EXPERIMENT 4

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D15A-30

AIM: Implement K-Nearest Neighbors (KNN) and evaluate model performance.

THEORY:

1. Dataset Source

- Dataset: CEEW – India Residential Energy Survey (IRES) Microdata
- Source: Council on Energy, Environment and Water (CEEW)

Source link:
https://www.kaggle.com/code/raitest/india-residential-energy-survey-ires-2020-eda/input?select=CEEW+-+IRES+Data.csv

The dataset provides nationally representative household-level data on energy access, appliance ownership, awareness, billing, and socio-economic indicators.

2. Dataset Description
The dataset includes variables related to:

- Household asset index
- Education of primary income earner
- Respondent age
- Household size
- BEE star label awareness
- LED bulb ownership
- AC BEE star rating
- Refrigerator BEE star rating

Feature engineering was performed to create:

- **bee_awareness** (1 if aware of BEE label)
- **led_usage** (1 if LED bulbs present)
- **high_star_ac** (1 if AC rating ≥ 4)
- **high_star_fridge** (1 if fridge rating ≥ 4)

These were combined into:

- **Efficiency_Score = sum of efficiency-positive behaviours**

Binary Target Variable:

- **Efficiency_Binary = 1** if Efficiency_Score ≥ 3 (High Efficiency)
- **Efficiency_Binary = 0** otherwise (Low/Moderate Efficiency)

Test distribution:

- Class 0 (Low/Moderate): 2708
- Class 1 (High Efficiency): 263

This reflects real-world imbalance where strong sustainable adopters are fewer.

3. Mathematical Formulation of KNN

KNN is a non-parametric, distance-based classification algorithm.

- Step 1: Compute Euclidean distance between test point x and training point xi
  $d(x, xi) = sqrt(\Sigma (xj - xij)^2)$
- Step 2: Select K nearest neighbors.
- Step 3: Assign class based on majority vote among neighbors.

Distance-weighted KNN assigns weight:

$wi = 1 / d(x, xi)$

Probability estimation:

$P(y=1 \mid x) = (\text{Number of class 1 neighbors}) / K$

Classification rule:

