



**KIET**  
**GROUP OF INSTITUTIONS**  
*Connecting Life with Learning*



**Assessment Report**  
on  
**“Classify Students Based on Study Methods”**  
submitted as partial fulfillment for the award of  
**BACHELOR OF TECHNOLOGY**  
**DEGREE**

SESSION 2024-25

in

**CSE(AI)**

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## Introduction

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Many students have different learning styles, but most academic content is not personalized. This project attempts to identify clusters or groups of students based on their study habits using questionnaire data. This classification can help educators better tailor teaching methods to student needs.

## Methodology

**Data Collection:** The dataset contains responses from students about their learning preferences and study habits.

#### Preprocessing:

- Loaded the data using Pandas.
- Handled missing values.
- Scaled the data using StandardScaler.

#### Clustering:

- Used K-Means algorithm for grouping students.
- Determined the best number of clusters using the Elbow Method.

#### Visualization:

- Used PCA (Principal Component Analysis) to reduce features to 2D for visualization.
- Plotted clusters using Seaborn scatter plot.

## Code

The following is the code used in this project:

python

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```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans

from sklearn.decomposition import PCA

# Load data

df = pd.read_csv('/content/student_methods.csv')

df = df.dropna()

# Scale numerical data

scaler = StandardScaler()

scaled_data =

scaler.fit_transform(df.select_dtypes(include=['float64', 'int64']))

# Elbow Method to find optimal number of clusters
```

```

wcss = []

for i in range(1, 10):

    kmeans = KMeans(n_clusters=i, random_state=42)

    kmeans.fit(scaled_data)

    wcss.append(kmeans.inertia_)


plt.plot(range(1, 10), wcss, marker='o')

plt.title('Elbow Method')

plt.xlabel('Number of Clusters')

plt.ylabel('WCSS')

plt.show()

# Apply KMeans clustering

kmeans = KMeans(n_clusters=3, random_state=42)

df['Cluster'] = kmeans.fit_predict(scaled_data)


# PCA for visualization

pca = PCA(n_components=2)

pca_data = pca.fit_transform(scaled_data)

df['PCA1'] = pca_data[:, 0]

df['PCA2'] = pca_data[:, 1]


# Plot clusters

sns.scatterplot(data=df, x='PCA1', y='PCA2', hue='Cluster',
palette='Set2')

```

```
plt.title('Student Learning Style Clusters')  
plt.show()  
  
