Report

K- Nearest Neighbors

K -Nearest Neighbors is a discriminative classification algorithm. It is memory-based approach. The classifier immediately adapts as we collect new training data.

Data Handling

1. Checked for missing values in the data sets, if there are missing values, we can fill missing values by mean or median for the numeric features, and by mode for categorical values.

   In the given data sets, we didn't find any missing value.

2. Imported data files as Data Frame and converted the Data Frame to into Numpy Array for more convenience of using data and conversion in Numpy Array helped to decrease the time of execution.

Steps for Implementation

1. **Defined a function (def distance(x,y)) to calculate Euclidean Distance. Here, for each test data, this function calculates the distance with each training training data.**
2. **Defined a function (Function name: def knn(test_data,train_data,k)) to find the nearest neighbors by finding their index. The function takes train data , test data and k value as input and returns index of the k nearest neighbors as output.**
3. **Defined a function (Function name: def find_max_mode(list_data)) to find mode of the labels of nearest neighbors (voting on correct orientation). This function takes labels of k nearest neighbors as input and produces output of the label having maximum frequency.**
4. **Defined a prediction function (Function name: def prediction (a,b,train_label, k)) to predict the labels of the given test data. Here a – train data, b-test data, k – number of nearest neighbors).**
5. **Defined a function (Function name: def accuracy(predicted,actual)) to calculate accuracy of the model by comparing the predicted labels and actual test labels.**
6. **Calculated by maximum accuracy by tuning the hyperparameter (k – number of nearest neighbors) and plotted the graph of K-value vs Accuracy**

Hyperparameter tuning:

K- number of nearest neighbors

As we can observe from the graph that we are getting maximum accuracy for k = 41,
max accuracy =0.71898197242842

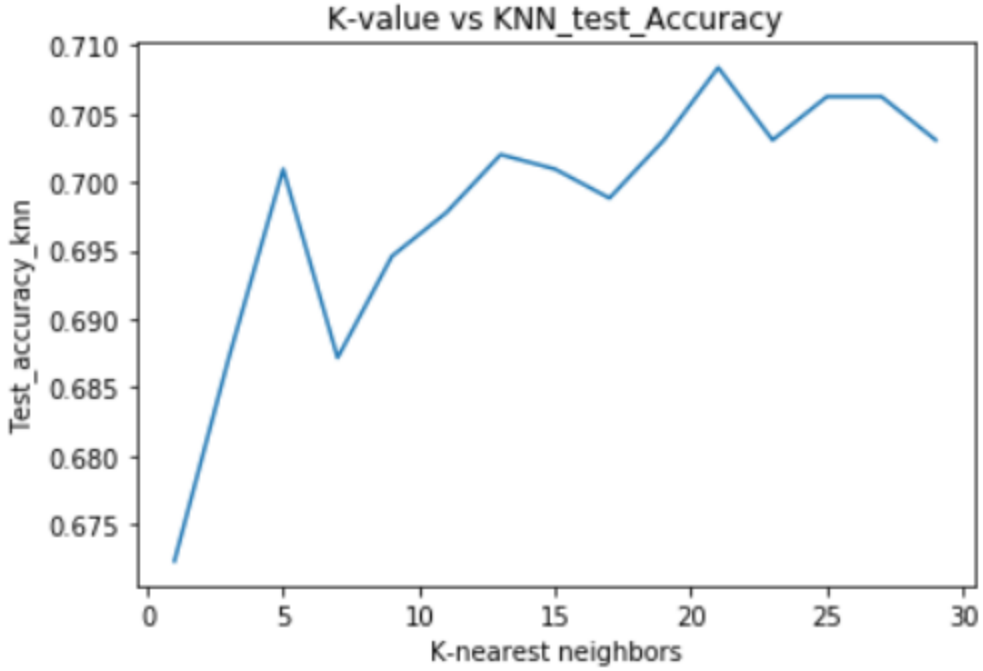
K value	Accuracy
1	0.672322375397667
3	0.6871686108165429

5	0.7009544008483564
7	0.6871686108165429
9	0.694591728525981
11	0.6977730646871686
13	0.7020148462354189
15	0.7009544008483564
17	0.6988335100742312
19	0.7030752916224814
21	0.7083775185577943
23	0.7030752916224814
25	0.7062566277836692
27	0.7062566277836692
29	0.7030752916224814
30	0.7051961823966065
40	0.7168610816542949
41	0.71898197242842
50	0.7051961823966065

Key points observed.

- Increasing the value of k after certain point would decrease the accuracy as increasing k-value leads to increase in bias.
- As the value of K increases variance decreases.
- In case of small value of k, algorithm is very sensitive to noise
- In case of large value of k, we may include points from other classes.

