# Prediction of Eye States using k-NN Algorithm: A Comparison Study for Different Distance Metrics and Number of Neighbour Parameters

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***Abstract*—Eye state prediction is the process of determining whether the users' eyes are in opened or closed state. It has been widely employed in human computer interaction, brain–computer interfaces, etc. In this paper, we investigated the classification performances of different distance metrics and number of neighbour parameters on the problem of predicting eye states. We conducted experiments on real-world EEG Eye State Data set which is intended to find appropriate approaches for eye state prediction. The classification performances were evaluated for accuracy measurement using the ten-fold leave-one-out cross-validation. The results demonstrate that the distance metrics and number of neighbour parameters highly affect the performance. Compared to previous works, the following two points were improved: (i) not only the euclidean distance but also other distance metrics' performances were investigated for EEG based eye state prediction and (ii) better classification accuracy rates were achieved compared to previous k-NN based studies.**

***Keywords*—*eye state prediction, k-nearest-neighbour, brain–computer interface, EEG, distance metric***

## I. Introduction

Eye state prediction is the process of determining whether the eyes are opened or closed. It has been widely employed in Human Computer Interaction (HCI), Brain Computer Interfaces (BCIs), driver fatigue/drowsiness detection, alternative interfaces for people with severe physical & cognitive disabilities, etc [1], [2]. Therefore, real time eye state prediction systems that have a good accuracy play a crucial role.

In previous studies, different types of devices were used to acquire and process eye state signals [1]–[4]. The first one is image and video based methods. These methods use eye region images as input and predict eye state using image processing/computer vision techniques. However, free head movements, image artefacts, changing pose and illumination are some of the main challenges that are currently not fully solved using these methods [2]. The second one is electro-oculography (EOG) in which the electro-physiological signals are measured on the skin surface around the eyes. In this method, eye blinks are detected by measuring the corneal-retinal potential. However, it is prone to artefacts and needs convenient preprocessing [4]. The third one is Electroencephalography (EEG) where surface electrodes are located on human scalp and electrical activity of brain is recorded. These signals are widely used in many popular fields such as BCIs, neuroscience, epilepsy and related disorders, etc.

In previous studies, different approaches have been investigated to estimate the eye state using EEG signals. Rösler et al. used 42 different classifier and multiple settings of tuning parameters using Weka Data Mining Software [3]. Hamilton et al. intended to propose a system that has enough speed to be utilized within a BCI while preserving classification accuracy compared to [3]. They developed three ensemble learners and achieved these performance goals by using a rotational forest [1]. Wang et al. proposed an approach using incremental attribute learning (IAL) strategy that gradually imports and trains features one by one [5]. Sabanci et al. used k-Nearest Neighbour (k-NN) with euclidean distance metric and multi-layer perceptron neural networks as classifier. They achieved highest classification performance with k-NN [6]. Reddy et al. applied various deep learning architectures and algorithms [7]. Similarly, Narejo et al. used Deep Belief Network and Stacked AutoEncoders as classifier and obtained a high-accuracy eye state classification method [8]. In recent years, Hua et al. proposed a L1-norm loss-based projection twin support vector machine (L1LPTSVM) [9]. They evaluated a portion of data set separately while increasing the ratio gradually. Zhou et al. developed a novel effective and efficient system [10]. They extracted features by utilizing the information accumulation algorithm based on wavelet transform and classified features with Random Forest. Lastly, Hodge and Austin aimed to evaluate algorithms for classification and outlier detection accuracies [11].

k-NN is an instance based supervised learning method and widely used in data mining, pattern recognition for classification, regression tasks, etc [12]. In this simple and practical method, most important parameters are distance metric and number of nearest neighbours [13], [14]. These parameters highly affect the classification performances. In order to propose a method that can effectively utilize daily life applications these parameters must be taken into account carefully. Due to this, in this paper, we aimed to investigate an EEG-based eye state prediction method using k-NN that is based on different parameters. Experiments were carried out on real-world EEG Eye State Data set which is intended to find appropriate approaches for eye state prediction. We also compared the classification performances of different distance metrics and

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number of nearest neighbours to determine best parameters.

The paper is organized as follows: Sec. 2 describes the EEG Eye State data set and k-NN algorithm. In Sec. 3, the design and implementation of method are explained, and the results are presented. Lastly, a conclusion is given in Sec. 4.

## II. Materials and Methods

### A. EEG Eye State Data Set

In this paper, EEG Eye State Data set which is available via the UCI Machine Learning repository [15] was used for the purpose of training and testing. The data set was donated by Roesler [3] and contains multivariate, sequential and time-series real-world EEG data. Experiments were carried out using this data set which aims to represent users' eye state, or in other words, whether the users' eyes are opened or closed.

