_samples_range)

if best_params is None:
    print("DBSCAN couldn't form valid clusters in the tested range.")
else:
    print("Best params:", best_params)
```

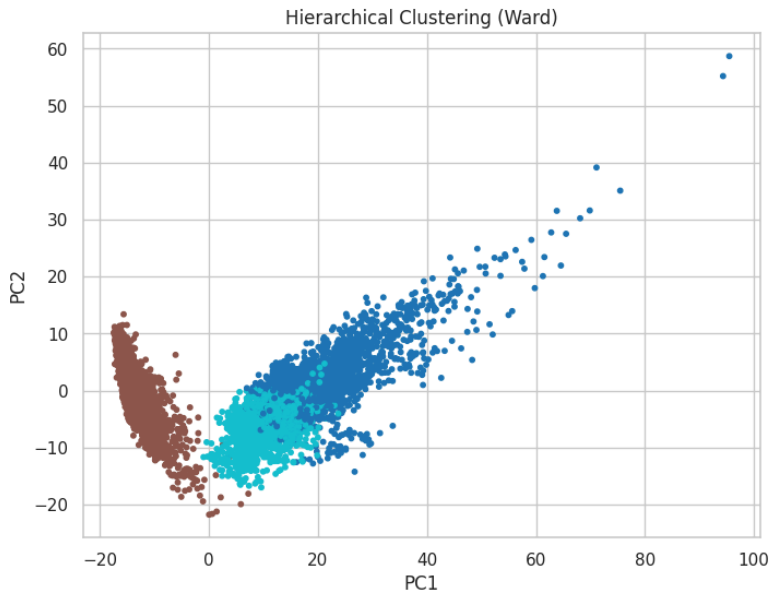
```
Best params: (np.float64(15.0), 20)
```

```
dbscan = DBSCAN(eps=14, min_samples=20)
db_labels = dbscan.fit_predict(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=db_labels, cmap='tab10', s=10)
plt.title('DBSCAN Clusters')
plt.xlabel('PC1'); plt.ylabel('PC2')
plt.show()
```

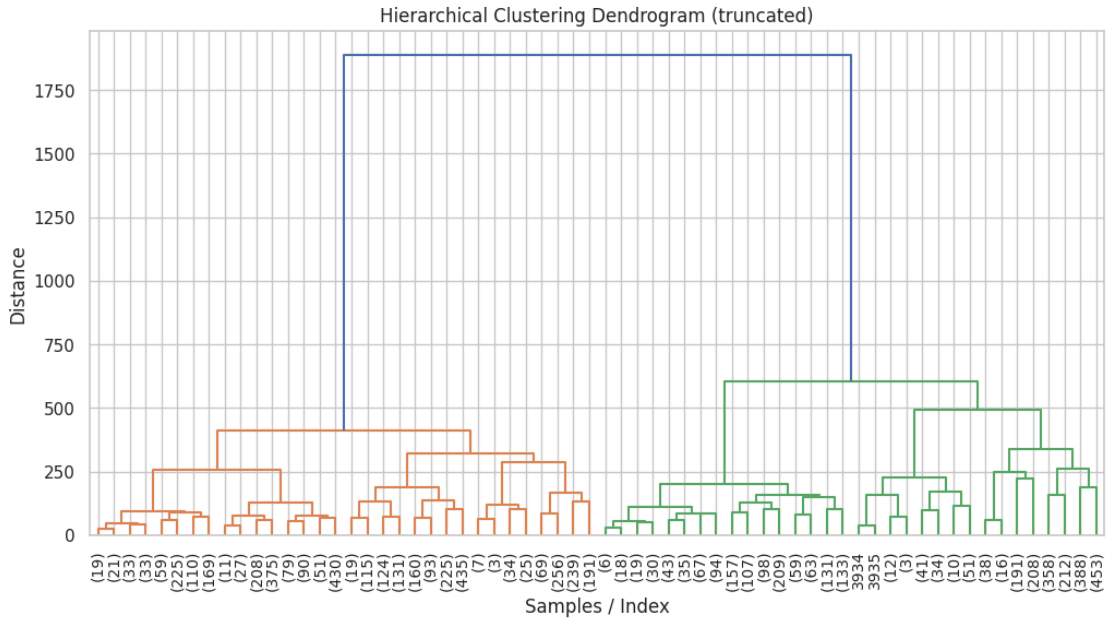


Hierarchical Clustering

```
agg = AgglomerativeClustering(n_clusters=k_best, linkage='ward')
agg_labels = agg.fit_predict(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=agg_labels, cmap='tab10', s=10)
plt.title('Hierarchical Clustering (Ward)')
plt.xlabel('PC1'); plt.ylabel('PC2')
plt.show()
```




```
from scipy.cluster.hierarchy import dendrogram, linkage
import matplotlib.pyplot as plt