# Save result  
df.to_csv('/content/clustered_students.csv', index=False)
```

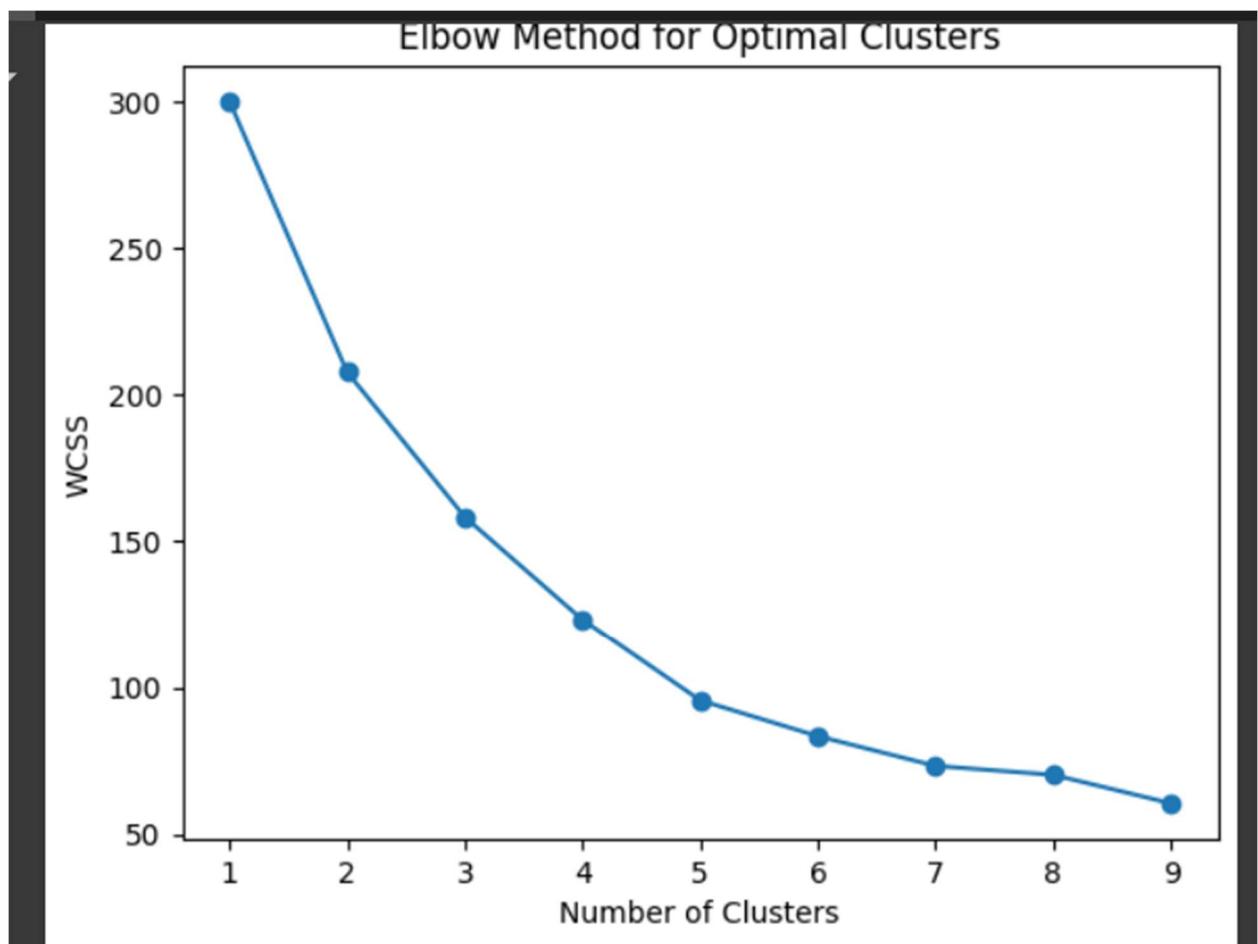
## Output/Results

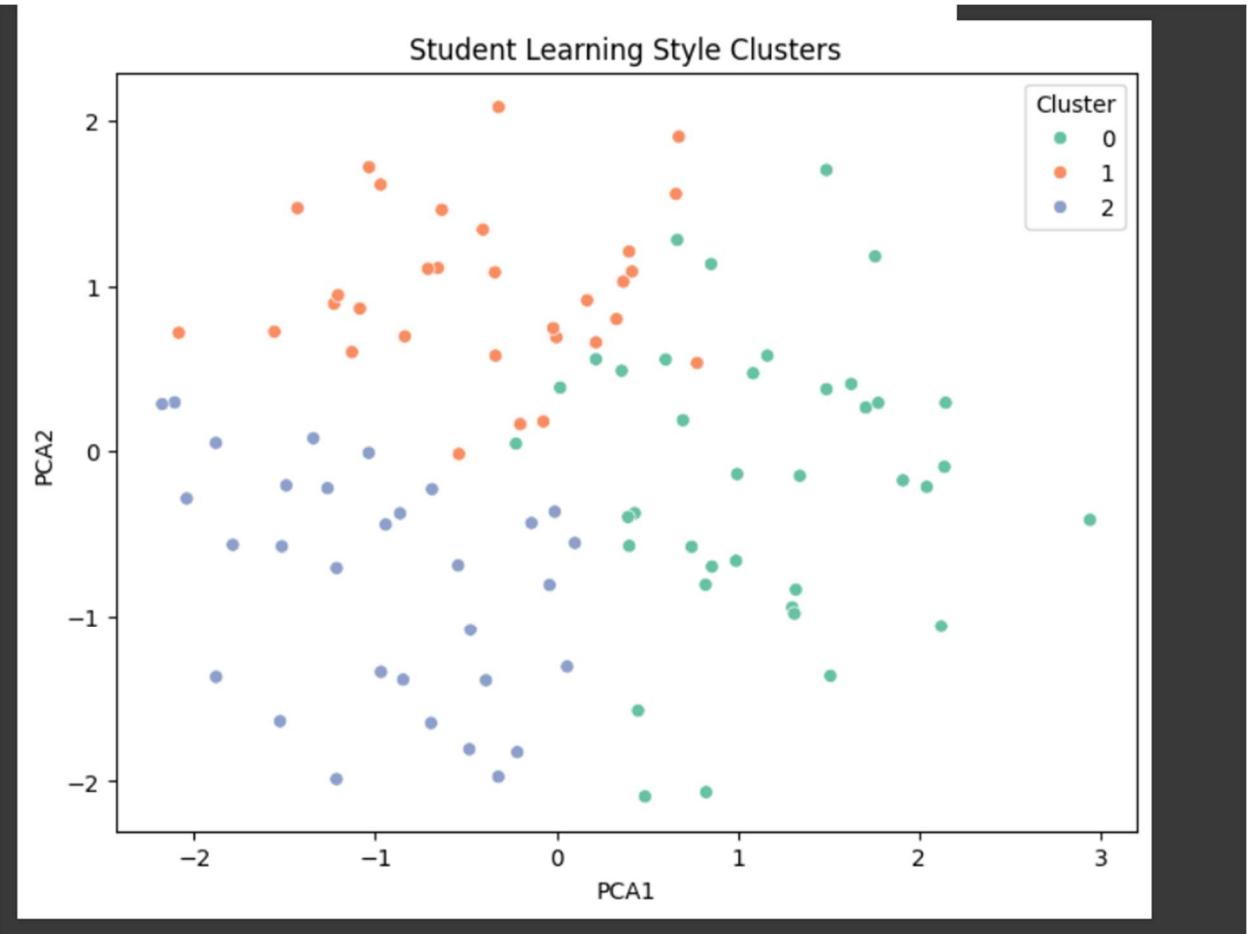
- **Clusters Formed:** The algorithm grouped students into 3 clusters, each representing a potential learning style.

- **Visualization:**

