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Article

ADAPTIVE_CLASSIFIER: A NOVEL APPROACH FOR KNN PARAMETERIZATION

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Abstract: The k-Nearest Neighbors (kNN) algorithm is a widely used method in machine learning, particularly for pattern recognition and classification tasks. Despite its popularity, the determination of the k parameter, which influences the number of nearest neighbors to consider, remains a significant challenge. This research introduces a novel enhancement to the kNN algorithm that specifically targets the calculation of the k parameter, aiming to improve the algorithm's performance across various data mining tasks. Building on a rich body of work, the study proposes a mathematical technique for intelligent clustering of points for classification. This method involves creating an n-dimensional sphere, where n equals the number of features, effectively eliminating the manual trial and error approach traditionally associated with the kNN algorithm. The equation of the sphere is formulated based on the dimension and feature values, with the radius determined through a specific mathematical equation. The proposed algorithm, named Adaptive classifier, was tested against six existing unsupervised algorithms using the diabetes dataset. The results demonstrated superior performance of the Adaptive classifier, with statistical proof provided through a paired t-test. The t-test results showed that the Adaptive Classifier outperforms the other algorithms, reinforcing its effectiveness. This research contributes significantly to the field of machine learning by offering a more efficient and accurate method for k parameter calculation in the kNN algorithm. By improving the algorithm's performance, the proposed method has the potential to enhance results in various data mining tasks, thus broadening the applicability of the kNN algorithm

Keywords: k-Nearest Neighbors, intelligent clustering, n-dimensional sphere, Adaptive classifier.

1. INTRODUCTION

The k-Nearest Neighbors (kNN) algorithm is a cornerstone of machine learning, renowned for its simplicity and effectiveness in pattern recognition and classification tasks [1]. Despite its popularity, it has limitation of huge memory requirement, high computational cost, equal weightage to features and the most important the choice of the k parameter, which determines the number of nearest neighbors to consider, remains a critical and challenging aspect of the algorithm [2]. The kNN algorithm has seen numerous improvements over the years. Some researchers have focused on optimizing the algorithm for specific types of data, such as spherical region-based algorithms [3]. Others have proposed weighted KNN to improve the algorithm's performance [4-5]. Some studies have addressed the algorithm's shortcomings and proposed solutions with Hybrid KNN[6], while others have suggested methods for predicting the k parameter for kNN classification [7]. There have also been attempts to improve the efficiency of kNN processing [6], select the nearest neighbour for iteratively kNN imputation [8], and compute the k parameter in a data-driven manner [9]. Some researchers have proposed random kNN feature selection as a fast and stable alternative to

Random Forests [10], while others have proposed efficient methods for kNN join processing [11]. There have also been efforts to improve kNN classification using genetic algorithms [12].

This research proposes novel enhancements to the kNN algorithm, specifically targeting the calculation of the k parameter. Building on this body of work, this research proposes a novel approach to calculating the k parameter in the kNN algorithm. The proposed enhancements aim to address the challenges associated with the choice of k, improving the algorithm's performance in various data mining tasks. The following sections will detail the proposed enhancements, the methodology used to implement and test them, and the results and implications of this research. This paper presents novel KNN algorithm for binary classification. The paper is organized as follows: Section 2 describes related work related to development of KNN variants. Section 3 describes proposed Adaptive_Classifier algorithm. Section 4 describes experimental results. Section 5 provides discussion and future scope.

