

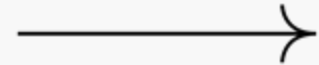
2023-2024

# Investigate and Implement KNN Classifier

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**Group Member:** Muhammad Haris (1440274)

Zaka Ahmad (1436851)



# Project Goal

1. KNN Experiment and Unit Test demonstrating how KNN works.
2. KNN Implementation with SP generated SDR's.
3. KNN Implementation with TM generated SDR's and Unit Test of the experiment.
4. Replace the HTMClassifier with your KNN Classifier

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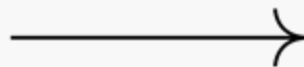
# KNN Classifier Introduction

The K-Nearest Neighbors (KNN) algorithm is a simple yet effective method for classification tasks in machine learning. It is a non-parametric, instance-based learning algorithm, which means it doesn't make strong assumptions about the underlying data distribution and instead relies on the data itself during the prediction phase.

At its core, KNN makes predictions based on the majority class of the K nearest neighbors to a given data point. In other words, it classifies a new instance by finding the K most similar instances in the training data and assigning the most common class label among them to the new instance. However, it's important to note that KNN's performance can be sensitive to the choice of the number of neighbors (K) and the distance metric used to measure similarity between data points.

01

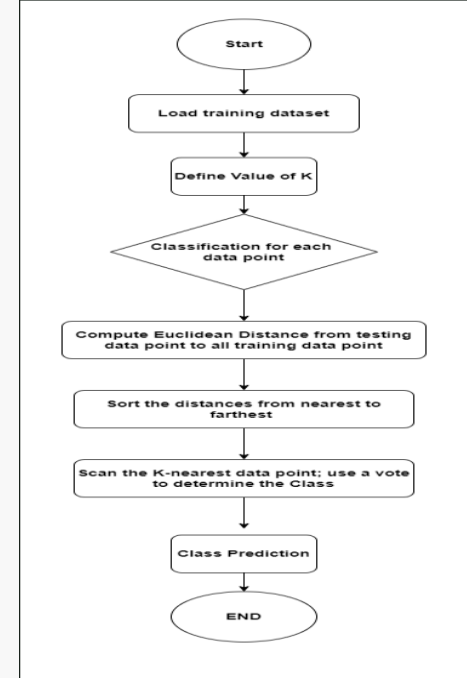
# KNN Classifier Working Principle



Navigating the principles that form the Classifier of in-depth KNN studies

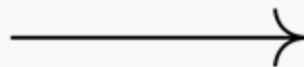
# KNN Classifier Working Principle

1. Loading Dataset
2. Defining the Value of K
3. Calculate the distance between the testing data point and all the training data point.
4. Sort the distances and select the K nearest neighbors.
5. Assign the class label of test data by majority vote.
6. Predicting the Class