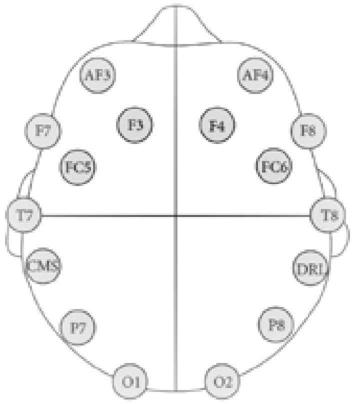


Figure 1: Emotiv EEG Neuroheadset sensor positions according to the international 10-20 system (taken from [5])

EEG Eye State Data set contains one continuous trial EEG measurement lasted 117 seconds and acquired while user's eyes are in open or closed state. The data was recorded using the Emotiv EEG Neuroheadset [16], and simultaneously eye state was recorded by a camera. The following electrode sites were used according to the international 10-20 system [3]: AF3-4; F3-4; F7-8; FC5-6; T7-8; P7-8; and O1-2 as shown in Fig. 1 (for abbreviations and details of electrodes, see [17]). After obtaining data, using video camera records, data was labelled as "1" that refers to the completely closed eye state and "0" to the partially or fully open eye states. The whole data set contains 14.980 instances and 15 attributes. In this definition, the 14 numerical values are the attributes obtained from electrodes and the last one is the class label attribute indicating the eye states [3], [18]. In the data preparation stage, 3 instances which have transmission errors were eliminated and 14977 instances were used as the complete data set. All of these instances were arranged in chronological order with the first measured value at the top of the data [3], [15]. The summary of the data set is as shown in Table I.

### B. K-Nearest Neighbour Algorithm

K-Nearest Neighbour Algorithm (k-NN) is one of the most simple learning algorithm. It is an instance based supervised

Table I: Description of EEG Eye State Data Set

| **Instances** | |
|---|---|
| Total no. of instances | 14977 |
| No. of open-eye instances | 8255 (55.12%) |
| No. of closed-eye instances | 6722 (44.88%) |
| **Attributes** | |
| No. of feature attributes | 14 (numerical) |
| Class label attribute | 1 (numerical 0 or 1) |

learning method and widely used in data mining, pattern recognition for classification and regression [12]. In this algorithm, learning model is constructed based on initial class labels in training and learning is done only if there is a request for testing. In other words, this method does not explicitly train a model and can be thought as a memory-based learning algorithm [13], [14].

In this method, all of the similarity measures between a test and label-known training set instances are calculated first. Then, test instance's category is determined via the majority of $k$ most similar training instances which belong to a certain category [12], [14]. Let a sample instance is described by an $\langle attr\_vect(x), c(x)\rangle$ vector. In this notation, $attr\_vec(x)$ denotes the corresponding $\langle a_1(x), a_2(x), \dots a_\varphi(x)\rangle$ attribute (feature) vector where $a_r(x)$ is the value of the $r$-th attribute of the instance, $\varphi$ is the length of the attribute vector, and, $c(x)$ denotes the class label for an instance $x$. When euclidean distance is used to find the similarity measure between the $x_i$ attribute vector in training set and $x_t$ attribute vector in test (query) set, the distance-based similarity measure $d(x_i, x_t)$ (as seen in (1)) can be defined as follow [13], [14]:

$$d(x_t, x_i) = \sqrt{\sum_{r=1}^{\varphi} (a_r(x_i) - a_r(x_t))^2} \quad (1)$$

In this method, the training and testing stages are performed as follows: In training, all distance-based similarity measures between the $t$-th test instance and every $i = 1, 2, \dots, I$. training instances are calculated and final $I$ number of $d(x_i, x_t)$ distances are stored. In testing, for a given $x_t$ test instance, a test instance's category $c(x_t)$ is determined using the majority of $k$ most nearest neighbours as defined in (2) below [13], [14]. In this equation, k-NN assigns the test instance to the most frequently occurring class of its $k$ neighbours using the majority voting rule [19]. In this notation, $C$ is a set of n numbered $\{c_1, c_2, \dots, c_n\}$ classes and $c(y_i)$ is the $i$-th neighbour's class label. $\{y_1, y_2, \dots, y_k\}$ are the $k$ nearest neighbours of $x_t$ test data from the whole training set. $\delta(c, c(y_i)) = 1$ if $c = c(y_i)$ and $\delta(c, c(y_i)) = 0$ otherwise [14], [19].

$$c(x_t) = \underset{c \in C}{\text{argmax}} \sum_{i=1}^{k} \delta(c, c(y_i)) \quad (2)$$

Distance-based similarity metrics can make large variations in classification performance, time and space complexity [20], [21]. k-NN is an instance-based learning method and a comparison must be made under varied distance metrics for every problem. Some of the distance metrics investigated in this paper are as defined in (3), (4), (5), (6) and (7). In this notation, $q_t$ is the $(1 \times \varphi)$-sized $t$-th test instance attribute vector in test set, $x_i$ is the $(1 \times \varphi)$-sized $i$-th training instance attribute vector in training set , $d(q_t, x_i)$ is the distance between test and training instances, and $j$ represents the $j$-th entry in $(1 \times \varphi)$-sized attribute vector.