2. RELATED WORK

The k-Nearest Neighbor (kNN) algorithm is a non-parametric algorithm and popular choice for pattern recognition and classification tasks. In spite of simplicity, it has major limitation of greater time complexity and tuning k appropriately. This fetched attention of researchers and hence various improvements to the algorithm were proposed for addressing its limitations and enhancing its performance. In recent past, two improved kNN algorithms viz. KNN^{TS} and $KNN^{TS\text{-}PK+}$ based on the KNN^{PK+} algorithm were proposed [3]. Their approach involved using the PK- Means ++ algorithm to select the center of spherical regions and setting the radius of the region to divide the dataset in space. Their experiments showed improved classification accuracy and efficiency. In order to address the issue of kNN's susceptibility to the choice of k-nearest neighbors and the method of class judgment was proposed [13]. The proposed DCT-kNN, algorithm based on class contribution and feature weighting, which showed improved classification accuracy on UCI datasets. A survey of methods was conducted to overcome the three main shortcomings of kNN, providing a comprehensive overview of improved algorithms and their effectiveness [14].A novel learning was proposed with a correlation matrix for assigning different k values to different test data points, which resulted in a more accurate and efficient kNN method for data-mining applications [15].The attempt was made by presenting an efficient method, iDistance, for kNN processing in high-dimensional space [16]. The method involved partitioning the data and selecting a reference point for each partition, resulting in an effective adaptation of the index structure to the data distribution. A novel kNN imputation method was proposed, GkNN, for dealing with missing data in heterogeneous datasets [17]. The approach used a gray distance metric to capture the proximity relationship of instances and deal with mixed attributes, resulting in a more efficient kNN imputation method. Further, a novel kNN algorithm was proposed with data-driven k parameter computation [9]. The approach involved reconstructing a sparse coefficient matrix between test samples and training data, resulting in a more accurate and efficient kNN method for classification, regression, and missing data imputation. RKNN-FS algorithm was proposed with an innovative feature selection

procedure for "small n, large p problems" [10]. The approach was based on Random KNN (RKNN), a novel generalization of traditional nearest-neighbor modeling, and was shown to be more stable, robust, and faster than Random Forests for feature selection. A novel KNN-join algorithm was proposed, Gorder, which exploited sorting, join scheduling, and distance computation filtering and reduction to reduce both I/O and CPU costs [11]. The experiments showed that Gorder outperformed existing methods by a wide margin. Later, an improved version of kNN using Genetic Algorithm (GA) was proposed [12]. The approach involved use of GA to take k-neighbours straightaway and then calculate the distance to classify the test samples, resulting in improved classification performance. These studies provide a broad perspective on the advancements in kNN algorithms, offering insights into potential improvements and modifications that could enhance the performance of the existing kNN algorithm.

3. PROPOSED ALGORITHM

The proposed algorithm suggests a mathematical technique to cluster the points for classification. The technique involves creating an n-dimensional sphere (n = no of features) for intelligent cluster and to overcome the manual trial and error method proposed in K-Nearest Neighbor algorithm.

In any machine learning algorithm number of features represents dimensionality. In large number of features this dimensionality is curse so we have to exclusively work on algorithms like Principle Component Analysis (PCA) whereas for less features increase in dimensionality is necessary so we have to take help of algorithms like Support Vector Machine (SVM). The proposed algorithm is also an effort in the direction of dimensionality and the value of k for finding nearest neighbour. The classical KNN computes the distance between every sample test data points with every sample in training data points. Based on the distance, the most nearest “k‟ neighbours are identified. The test sample is labelled with the class which has the maximum count that belongs to “k“ nearest neighbour. This simple logic of formation of group based on distance may be troublesome if we increase total number of features. So this algorithm is novel contribution in terms of mathematical formulation of finding the value of “k” by considering equation of sphere in n-dimension.

Initially classical mathematical concept of generating an equation of a sphere was taken into consideration. But it has been observed that if we apply preliminary mathematical concepts then the length of radius is creating the problem. The radius was too large in many cases, covering all the points in the plane eventually decreasing the accuracy and model's performance metrics. Reduction in size of radius was mandatory to avoid the underfitting or overfitting problem. In line with this idea the proposed algorithms was tested for various number of features. Major Datasets from Kaggle was considered while designing this algorithm. The datasets tested were ranging from 6 features to 60 features. Multiple factors were tested and taken into consideration, the best factor was considered as multiplying with gamma(1.5) and then dividing it with (4*n*(pi)) which roughly leads us to the value of 1/(8 x n). This value actually solved the low accuracy problem. The value was repeatedly tested on many datasets. The mathematical formulations are as follows:

The equation of the sphere is given as,

$$(D_0 - n_0)^2 + (D_1 - n_1)^2 + (D_2 - n_2)^2 + \cdots + (D_{n-1} - n_{n-1})^2 - R^2 = 0 \qquad (1)$$