02

# KNN Parameters and Matrix

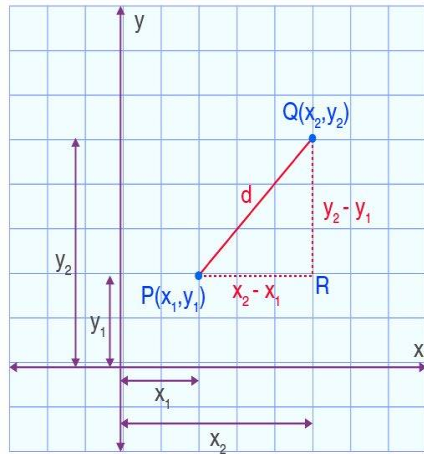


Distance matrix, K-Value selection, and Voting



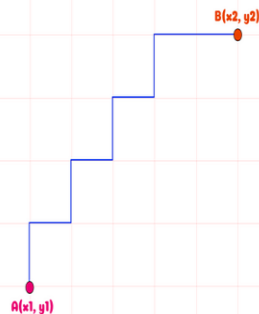
# Distance Metrix

Euclidean Distance

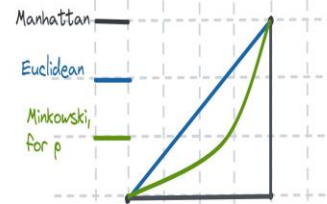


Manhattan Distance

$$\text{Manhattan}(A, B) = |x_1 - x_2| + |y_1 - y_2|$$

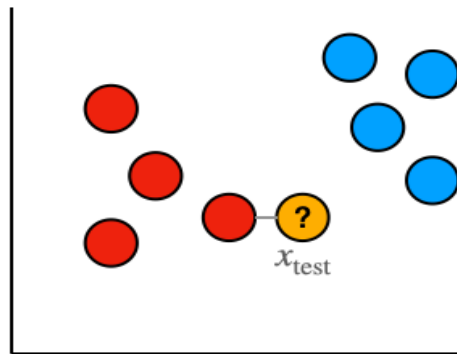


Minkowski distance



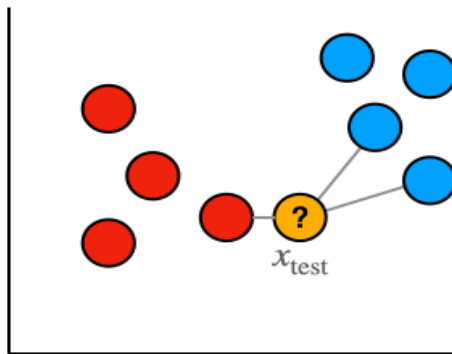
Minkowski when  $p = 1 \rightarrow$  Manhattan  
Minkowski when  $p = 2 \rightarrow$  Euclidean

# Define the Value of K



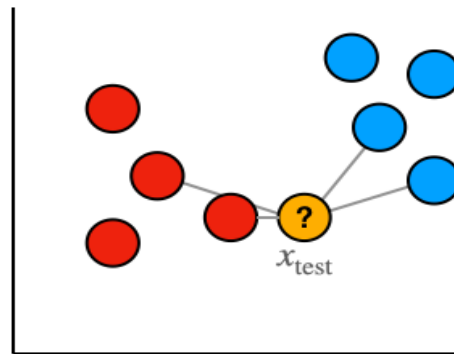
$k = 1$

Nearest point is **red**, so  $x_{\text{test}}$  classified as **red**



$k = 3$

Nearest points are {**red**, **blue**, **blue**} so  $x_{\text{test}}$  classified as **blue**



$k = 4$

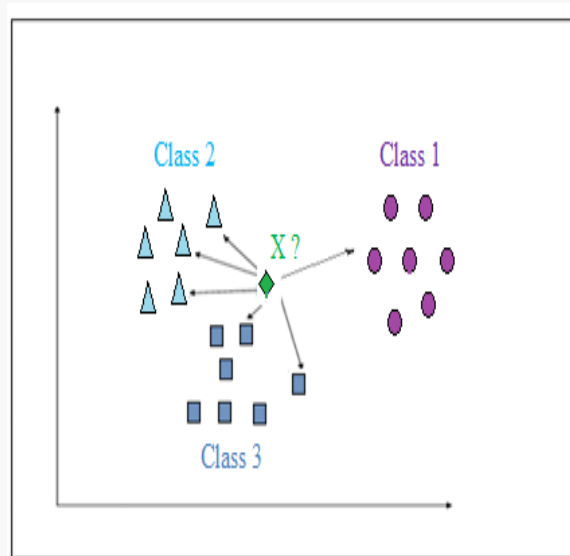
Nearest points are {**red**, **red**, **blue**, **blue**} so classification of  $x_{\text{test}}$  is not properly defined

# Voting Method

- Prediction in KNN is based on K nearest neighbors.
- The predicted or Winning class determined by majority voting principle.
- Class with highest number of votes assigned to the element.

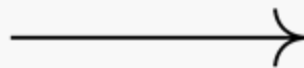
## Important Thing to Consider

- Choice of K impacts voting outcome.
- Higher K values may lead to less confident predictions.
- Imbalanced data scenarios can bias majority voting.
- One class outweighing the other can skew predictions.
- Techniques to resolve bias in majority voting are Distance-weighted voting and Weighted voting.