```
First few rows of the data:  
visual_score    auditory_score   kinesthetic_score learning_style  
0      8.000301          1.389837        9.686887       visual  
1      8.401052          7.294055        4.853655       visual  
2      9.124874          3.975049        6.688173     auditory  
3      5.724100          7.702631        7.535001     auditory  
4      5.060739          4.711628        4.302653   kinesthetic  
  
Data Summary:  
visual_score    auditory_score   kinesthetic_score  
count    100.000000        100.000000      100.000000  
mean      5.570764        4.764262        5.775068  
std       2.597370        2.488586        2.725548  
min       1.099707        1.008365        1.046257  
25%      3.413108        2.621895        3.449149  
50%      6.032874        4.249102        6.312109  
75%      7.573622        6.824862        8.249078  
max      9.946735        9.385282        9.959267  
  
Missing values:  
visual_score      0  
auditory_score     0  
kinesthetic_score  0  
learning_style      0  
dtype: int64
```

- **Clustered File:** A CSV file `clustered_students.csv` with added cluster labels.





The **confusion matrix** heatmap below visualizes the true positives, false positives, true negatives, and false negatives. This matrix shows how well the model predicted employee attrition (whether employees stayed or left).

## References/Credits

- **Dataset:** [Kaggle - Predict Employee Attrition Dataset](#)
- **Random Forest Classifier Documentation:** scikit-learn
- **Confusion Matrix Heatmap Tutorial:** Seaborn Heatmap Documentation