Where, Dx represents the x^{th} dimension and nx represents the x^{th} feature value and R (radius) is given as,

$$R = [n_0^2 + n_1^2 + n_2^2 + \cdots + n_{n-1}^2] * \left(\frac{\gamma(1.5)}{n*4*\sqrt{\pi}}\right) \qquad (2)$$

where γ is the gamma function ,

So the final equation of the n dimension sphere becomes,

$$(D_0 - n_0)^2 + (D_1 - n_1)^2 + (D_2 - n_2)^2 + \cdots + (D_{n-1} - n_{n-1})^2 - [n_0^2 + n_1^2 + n_2^2 + \cdots + n_{n-1}^2] * \left(\frac{\gamma(1.5)}{n*4*\sqrt{\pi}}\right) = 0 \qquad (3)$$

The (γ(1.5))/(n x 4 x (√π)) is the multiplication factor to the radius was considered for the reduction of radius size. The proposed shrink in the size of radius to cover appropriate points and to eventually miss out the false and misleading data points.

The problem with considering the radius without the reduction factor is that the radius of the sphere grows too big in number which eventually leads in encompassing all the data points thereby increasing the loss factor, time taken for algorithm to run as the algorithm would have to iterate through each and every data point present in the dataset making the time complexity as directly proportional to the size of dataset.

The working of entire algorithm is provided as pseudo code as follows:

```
Procedure Fit_ndim_Sphere(train_set,test_set)
Begin
  radius_sq = 0
  for i= 1 to dataset_size:
     new_X[i]=train_set
   radius_sq += sqr( new_X[i])
   sum=sum(sqr(X[test_set]-new_X[i]))
   k = gamma(1.5)0.25/(len(X[0])(sqrt(pi)))
   return array(sum-(radius_sq*k))
    End Procedure
```

```
Procedure predict(test_sample):
    class1 = 0
    class2 = 0
    for i 1 to  radius:
        if radius[i]==class1:
            class1+=1
        else:
            class2+=1
    return class_of_maximum_volume(class1,class2)
End Procedure
```

4. EXPERIMENTAL RESULTS

Datasets:

The proposed algorithm is presented as an improvement of the classical KNN algorithm. The performance of the algorithms is compared with other machine learning algorithms. The dataset considered here is from Kaggle which has number of features ranging from six to sixty. The dataset is made clean with appropriate statistical treatment for handling missing values. The dataset under consideration has two classes. The brief description of each dataset is provided herewith:

1. Diabetes Dataset:

The National Institute of Diabetes and Digestive and Kidney Diseases is the original source of this dataset[18]. Based on specific diagnostic metrics included in the collection, the dataset aims to diagnostically predict the presence or absence of diabetes in a patient. These examples were chosen from a bigger database under a number of restrictions. Specifically, all of the patients in this facility are Pima Indian women who are at least 21 years old.

The datasets include one target variable, outcome, and multiple medical predictor factors. The patient's age, BMI, insulin level, number of pregnancies, and other factors are examples of predictor variables.

2. Breast Cancer Dataset

Worldwide, breast cancer[19] is the most frequent cancer to affect women. It affects about 2.1 million people in 2015 alone and makes up 25% of all cancer cases. It all begins when breast cells start to proliferate uncontrollably. Usually, these cells develop into tumors that are felt as lumps in the breast area or that are visible on X-rays. The main obstacle to its discovery is determining whether a tumor is benign (not cancerous) or malignant (cancerous). Please finish the analysis of the Breast Cancer Wisconsin (Diagnostic) Dataset and machine learning (using SVMs) to classify these tumors.

3.Sonar Dataset

The 111 patterns in the "sonar.mines" file were produced by reflecting sonar sounds off a metal cylinder at different angles and in different circumstances[20]. The 97 patterns found in the file "sonar.rocks" were collected from rocks in comparable environments. A frequency-modulated chirp that increases in frequency is the sent sonar signal. Signals from a wide range of aspect angles—90 degrees for the cylinder and 180 degrees for the rock—are included in the data set.There are 60 numbers in the range of 0.0 to 1.0 for each design. The energy integrated over a specific time interval within a given frequency band is represented by each integer. Higher frequencies have an integration aperture later in time because they are broadcast later in the chirp.