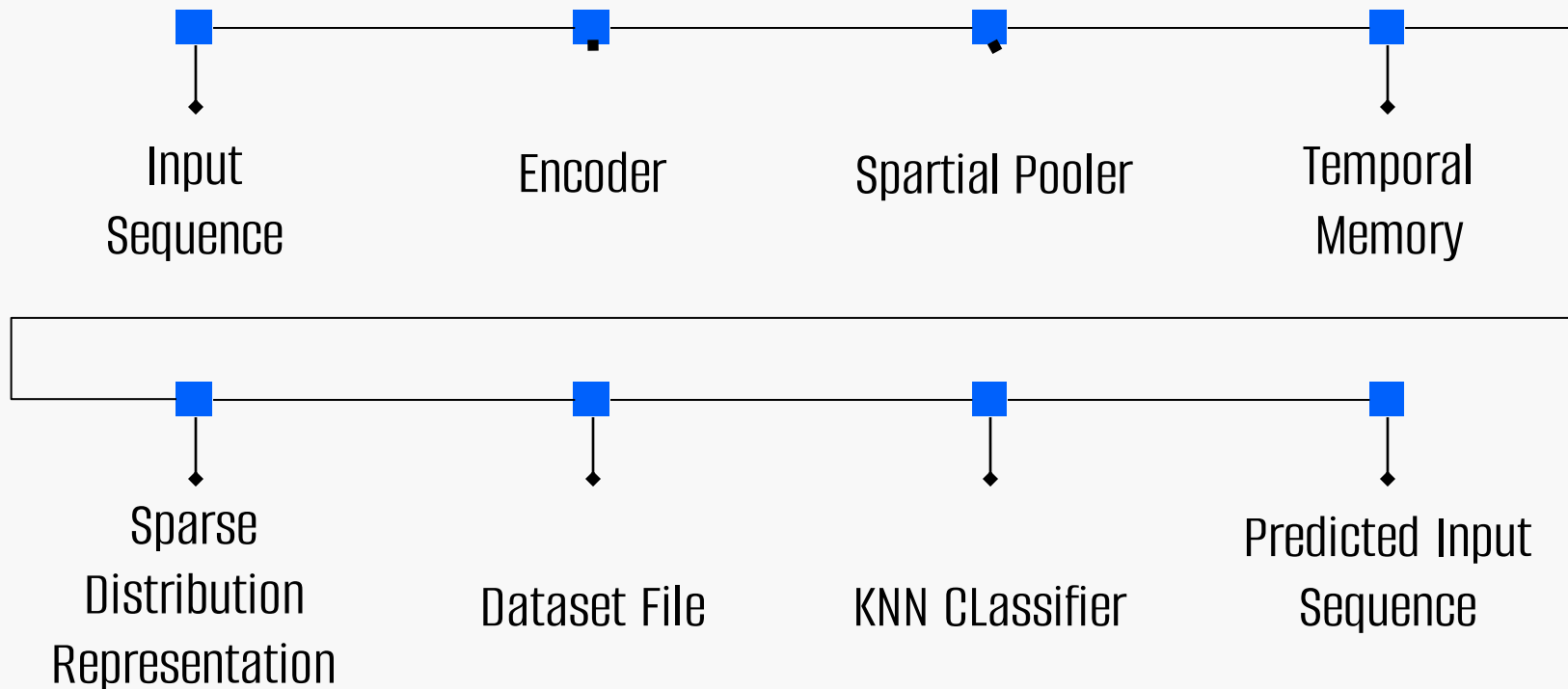
03

# Project Methodology

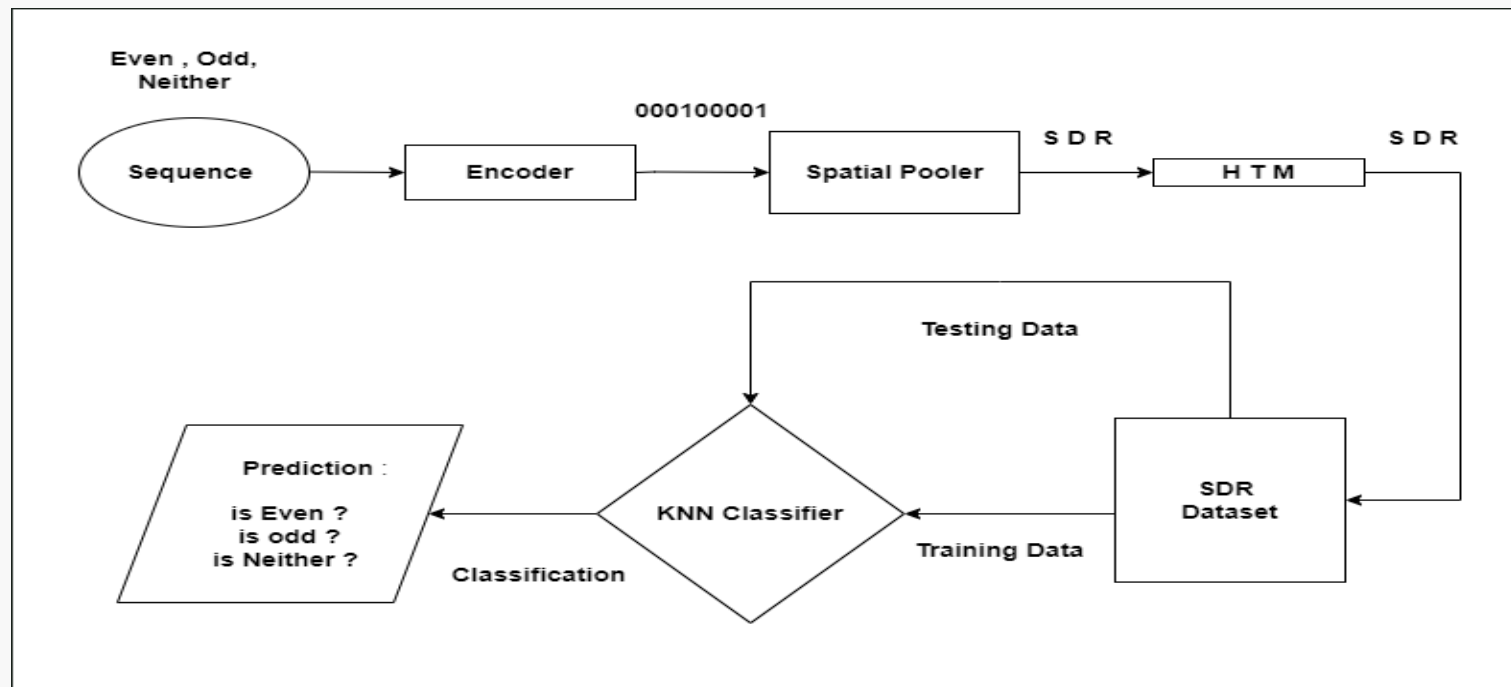


Following a structured approach to efficiently manage project tasks

# Project WorkFLOW

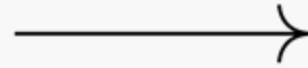


# Process Diagram



# 04

## Approaches and Challenges



Approaches and challenges face while executing the project

# Approaches and Challenges

## 1. Classification of numbers from 0 to 9 in a sequence based on Sparse Distributed Representations (SDRs)

```
Classified data = [  
  { 7, 18, 24, 29,....., 1012, 0 };  
  { 25, 31, 44, 48,..... ,188, 1 };  
  { 118, 123, 127, 156,....., 340, 2 };  
  { 240, 242, 257, 266,....., 444, 3 };  
  { 302, 314, 324, 327,....., 518, 4 };  
  { 393, 405, 428, 429,....., 624, 5 };  
  { 483, 487, 500, 509,....., 726, 6 };  
  { 579, 587, 595, 607,....., 814, 7 };  
  { 676, 691, 700, 707,..... , 916, 8 };  
  { 772, 779, 780, 800,....., 1007, 9 };  
]
```

```
Unclassified data = {461, 495, 515, 501,..., 712 }
```



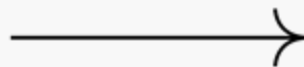
# Approaches and Challenges

## 2. Classification of different Sets of Numbers sequences based on Sparse Distributed Representations (SDRs)

```
[
  {
    "SequenceName": "S1",
    "SequenceData": [8039, 8738, 9334, 9558, 9604, 9697, 9772, 9841, 9851, 9922, 9963, 10023, 10121, 10197, 10373, 10459,
10594, 10629, 10664, 11124]
  },
  {
    "SequenceName": "S2",
    "SequenceData": [9051, 9075, 9133, 9178, 9365, 9448, 9481, 9599, 9635, 9740, 10032, 10224, 10281, 10762, 10778, 10934,
11143, 11306, 11494, 11763]
  },
  {
    "SequenceName": "S3",
    "SequenceData": [10808, 10834, 11053, 11085, 11434, 11471, 11479, 11553, 11597, 11634, 11720, 11743, 11766, 11812,
11872, 11897, 11909, 12094, 12332, 12504]
  }, ...
]
```