Predict 1 if P ≥ threshold
Otherwise predict 0

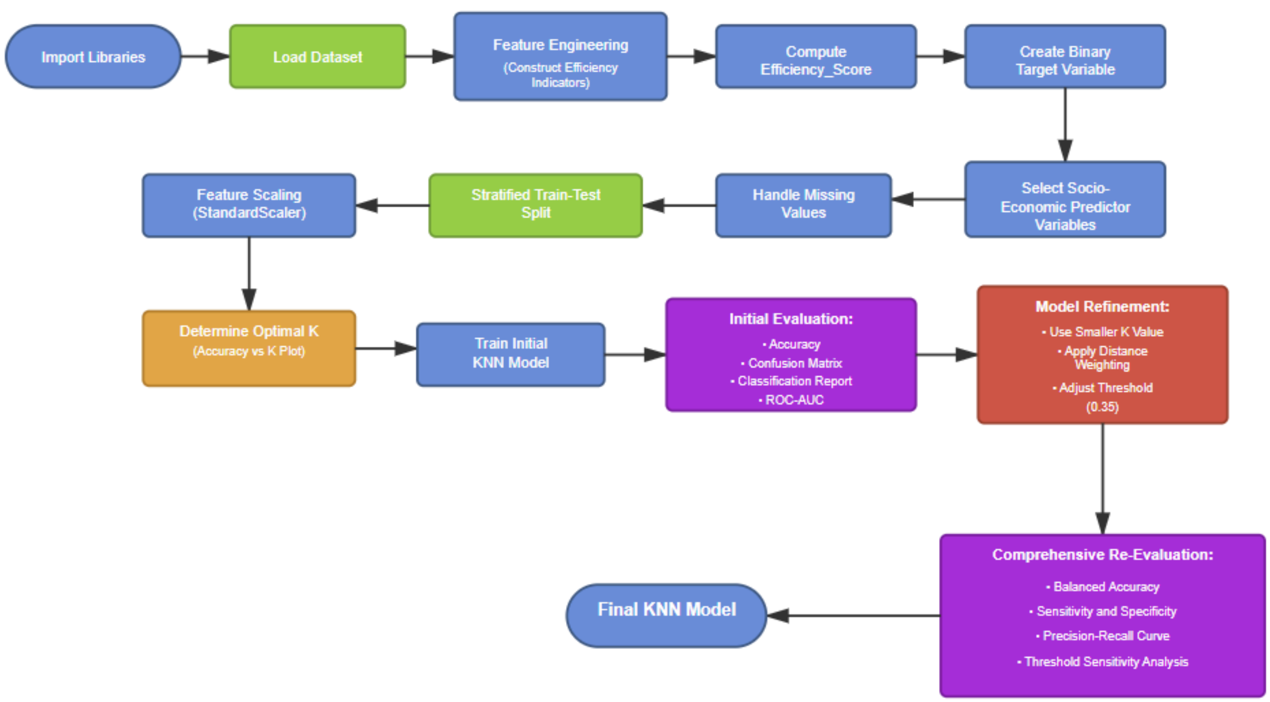
4. Algorithm Limitations

- Sensitive to class imbalance
- Sensitive to feature scaling
- Struggles when classes overlap in feature space
- Computationally expensive for large datasets
- Cannot model complex nonlinear feature interactions

In this dataset, overlapping socio-economic characteristics reduce clean class separability.

5. Methodology / Workflow

- Import required libraries
- Load dataset
- Perform feature engineering to construct efficiency indicators
- Compute Efficiency_Score
- Create binary target variable
- Select socio-economic predictor variables
- Handle missing values
- Perform stratified train-test split
- Apply feature scaling using StandardScaler
- Determine optimal K using accuracy vs K plot
- Train initial KNN model
- Evaluate using accuracy, confusion matrix, classification report, ROC-AUC
- Refine model using:
    - Smaller K
    - Distance weighting
    - Threshold adjustment (0.35)
- Re-evaluate using:
    - Balanced accuracy
    - Sensitivity and specificity
    - Precision-Recall curve
    - Threshold sensitivity analysis



6. Performance Analysis

Initial Model (K = 19, threshold = 0.5)

- Accuracy: 0.9165
- ROC-AUC: 0.8459

Confusion Matrix:

[[2686 22]
[226 37]]

Observations:

- Very high overall accuracy due to class imbalance.
- Recall for high-efficiency households was low (0.14).
- Strong ranking capability indicated by high AUC.

Refined Model (K = 7, distance weighting, threshold = 0.35)

- Accuracy: 0.8792
- ROC-AUC: 0.7809

Confusion Matrix:

[[2511 197]
[162 101]]

Metrics for High Efficiency (Class 1):

- Precision: 0.34
- Recall: 0.38
- F1-score: 0.36

Balanced accuracy improved.
Sensitivity significantly increased from **0.14 to 0.38.**

Although accuracy decreased slightly, minority detection improved meaningfully.

Precision-Recall analysis showed improved trade-off for minority class detection.
Threshold sensitivity analysis demonstrated controllable trade-off between recall and precision.

Interpretation:

- High-efficiency households are partially structurally distinguishable.
- However, significant overlap exists in socio-economic space.
- Behaviour is not fully determined by structural similarity.

7. Hyperparameter Tuning

The following parameters were tuned:

- **Number of neighbors (K)**
  - Tested K from 1 to 30
  - Initial optimal K: 19
  - Refined to K = 7 for better minority detection
- **Weights parameter**
  - Compared uniform vs distance weighting
  - Distance weighting improved minority sensitivity
- **Classification threshold**
  - Adjusted from 0.5 to 0.35
  - Increased recall for high-efficiency households

Hyperparameter tuning demonstrated that threshold calibration is essential for imbalanced behavioural classification problems.