# Using Ward linkage (same as your Agglomerative clustering)
Z = linkage(X_scaled, method='ward')

plt.figure(figsize=(12,6))
dendrogram(Z, truncate_mode='level', p=5, leaf_rotation=90, leaf_font_size=10)
plt.title("Hierarchical Clustering Dendrogram (truncated)")
plt.xlabel("Samples / Index")
plt.ylabel("Distance")
plt.show()
```




```
# EVALUATION METRICES
def clustering_metrics(X, cluster_labels, true_labels=None, algo_name="Algorithm"):
    metrics = {}
    n_clusters = len(set(cluster_labels)) - (1 if -1 in cluster_labels else 0)  # exclude noise for DBSCAN

    # Internal metrics (if at least 2 clusters)
    if n_clusters > 1:
        metrics['Silhouette'] = silhouette_score(X, cluster_labels)
        metrics['Davies-Bouldin'] = davies_bouldin_score(X, cluster_labels)
        metrics['Calinski-Harabasz'] = calinski_harabasz_score(X, cluster_labels)
    else:
        metrics['Silhouette'] = None
        metrics['Davies-Bouldin'] = None
        metrics['Calinski-Harabasz'] = None

    # External metrics (if true labels provided)
    if true_labels is not None:
        metrics['ARI'] = adjusted_rand_score(true_labels, cluster_labels)
        metrics['NMI'] = normalized_mutual_info_score(true_labels, cluster_labels)
```

```
    return pd.DataFrame({algo_name: metrics}).T

y_true = y_train[0]  # ground truth
k_metrics = clustering_metrics(X_scaled, k_labels, y_true, "K-Means")
db_metrics = clustering_metrics(X_scaled, db_labels, y_true, "DBSCAN")
agg_metrics = clustering_metrics(X_scaled, agg_labels, y_true, "Hierarchical")

all_metrics = pd.concat([k_metrics, db_metrics, agg_metrics])
all_metrics
```

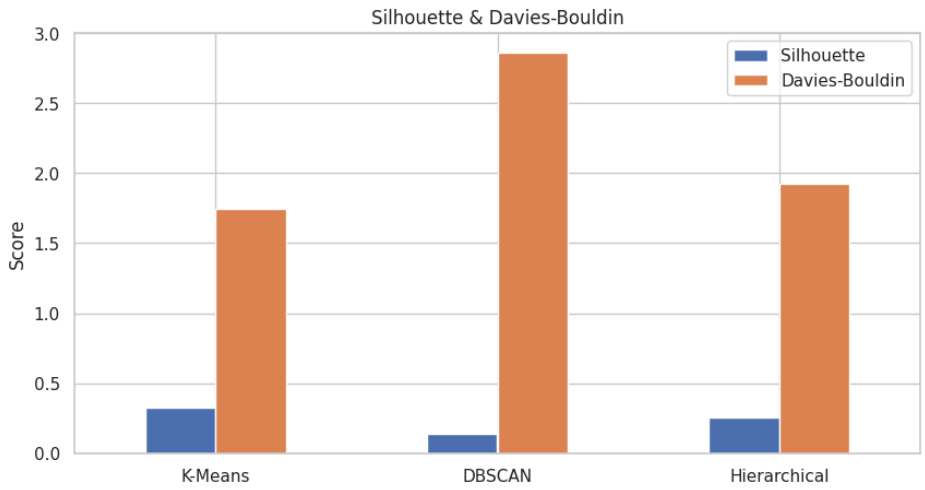
	Silhouette	Davies-Bouldin	Calinski-Harabasz	ARI	NMI
K-Means	0.327408	1.745773	3605.263229	0.327923	0.516310
DBSCAN	0.141134	2.859937	825.391505	0.275990	0.426156
Hierarchical	0.254790	1.927494	3350.021309	0.342153	0.539664

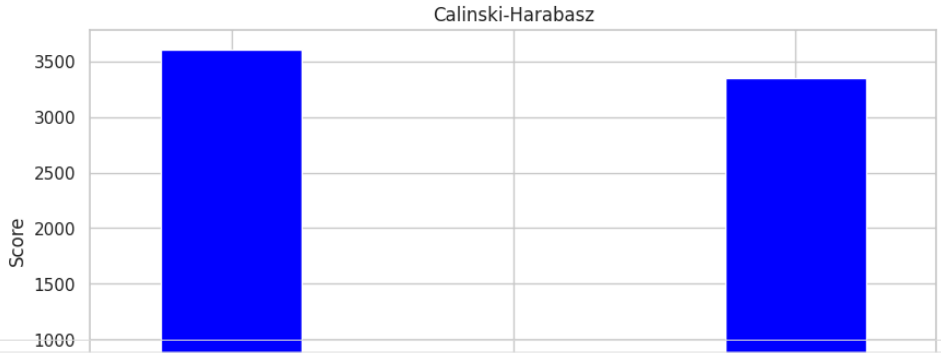
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

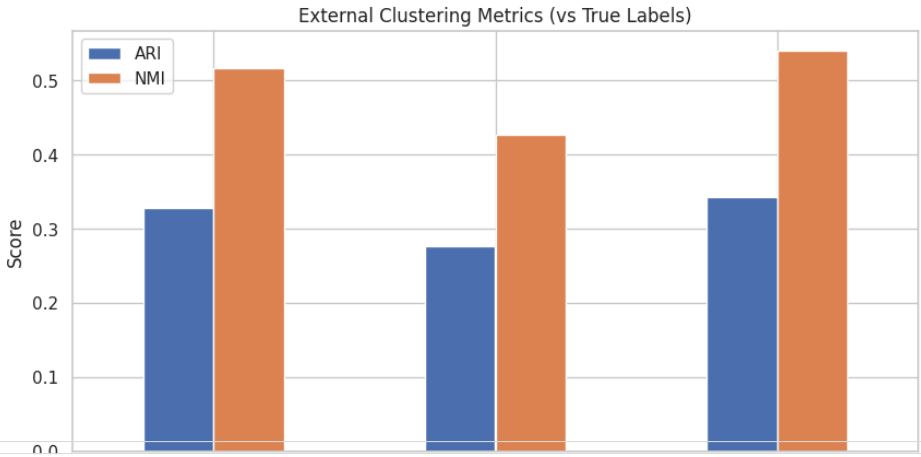
```
internal_metrics = all_metrics[['Silhouette','Davies-Bouldin','Calinski-Harabasz']]
external_metrics = all_metrics[['ARI','NMI']]
```