05

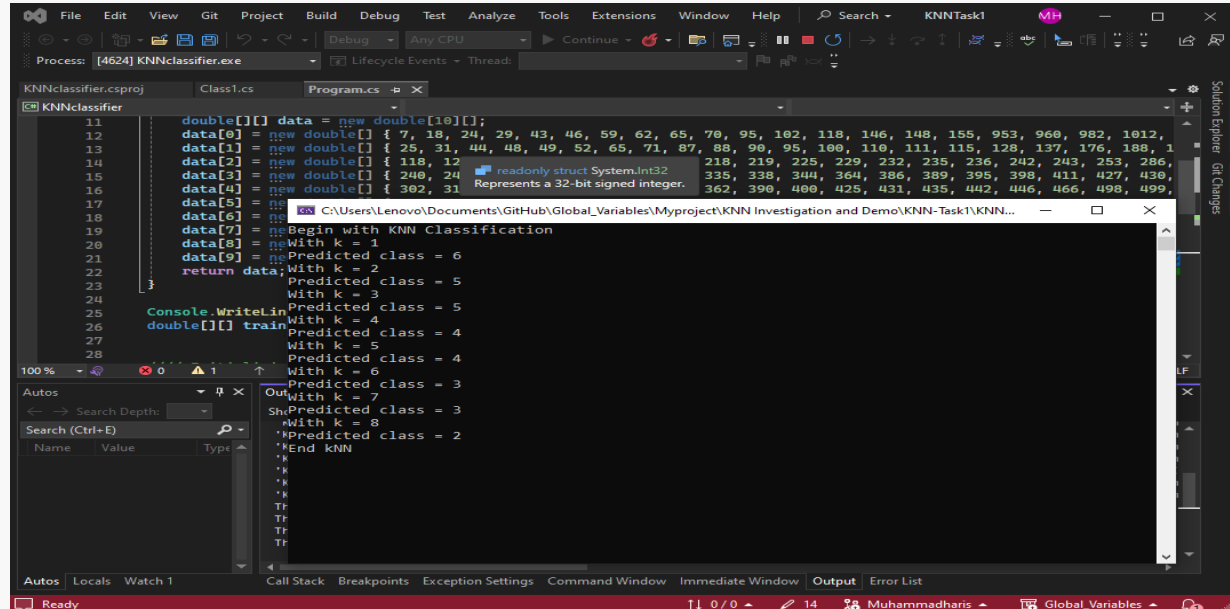
# Result



Classification of the SDR Class on Output Window

# Result

## 1. Classification of numbers from 0 to 9 in a sequence based on Sparse Distributed Representations (SDRs)



```
11 double[][] data = new double[10][];
12 data[0] = new double[] { 7, 18, 24, 29, 43, 46, 59, 62, 65, 70, 95, 102, 110, 146, 148, 155, 953, 960, 982, 1012,
13 data[1] = new double[] { 25, 31, 44, 48, 49, 52, 65, 71, 87, 88, 90, 95, 100, 110, 111, 115, 128, 137, 176, 188, 1
14 data[2] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
15 data[3] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
16 data[4] = new double[] { 302, 31, 362, 390, 400, 425, 431, 435, 442, 446, 466, 498, 499,
17 data[5] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
18 data[6] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
19 data[7] = new double[] { 302, 31, 362, 390, 400, 425, 431, 435, 442, 446, 466, 498, 499,
20 data[8] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
21 data[9] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
22 return data;
23 }
24 Console.WriteLine("Begin with KNN Classification");
25 double[][] train = new double[10][];
26 train[0] = new double[] { 7, 18, 24, 29, 43, 46, 59, 62, 65, 70, 95, 102, 110, 146, 148, 155, 953, 960, 982, 1012,
27 train[1] = new double[] { 25, 31, 44, 48, 49, 52, 65, 71, 87, 88, 90, 95, 100, 110, 111, 115, 128, 137, 176, 188, 1
28 train[2] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
29 train[3] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
30 train[4] = new double[] { 302, 31, 362, 390, 400, 425, 431, 435, 442, 446, 466, 498, 499,
31 train[5] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
32 train[6] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
33 train[7] = new double[] { 302, 31, 362, 390, 400, 425, 431, 435, 442, 446, 466, 498, 499,
34 train[8] = new double[] { 118, 12, 218, 219, 225, 229, 232, 235, 236, 242, 243, 253, 286,
35 train[9] = new double[] { 240, 24, 335, 338, 344, 364, 386, 389, 395, 398, 411, 427, 430,
36 return train;
37 }
```