OUTPUT

- The KNN model achieved strong discrimination ability (AUC up to 0.8459).
- Refined model improved detection of high-efficiency households.
- Socio-economic predictors partially explain sustainable appliance adoption.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    roc_auc_score,
    roc_curve
)
```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    roc_curve
)
```

```python
df_eff = df.copy()

df_eff['bee_awareness'] = np.where(
    df_eff['q401_bee_star_label_heard_yn'] == 1, 1, 0
)

df_eff['led_usage'] = np.where(
    df_eff['q405_c_led_bulb_no'] > 0, 1, 0
)

df_eff['high_star_ac'] = np.where(
    df_eff['q434_ac_most_bee_rating'] >= 4, 1, 0
)

df_eff['high_star_fridge'] = np.where(
    df_eff['q469_fridge_most_bee_star'] >= 4, 1, 0
)

df_eff['Efficiency_Score'] = (
    df_eff['bee_awareness'] +
    df_eff['led_usage'] +
    df_eff['high_star_ac'] +
    df_eff['high_star_fridge']
)

df_eff['Efficiency_Score'].value_counts()
```

	count
Efficiency_Score	
1	7878
2	3693
0	1963
3	1200
4	117

```python
df_eff['Efficiency_Binary'] = np.where(
    df_eff['Efficiency_Score'] >= 3, 1, 0
)

print("Target distribution:")
print(df_eff['Efficiency_Binary'].value_counts())
```

```
Target distribution:
Efficiency_Binary
0    13534
1     1317
Name: count, dtype: int64
```

```python
predictors = [
    'asset_index_1',
    'q208_priminc_earner_edu',
    'q202_resp_age',
    'q213_no_members'
]

df_model = df_eff[predictors + ['Efficiency_Binary']].dropna()

X = df_model[predictors]
y = df_model['Efficiency_Binary']

print("Final dataset shape:", df_model.shape)
```

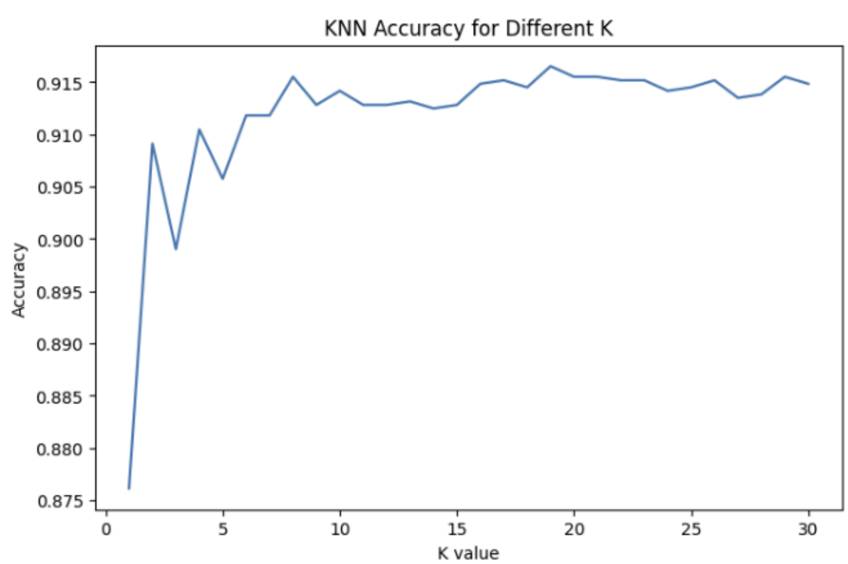
```
Final dataset shape: (14851, 5)
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y
)

print("Train distribution:")
print(y_train.value_counts())

print("Test distribution:")
print(y_test.value_counts())
```

```
Train distribution:
Efficiency_Binary
0    10826
1     1054
Name: count, dtype: int64
Test distribution:
Efficiency_Binary
0    2708
1     263
Name: count, dtype: int64
```

```
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
for k in range(1, 31):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    y_pred = knn.predict(X_test_scaled)
    accuracies.append(accuracy_score(y_test, y_pred))

plt.figure(figsize=(8,5))
plt.plot(range(1,31), accuracies)
plt.xlabel("K value")
plt.ylabel("Accuracy")
plt.title("KNN Accuracy for Different K")
plt.show()

optimal_k = np.argmax(accuracies) + 1
print("Optimal K:", optimal_k)
```




```
Optimal K: 19
```