Below is the plot of K-value vs KNN-Test Accuracy



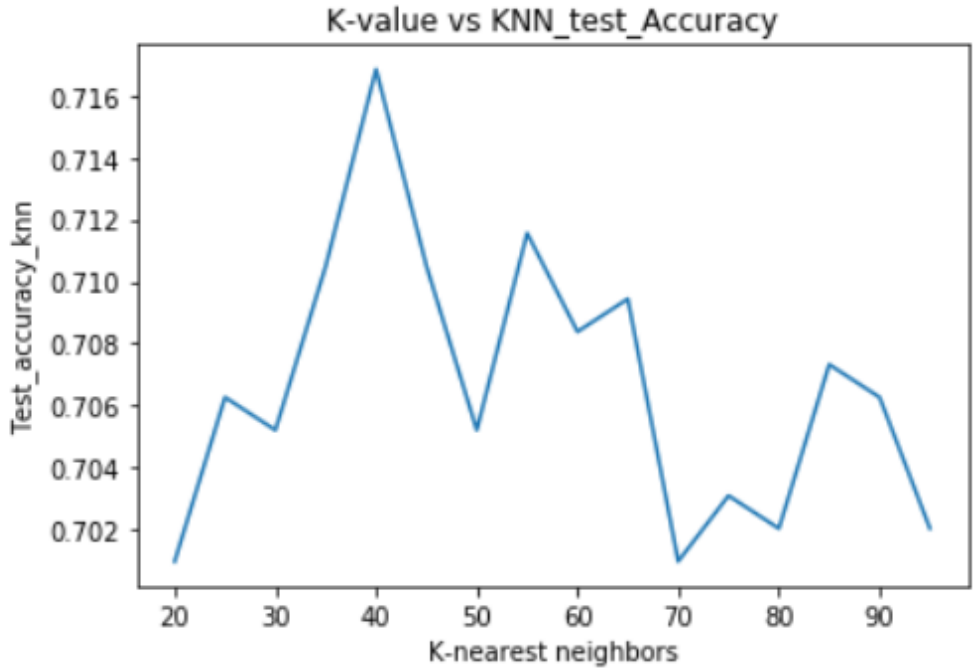
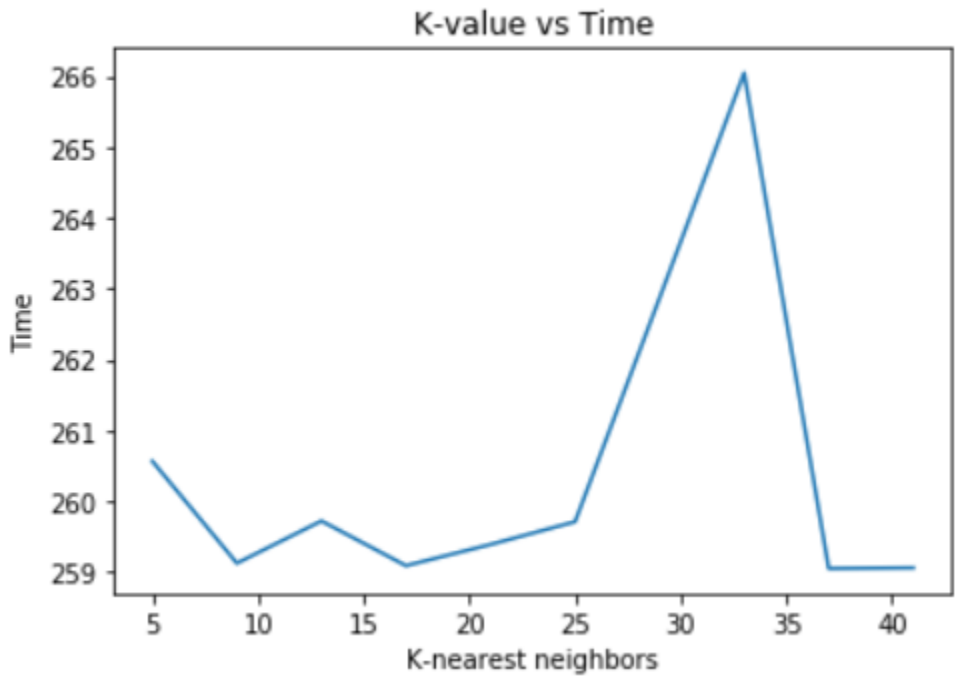


Table: Representing K-value and corresponding time elapsed.