Output:

```
With k = 1 Predicted class = 6
With k = 2 Predicted class = 5
With k = 3 Predicted class = 5
With k = 4 Predicted class = 4
With k = 5 Predicted class = 4
With k = 6 Predicted class = 3
With k = 7 Predicted class = 3
With k = 8 Predicted class = 2
End KNN
```

# Result

## 2. Classifying Sets of Numbers based on SDR's Value

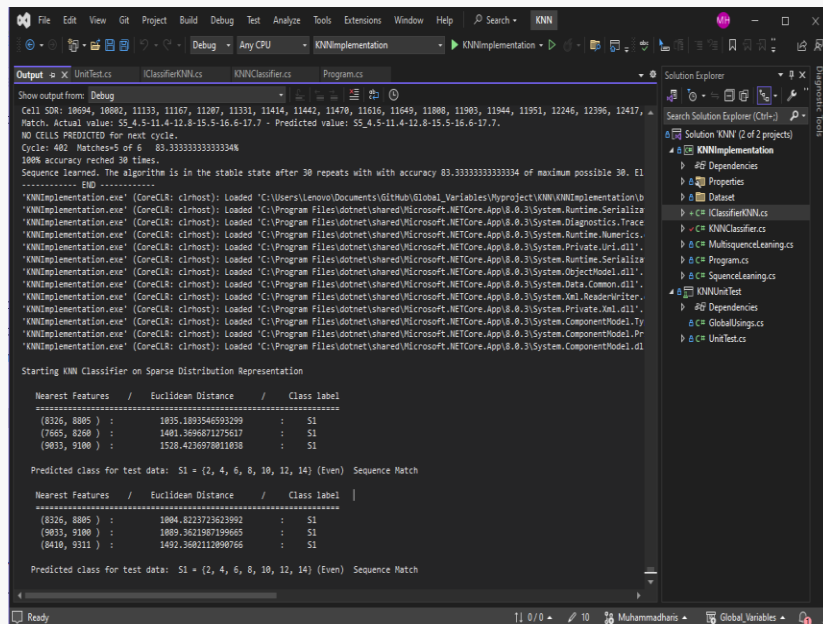
K	Accuracy	Random Generated Test Data Accuracy in Percentage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	100	90.9	90.9	90.9	90.9	90.9	90.9	100
2	100	100	90.9	90.9	90.9	90.9	90.9	100
3	100	100	100	100	100	90.9	90.9	100
4	90.9	100	100	90.9	90.9	90.9	90.9	100
5	100	100	100	90.9	100	90.9	90.9	100