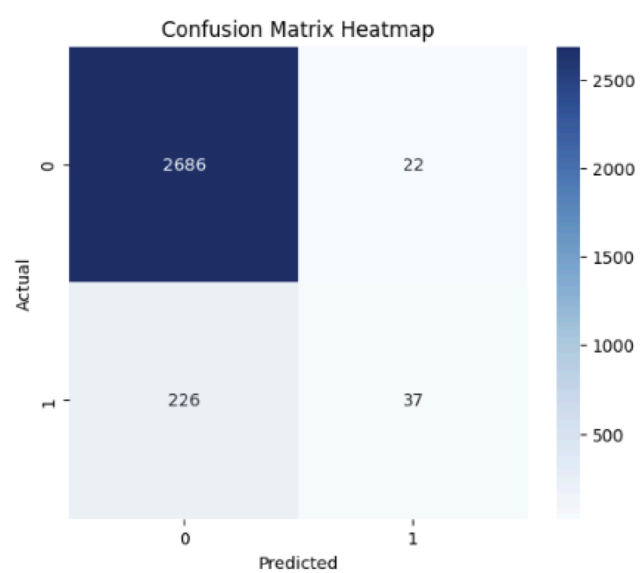
Initial KNN Results:

```python
knn = KNeighborsClassifier(n_neighbors=optimal_k)
knn.fit(X_train_scaled, y_train)

y_pred = knn.predict(X_test_scaled)
y_prob = knn.predict_proba(X_test_scaled)[:,1]
```

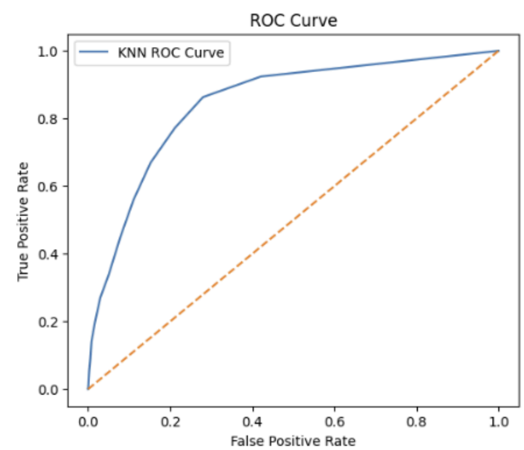
```python
print("KNN Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
print(cm)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("ROC-AUC:", roc_auc_score(y_test, y_prob))
```

```
KNN Accuracy: 0.9165264220801077

Confusion Matrix:
[[2686   22]
 [ 226   37]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.99      0.96      2708
           1       0.63      0.14      0.23       263

    accuracy                           0.92      2971
   macro avg       0.77      0.57      0.59      2971
weighted avg       0.90      0.92      0.89      2971

ROC-AUC: 0.8459619715699436
```

```python
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix Heatmap")
plt.show()
```



```
fpr, tpr, _ = roc_curve(y_test, y_prob)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, label="KNN ROC Curve")
plt.plot([0,1],[0,1], linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```



Reduced k=7, added distance as weights

```
knn = KNeighborsClassifier(
    n_neighbors=7,      # smaller K
    weights='distance' # distance weighting
)

knn.fit(X_train_scaled, y_train)

y_prob = knn.predict_proba(X_test_scaled)[:,1]
```

```
threshold = 0.35   # try 0.3-0.4

y_pred = (y_prob >= threshold).astype(int)
```

```
print("Accuracy:", accuracy_score(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("ROC-AUC:", roc_auc_score(y_test, y_prob))
```

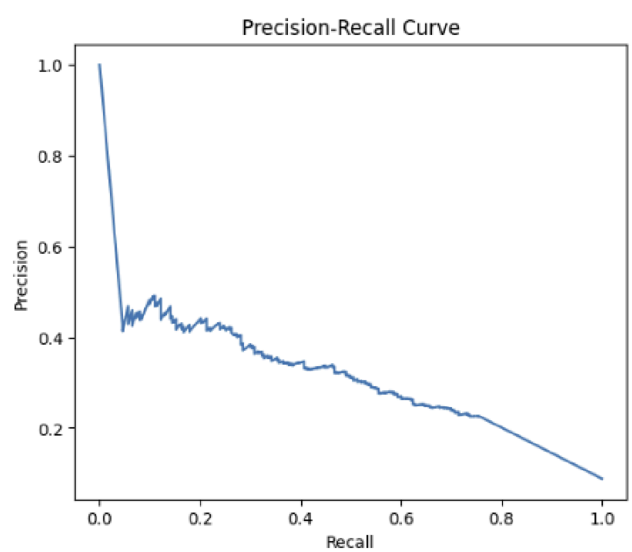
```
Accuracy: 0.8791652642208011