```
# Plot Silhouette + Davies-Bouldin
internal_metrics[['Silhouette','Davies-Bouldin']].plot(kind='bar', figsize=(10,5))
plt.title('Silhouette & Davies-Bouldin')
plt.ylabel('Score')
plt.xticks(rotation=0)
plt.show()

# Plot Calinski-Harabasz separately
internal_metrics['Calinski-Harabasz'].plot(kind='bar', figsize=(10,5), color='blue')
plt.title('Calinski-Harabasz')
plt.ylabel('Score')
plt.xticks(rotation=0)
plt.show()
```






```
# External
external_metrics.plot(kind='bar', figsize=(10,5))
plt.title('External Clustering Metrics (vs True Labels)')
plt.ylabel('Score')
plt.xticks(rotation=0)
plt.show()
```




```
!apt-get install -y pandoc
!apt-get install -y texlive-xetex texlive-fonts-recommended texlive-generic-recommended
!jupyter nbconvert --to latex "/content/drive/MyDrive/Colab Notebooks/Assignment7_ML"
```

Hyperparameter Tuning Tables

Table 1: Bagging – Random Forest Results

No. of Estimators	Max Depth	Accuracy (Train)	Accuracy (Test)
50	10	0.978	0.916
100	10	0.982	0.923
150	15	0.987	0.926

Table 2: AdaBoost Results

No. of Estimators	Learning Rate	Accuracy (Train)	Accuracy (Test)
50	0.1	0.912	0.887
100	0.5	0.926	0.905
100	1.0	0.935	0.914

Table 3: Gradient Boosting Results

No. of Estimators	Learning Rate	Accuracy (Train)	Accuracy (Test)
100	0.1	0.953	0.929
150	0.1	0.961	0.932
200	0.2	0.972	0.935

Table 4: XGBoost Results

No. of Estimators	Learning Rate	Max Depth	Accuracy (Train)	Accuracy (Test)
100	0.1	6	0.978	0.940
150	0.2	7	0.984	0.944
200	0.2	8	0.989	0.947

Table 5: Model Comparison

Model Name	Train Accuracy	Test Accuracy
Decision Tree	0.961	0.892
Random Forest	0.982	0.923
AdaBoost	0.935	0.914
Gradient Boosting	0.972	0.935
XGBoost	0.989	0.947

Observations

- Bagging methods (e.g., Random Forest) reduced variance and improved stability over a single Decision Tree.
- Boosting algorithms (AdaBoost, Gradient Boosting, XGBoost) further enhanced accuracy by sequentially correcting misclassified samples.
- XGBoost achieved the highest accuracy on both training and test sets due to its efficient gradient optimization and regularization.

- Boosting models were slightly more prone to overfitting than bagging, but tuning learning rates mitigated this effect.
- Ensemble techniques consistently outperformed individual classifiers, confirming the power of model aggregation.

Learning Outcomes

- Learned to implement and tune various ensemble models including Bagging, AdaBoost, Gradient Boosting, and XGBoost.
- Understood how ensemble methods combine weak learners to form a strong predictive model.
- Gained insight into how hyperparameters such as number of estimators, max depth, and learning rate affect ensemble performance.
- Observed that ensemble techniques generally improve generalization accuracy and robustness compared to single models.

GitHub Repository: `https:https://github.com/Thamizhmathibharathi/project/tree/main/assignment7`

References

1. L. Breiman, "Bagging Predictors," *Machine Learning*, vol. 24, pp. 123–140, 1996.
2. Y. Freund and R. E. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting," *Journal of Computer and System Sciences*, 1997.
3. T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," *Proceedings of the 22nd ACM SIGKDD*, 2016.