TABLE I

ACCURACY OF THE KNN CLASSIFIER FOR DIFFERENT VALUE OF K FOR  
DIFFERENT TESTING DATA

|

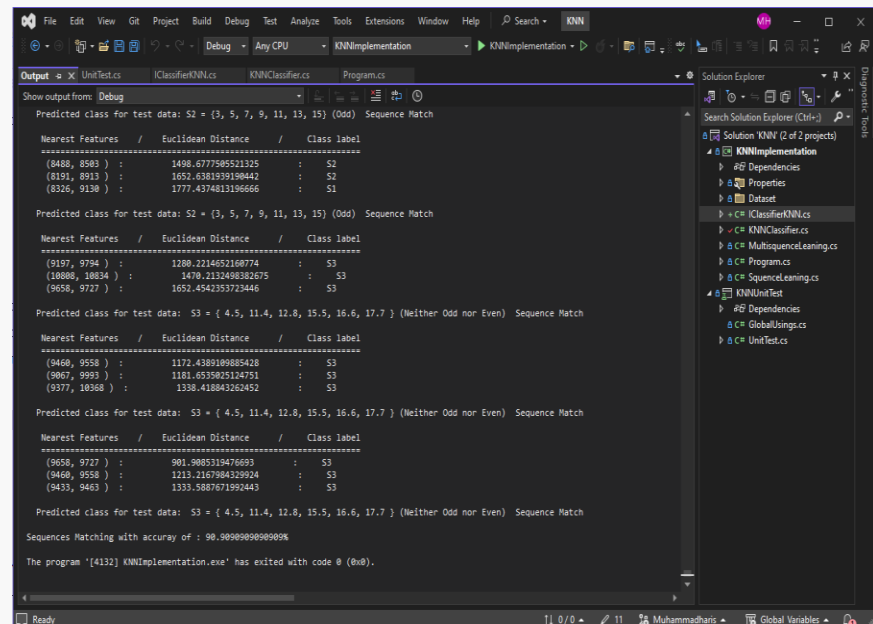
# Result



Output of KNN implementation for test data S1. The output shows the predicted class for test data S1 as (2, 4, 6, 8, 10, 12, 14) (Even) Sequence Match. The nearest features and their Euclidean distances are listed below.

Nearest Features	Euclidean Distance	Class label
(8326, 8805)	1800.8212723623992	S1
(9033, 9100)	1800.3621987229665	S1
(9019, 9311)	1492.3682112090766	S1

Predicted class for test data: S1 = (2, 4, 6, 8, 10, 12, 14) (Even) Sequence Match



Output of KNN implementation for test data S2 and S3. The output shows the predicted class for test data S2 as (3, 5, 7, 9, 11, 13, 15) (Odd) Sequence Match. The nearest features and their Euclidean distances are listed below.

Nearest Features	Euclidean Distance	Class label
(8488, 8593)	1498.6777585521325	S2
(8191, 8913)	1652.6381939190442	S2
(8326, 9138)	1777.4374813196666	S1

Predicted class for test data: S2 = (3, 5, 7, 9, 11, 13, 15) (Odd) Sequence Match

Output of KNN implementation for test data S3. The output shows the predicted class for test data S3 as (4, 5, 11, 4, 12, 8, 15, 16, 6, 17, 7) (Neither Odd nor Even) Sequence Match. The nearest features and their Euclidean distances are listed below.

Nearest Features	Euclidean Distance	Class label
(9468, 9558)	1172.4389180885428	S3
(9067, 9993)	1181.6358402318751	S3
(9377, 86308)	1338.418043262452	S3

Predicted class for test data: S3 = (4, 5, 11, 4, 12, 8, 15, 16, 6, 17, 7) (Neither Odd nor Even) Sequence Match

Sequences Matching with accuracy of: 90.90909090909090%

The program "[4132] KNNImplementation.exe" has exited with code 0 (0x0).

Figure 8 and 9 Output Window presenting the predicted result for test data with accuracy around 90 %.