K-Value	Time Elapsed(secs)
5	260.56389117240906
9	259.1237952709198
13	259.7204279899597
17	259.0888888835907
21	259.3880968093872
25	259.7094929218292
29	262.8705039024353
33	266.04530811309814
37	259.04996156692505
41	259.0589978694916



Observation:

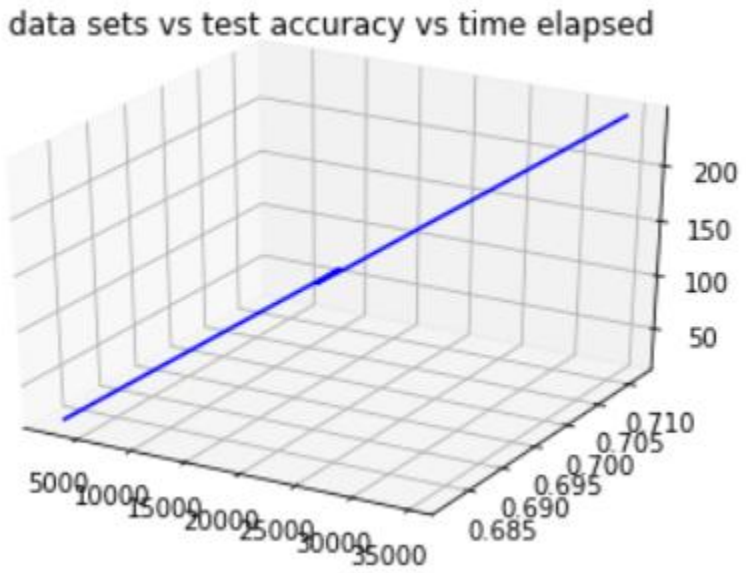
There is hardly any significant change in time duration due to change in value of K – Nearest Neighbours.

The time remains approximately same for different values of K.

Below is the table representing the Data Sets of different sizes and corresponding accuracy and time taken.

Data Sets	Accuracy	Time Elapsed(secs)
2311	0.6818663838812301	15.907667875289917
6933	0.6998939554612937	48.200096130371094
11555	0.7073170731707317	81.05984258651733
16177	0.6967126193001061	114.3927230834961
20799	0.6935312831389183	147.56714153289795
25421	0.6988335100742312	180.90625643730164
30043	0.6988335100742312	214.36259841918945
34665	0.711558854718982	247.00882172584534
36976	0.71898	254.09025678332961

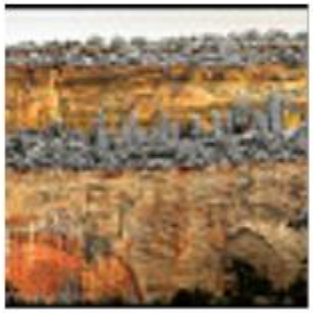
X-axis – Data sets, Y-axis-Test Accuracy, Z-axis – Time



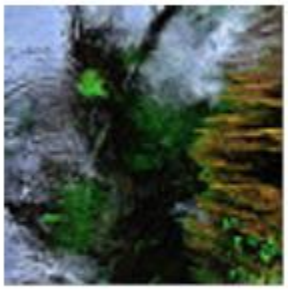
Observation:

The Accuracy of the model increases as we increase the size of training data set. At the same, time we can also see that the running time increase as the size of training data set increases.

Correctly Classified Images:



Misclassified Images:



Pattern of Error

From above samples of misclassified images, we can observe that, the model was not able to classify the images correctly which were taken in insufficient light as we can see, in above misclassified images, some images are taken in night, cloudy weather, dusk. Also, we can notice a trend that the images with blue pixels in the correct orientation that is at the top (for 0 degrees) and similarly for other orientations were classified correctly. Whereas, the images which were misclassified didn't have that. This might be why the algorithms weren't able to learn.

Random Forest

Implementation of random forest:

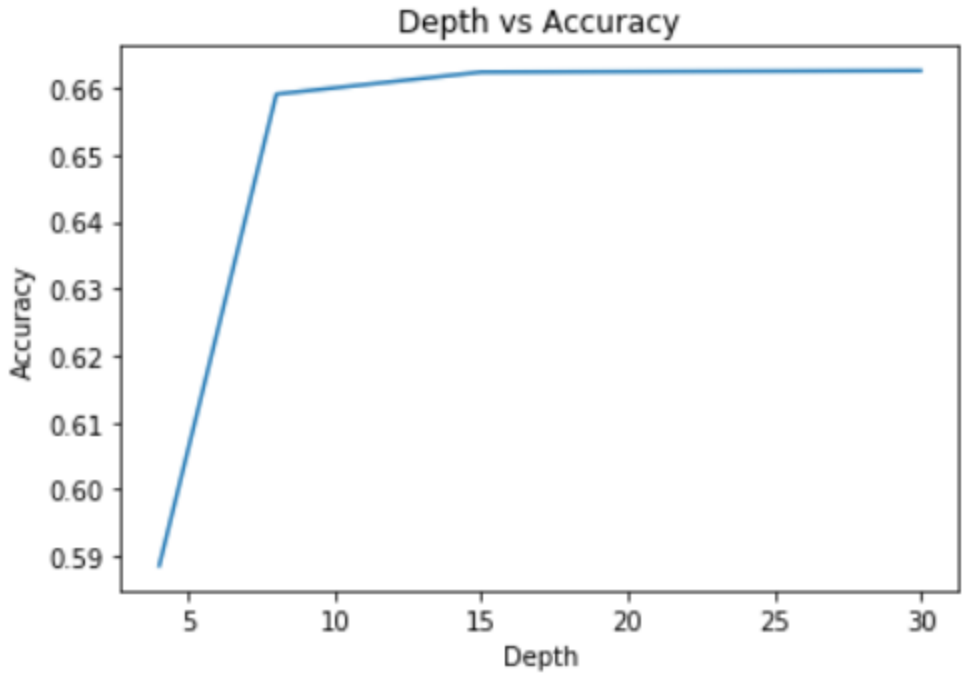
1. The main component of a random forest classifier is the decision tree.
2. In order to implement a decision we split iteratively using a greedy algorithm. At each node we find the best attribute to split on.
3. We handle the continuous splitting criteria by setting the threshold to half the value of the highest pixel. (128).
4. In order to the select the best splitting attribute we calculate the information gain of the split. Whichever split has the maximum information gain is selected.
5. Now, we create a forest of such decision trees. Each tree is trained on a subset of the training data selected randomly.
6. On testing each decision tree predicts and then the final decision is made by selecting the class which has the maximum votes.

The following hyperparameters have been tuned on silo:

Depth (for 50 trees):

Depth is a important tuning parameter for the random forest algorithm. As we increase the depth of the tree the decision trees of the forest because more complex and hence, the train error on them decreases.

Depth	**Accuracy**	**Training Time (in Mins)**
4	0.5886	5
8	0.6591	14
15	0.6712	67
30	0.6626	203



Trees (for depth 15):

Trees vote and based on the votes a decision of classification is made. As, the number of trees increases the overfitting on the dataset descreases. This, is because multiple trees vote and the chances of all trees being biased is less.

No of Trees	**Accuracy**	**Training Time (in Mins)**
1	0.6135	0.53
15	0.6324	15
30	0.6419	39
50	0.6712	67

Split size (For 50 trees and depth 15):

The trees are trained on subsets of data. Various size splits have been tried and the following results are obtained.

Split Size	**Accuracy**	**Training Time (in Mins)**
Random size	0.6263	39
1/3	0.6129	10
1/2	0.6316	24
2/3	0.6712	67

Entropy value for decision:

The decision tree stops when the entropy value of a split is less than a threshold.

Value for entropy	**Accuracy**
0	0.6423
0.1	0.6470
0.2	0.6561
0.3	0.6502
0.4	0.6712
0.5	0.6497

The following hyper-parameters prove to be the best based on the tuning performed:

Depth = 15

Number of Trees = 50

Split size = ⅔

Entropy for decision = 0.4

Adaboost

- To solve the multi-class problem, we converted this into a one vs all problem. That is (0 vs 90), (0 vs 180), (0 vs 270), (90 vs 180), (90 vs 270), and (180 vs 270).
- This generated 6 sets of training data.
- For each training set, we take a majority vote. If majority vote for a class then that class is assigned Positive otherwise Negative.
- For each training set, we take a majority vote. If majority vote for a class then that class is assigned Positive otherwise Negative.
- -Initially the weights are initialized as 1/N. Whenever we get the correct answer we decrease the initialized weights otherwise we increase the weights of the incorrectly classified example. Normalization is then done.
- +Initially the weights are initialized as 1/N. Whenever we get the correct answer we decrease the initialized weights otherwise we increase the weights of the incorrectly classified example. Increase is done by adding the error.
- +Normalization is then done.
- An accuracy ranging from 68-71% was achieved. Even if we increased the number of random pixel pairs compared, the accuracy achieved didn't increase by more than 71% but at a much higher computation cost.
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Hyperparameter Tuning

Here the Hyperparameter used is Pixel Pairs

Pixel Pairs	**Accuracy**
10	47-55%
100	56-62%
500	64-68%

1000	68-71%

Selection of Model:

Model	Accuracy	Training Time (in secs)	Testing Time (in secs)
KNN	71.898	0	240-381
Random Forest	67.12	4020	3-7
AdaBoost	69	30	2-6

Selection of Model is the one of the important steps.

On the given data sets, we can observe that the performance of all three models, stated in the above table. KNN is the model with highest accuracy but it consumes more time and Adaboost is a close second with a much lesser training and testing time. So, if we have to recommend to the customer the model among the above models, we need to clarify upon their need, if they strictly want a model with the good enough accuracy, without compromising time taken, then definitely Adaboost would be the first choice of recommendation. On the other hand, if the customer is more stringent on accuracy, then KNN would be the best choice.