Comparison with other algorithms:

The dataset for demonstrating the effectiveness of Adaptive_ Classifier algorithm over other algorithms comprised of varied number of features. The dataset under consideration was diabetes dataset which has 6 trainable parameters, Breast cancer dataset which has total 31 trainable parameters and Sonar dataset which has total 60 trainable parameters. The comparative analysis clearly indicated that performance of Adaptive_Classifier was superior over other machine learning algorithms. The proposed algorithm was compared with 6 existing supervised algorithms and following results were obtained. The classification performance was evaluated by accuracy, precision, recall and F-score metrics. The evaluation metrics are calculated by means of following equations.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN) \quad (4)$$

$$Precision=TP/(TP+FP) \quad (5)$$

$$Recall=TP/(TP+FN) \quad (6)$$

$$F1\text{-}Score=2*TP/(2*TP+FP+FN) \quad (7)$$

where, TP and TN stands for True Positive and True Negative respectively and FP and FN stands for False Positive and False Negative respectively.

The comparative results using above metrics are documented in Table 1 for Diabetes dataset, Table 2 for Breast cancer dataset and Table 3 for Sonar dataset.

Table 1. Comparison of Performance of the existing algorithm and the Adaptive_Classifier for Diabetes dataset

Sr No	Algorithm	Accuracy	Precision	Recall	F1-Score
1	Proposed Algorithm	0.80	0.91	0.79	0.85
2	KNN	0.76	0.82	0.79	0.81
3	SVM	0.80	0.93	0.74	0.83
4	Random Forest Classifier	0.79	0.91	0.77	0.83
5	Decision Tree	0.68	0.78	0.72	0.75
6	ANN	0.68	-	-	-
7	Gausian Naïve Bayes	0.75	0.86	0.75	0.80

Table 2. Comparison of Performance of the existing algorithm and the Adaptive_Classifier for Breast Cancer dataset

Sr No	Algorithm	Accuracy	Precision	Recall	F1-Score
1	Proposed Algorithm	0.964	0.976	0.976	0.976
2	KNN	0.92	0.93	0.975	0.95

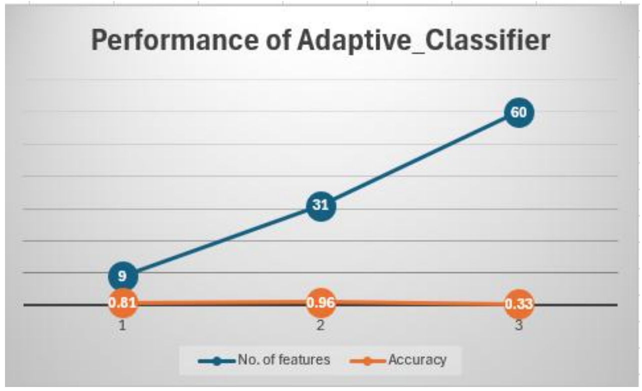
3	SVM	0.964	1.0	0.95	0.97
4	Random Forest Classifier	0.96	1.0	0.95 5	0.97
5	Decision Tree	0.94	0.976	0.95 4	0.965
6	Gausian Naïve Bayes	0.964	1.0	0.95	0.97
1	Proposed Algorithm	0.964	0.976	0.97 6	0.976

Table 3. Comparison of Performance of the existing algorithm and the Adaptive_Classifier for Sonar dataset

Sr No	Algorithm	Accura cy	Precisio n	Recal l	F1-Score
1	Proposed Algorithm	0.33	0.33	1.0	0.5
2	KNN	0.14	0.14	1.0	0.25
3	SVM	0.33	0.33	1.0	0.5
4	Random Forest Classifier	0.61	0.61	1.0	0.76
5	Decision Tree	0.71	0.71	1.0	0.83
6	Gausian Naïve Bayes	0.0	0.0	nan	nan

From the above table it is clear that the proposed algorithm outperforms the existing supervised algorithms. It is clearly seen that classical clustering algorithm fails when number of features goes on increasing but the Adaptive_Classifier can figure out the clusters. However Adaptive classifier may not be efficient if we copare it with other supervised algortihms and hence accuracy of Adaptive_Classifier over other supervised algorithm is not found be promising specialluy when number of features are more than 60. In real life examples if labels are not known then Adaptive_Classifier is ray of hope to provide a little insight about data. However, in order to know how the algorithm performs if the feature size increased, the comparative chart w.r. to number of features and accuracy was plotted which is depicted in Fig. 1.