# Result

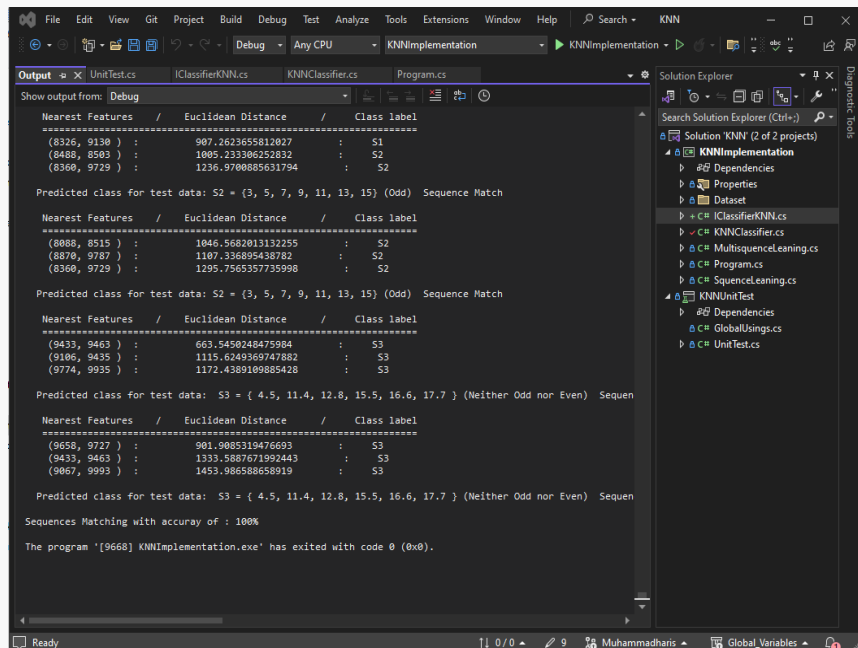
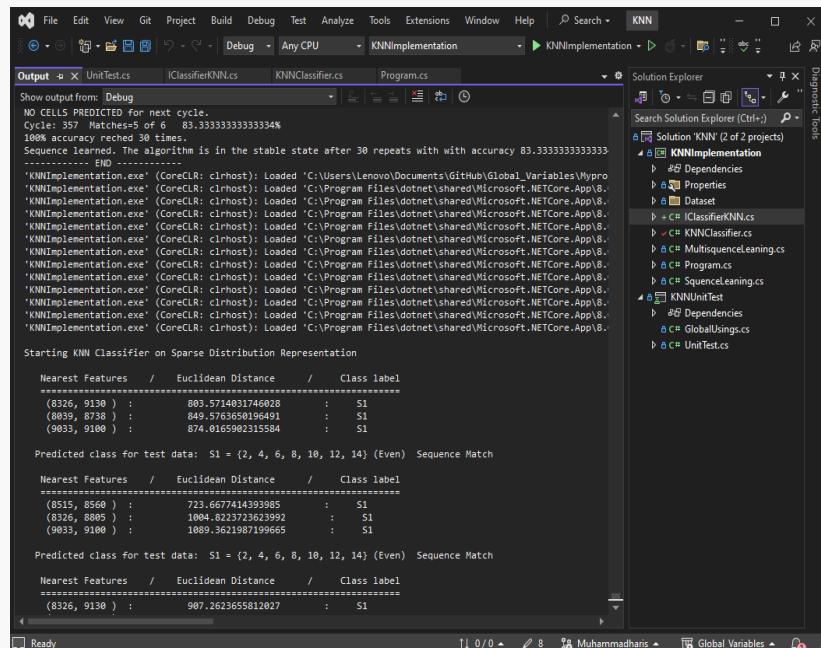
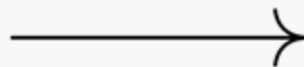


Figure 10 and 11 Output Window presenting the predicted result for test data with accuracy around 100 %.

06

# Unit Test



Unit test preform to test the algorithm

# Unit Test

The screenshot displays the Visual Studio IDE with a unit test run for the KNNClassifier. The test run finished successfully, showing 3 tests passed, 0 failed, and 0 skipped, running in 197 ms.

**Test Explorer:**

- Test run finished: 3 Tests (3 Passed, 0 Failed, 0 Skipped) run in 197 ms
- Test: KNNUnitTest (3)
  - Test: KNNUnitTest (3)
    - Test: UnitTest (3)
      - Test: TestKNNClassifier\_Kiswithinrange
      - Test: TestKNNClassifier\_trainingFeature...
      - Test: TestKNNClassifier\_unknownfeature...

**Test Details:**

- Test: TestKNNClassifier\_Kiswithinrange
- Source: UnitTest.cs line 42
- Duration: 40 ms
- Standard Output:

**Debug Trace:**

Starting KNN Classifier on Sparse Distribution Representation

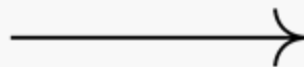
Nearest Features	/	Euclidean Distance	/	Class label
(8326, 9130)	:	1394.1610380440275	:	S1

Predicted class for test data: S1 = {2, 4, 6, 8, 10, 12, 14} (Even) Sequence Match



07

# Conclusion



Concluding the solution of the problem with results.

# Conclusions



## KNN Prototype

We initiated the project by designing a generic KNN prototype, achieving the desired outcomes.



## KNN integration

we developed the KNN model, seamlessly integrating it with the Neocortex API. The integrated model efficiently processes data streams to predict outcomes, with the KNN classifier accurately classifying sequences as matches or mismatches

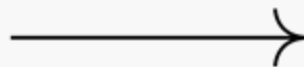


## Desired Result

our model demonstrates an exceptional accuracy rate of 100% across most input sequences. To ensure robustness, comprehensive unit tests, particularly referencing the HTM Classifier, have been implemented, yielding consistently satisfactory results.

08

# Reference



Research Paper reference used for the project

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- .....

Thank You!