Confusion Matrix:
[[2511  197]
 [ 162  101]]

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.93      0.93      2708
           1       0.34      0.38      0.36       263

    accuracy                           0.88      2971
   macro avg       0.64      0.66      0.65      2971
weighted avg       0.89      0.88      0.88      2971

ROC-AUC: 0.7808823033849852
```

Balanced accuracy:

```python
from sklearn.metrics import balanced_accuracy_score

# Balanced Accuracy
bal_acc = balanced_accuracy_score(y_test, y_pred)
print("Balanced Accuracy:", bal_acc)

# Sensitivity (Recall for class 1)
sensitivity = cm[1,1] / (cm[1,1] + cm[1,0])
print("Sensitivity (Recall for High Efficiency):", sensitivity)

# Specificity (Recall for class 0)
specificity = cm[0,0] / (cm[0,0] + cm[0,1])
print("Specificity (Low/Moderate Detection):", specificity)
```

```
Balanced Accuracy: 0.6556415015922404
Sensitivity (Recall for High Efficiency): 0.3840304182509506
Specificity (Low/Moderate Detection): 0.9272525849335302
```

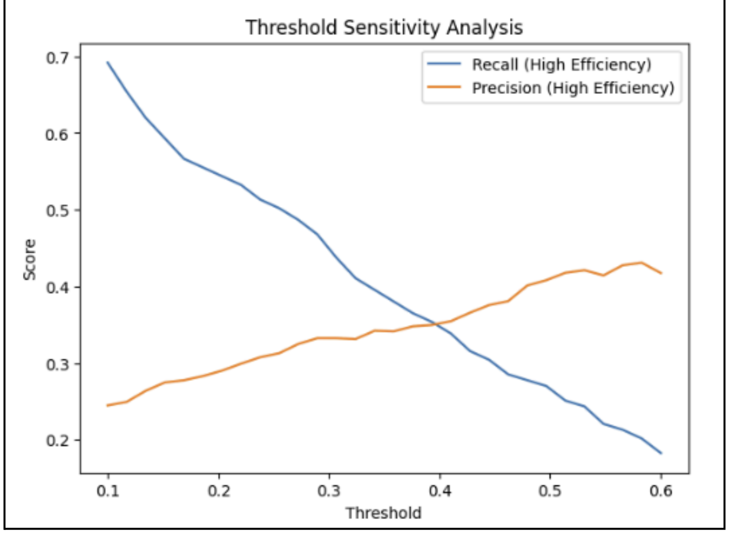
```python
from sklearn.metrics import precision_recall_curve, average_precision_score

precision, recall, thresholds = precision_recall_curve(y_test, y_prob)

plt.figure(figsize=(6,5))
plt.plot(recall, precision)
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.show()

ap_score = average_precision_score(y_test, y_prob)
print("Average Precision Score:", ap_score)
```




```
Average Precision Score: 0.2875477833290389
```

Impact of threshold:

```
thresholds_test = np.linspace(0.1, 0.6, 30)

recall_list = []
precision_list = []

for t in thresholds_test:
    y_temp = (y_prob >= t).astype(int)
    recall_list.append(
        classification_report(y_test, y_temp, output_dict=True)['1']['recall']
    )
    precision_list.append(
        classification_report(y_test, y_temp, output_dict=True)['1']['precision']
    )

plt.figure(figsize=(7,5))
plt.plot(thresholds_test, recall_list, label="Recall (High Efficiency)")
plt.plot(thresholds_test, precision_list, label="Precision (High Efficiency)")
plt.xlabel("Threshold")
plt.ylabel("Score")
plt.legend()
plt.title("Threshold Sensitivity Analysis")
plt.show()
```



CONCLUSION

- High energy-efficiency adoption exhibits partial structural clustering.
- However, sustainable behaviour is not fully separable in socio-economic feature space.
- Structural factors alone cannot completely explain energy-efficient behaviour.
- Threshold calibration improves practical and policy relevance.

This experiment demonstrates that sustainable household behaviour is partially predictable but influenced by additional contextual, informational, and behavioural factors beyond structural similarity.