Fig.1 Performance of Adaptive_Classifier on different feature set size



Statistical Proofs

The computational performance clearly provides the significance of Adaptive_Classifer however the performance is also validated by means of statistical significance. To validate the significance of proposed algorithm Adaptive_Classifier statistically, the results of Adaptive_ Classifier is compared with the results obtained by other machine learning algorithm. Paired t-test was performed to compare each algorithm with the proposed algorithm for providing a deep proof of the better algorithm based on the value obtained from t-test results. The test was carried out for Diabetes dataset, Breast Cancer dataset and Sonar dataset.

The following hypothesis are formulated.

H_0: There is no statistical significant difference between Adaptive _Classifier and other ML algorithms.

H_A: There is statistical significant difference between Adaptive _Classifier and other ML algorithms.

In this case degree of freedom is 9 because we created 10 folds of dataset for testing purposes. These values (t_ statistic_ values) of all other algorithm with Adaptive_Classifier were computed. Since Degree of Freedom (df) = 9 and p-value = 0.05, after observing these parameters from the t-table it is evident that if the t_statistic_val of the individual algorithm was in the range of (-2.262, 2.262) we can reject the null hypothesis. But it is clearly visible from the above table that none of the t_stat_val of any other algorithm fits in the criteria, hence it is evident that Adaptive_Classifier has performed well in the paired_t test measure. Hence it is concluded that Adaptive_Classifieris statistically significant.

Table 4. Paired t-test table for Diabetes Dataset

Sr No	Algorithm	t_statistic_val
1	KNN	5.01
2	SVM	3.9
3	Random Forest	4.57
4	Decision Tree	4.39
5	ANN	nan
6	Gausian Naïve Bayes	5.29

Table 5. Paired t-test table for Breast Cancer Dataset

Sr No	Algorithm	t_statistic_val
1	KNN	5.19
2	SVM	6.83
3	Random Forest	3.18
4	Decision Tree	4.37
5	ANN	Nan
6	Gausian Naïve Bayes	3.22

Table 6. Paired t-test table for Sonar Dataset

Sr No	Algorithm	t_statistic_val
1	KNN	6.56
2	SVM	6.91
3	Random Forest	6.69
4	Decision Tree	9.28
5	ANN	Nan
6	Gausian Naïve Bayes	4.82

The tabulated t- statsical values conforms the superiority of Adaptive_Classifer over classical ML algorithms . With Computationsl and Statistical validation it can be confirmed that the Adaptive_Classifer is superior unsupervised algorithm. The algorithm proved the efficiency for a varied number of features as well.

4. CONCLUSION AND FUTURE SCOPE

Adaptive_Classifieris an attempt to introduce a novel approach for calculating the k parameter in the k-Nearest Neighbors (kNN) algorithm. It proposes a mathematical technique for intelligent clustering of points for classification with the aim of enhancing the algorithm's performance in various data mining tasks. The proposed algorithm was tested against six existing supervised algorithms using the Kaggle dataset. The results exhibit that the Adaptive_Classifier outperform the existing algorithms not only in terms of accuracy, precision, recall, and F1-Score but also statistically significant. These findings suggest that the proposed enhancements to the kNN algorithm have the potential to significantly improve the algorithm's performance in data mining tasks.

The success of the Adaptive_Classifier opens up new avenues for future research. Exploring how these enhancements can be applied to other machine learning algorithms could be a potential direction. Furthermore, investigating the algorithm's performance in real-world applications would provide valuable insights into its practical implications. In conclusion, this research contributes to the on-going efforts to optimize the kNN algorithm, providing a promising new approach to the calculation of the k parameter. The proposed algorithm not only demonstrates superior performance in comparison to existing algorithms but also provides a foundation for future advancements in the field.

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