1) *Minkowski Distance*: It is a generalized distance metric and equal to the euclidean distance when $p = 2$ and Manhattan distance when $p = 1$. Larger values of p can affect the accuracy of the classification because of changing weights of the attributes [21], [22].

$$d(q_t, x_i) = \left( \sum_{j=1}^{d} |q_{tj} - x_{ij}|^p \right)^{1/p} \tag{3}$$

2) *Manhattan (city block) distance*: Represents the sum of absolute difference of attribute vectors. Distance value is zero for identical vectors which have maximum similarity, on the contrary, high for points which have low similarity [23].

$$d(q_t, x_i) = \sum_{i=1}^{d} |q_{tj} - x_{ij}| \tag{4}$$

3) *Chebychev distance:* It can be thought as a variant of Minkowski distance where $p = \infty$ and represents the distance information using only the most varied attribute variable [21], [24].

$$d(q_t, x_i) = \max_{j=1}^{d} \{|q_{tj} - x_{ij}|\} \tag{5}$$

4) *Cosine distance:* It is computed from one minus the cosine of the included angle between two attribute vectors [21], [25].

$$d(q_t, x_i) = \left( 1 - \frac{q_t {x'}_i}{\sqrt{(q_t {q'}_t)(x_i {x'}_i)}} \right) \tag{6}$$

5) *Mahalanobis distance:* It is a measure between two attribute vectors in the space defined by relevant features where $C$ is positive definite covariance matrix [21], [26].

$$d(q_t, x_i)^2 = (q_t - x_i) C^{-1} (q_t - x_i)' \tag{7}$$

Other than these distance metrics, we also investigated the following distance metrics' performances: (6) correlation, (7) standardized (std) euclidean and (8) spearman. Details of these metrics can be found in [21], [25].

## III. Experimental Results

Different distance metrics and number of neighbour parameters must be analysed and correctly interpreted in order to propose a k-NN based approach. Due to this, we performed an EEG-based eye state prediction using k-NN algorithm that is based on different distance metrics and number of neighbour parameters. We carried out experiments on real-world EEG Eye State Data set which is intended to find appropriate approaches for eye state prediction. The classification performances were evaluated for accuracy measurement using the ten-fold leave-one-out cross-validation technique and the optimum k value is searched in the range of $[1, 101]$.

Classification accuracies with different distance metrics and best $k$ number of neighbour values (shown in parentheses) are presented in Table II below. The mean classification accuracies were calculated using the correctness rate which is the percentage of correctly estimated samples divided by total number of test samples. k-NN algorithm is evaluated for different $k$ and the associated $k$ values are as given in parentheses for every accuracy rate. Learning and testing phases were carried out using Matlab software package and the experiments were performed using Intel Core i7 3.4 GHz with 8 GB RAM.

As can be seen from Table II, cosine metric achieved better results compared to others (with mean accuracy of 93.5%) and frequently used euclidean metric achieved lower results than cosine. The poorest results were observed with Spearman (with mean accuracy of 57.1%). All these results indicate that different parameters highly affect the performance.

The conclusions for EEG Eye State Data set were also compared with state-of-the-art. The results were summarized in terms of the percentage classification accuracies. Rösler et al. [3] predicted eye state with an accuracy of more than 97% using ten-fold cross-validation. Hamilton et al. [1] obtained accuracy of 95.1% with a rotational forest algorithm that implements random forests as its base classifiers. Similarly, they achieved 97.2% accuracy with the J48 trees as its base classifiers and is boosted by adaptive boosting (ada(RJ48F)). Each of these models used in [1] was assessed using 10-fold cross-validation. Wang et al. [5] used a time-series classification approach based on IAL with six different approaches and obtained classification error rate over 27.39%. Sabanci et al. [6] achieved highest classification rate of 84.0587% with k-NN for 3 neighbour values and euclidean distance metric. In their method [6], multi-layer perceptron neural networks classifier showed less accurate results (∼54%) compared to k-NN. Narejo et al. [8] employed Deep Belief Network and Stacked AutoEncoders as classifier and presented an error rate of 1.1% on the test set bearing accuracy of 98.9%. In recent years, Hua et al. obtained 88.10±13.43 accuracy when randomly chosen 5% portion of data set is evaluated using L1LTSVM (with ten-fold cross-validation) [9]. Zhou et al. reached the optimal performance of 99.8% using the information of 5 channels and frequency components of delta waves and alpha waves [10]. Hodge and Austin achieved 55.8% accuracy with Gradient Boosting Machine and 79.5% with k-NN [11].

In this paper, compared to [1], [3], [8], [10] less accurate result were obtained. However, only [3] used 10-fold cross-validation as in our work so that a direct comparison can be made only with this work. The aim of this paper is to show the affects of different distance metrics' and number of neighbour parameters' on classification accuracy. So, compared to [6], [11] which used k-NN based on euclidean distance metric, a higher mean classification accuracy was achieved with cosine distance. This is due to selecting appropriate parameters. It can be seen from Table II that only Spearman and standard euclidean metric are less accurate. Similarly, it can be understood that, euclidean distance obtained more accurate results compared to [6], [11] thanks to using more appropriate k parameter. Also, the proposed k-NN method achieved more accurate results than [5] and [9]. [5] employed IAL based on

Table II: Classification Accuracies of Eye State Prediction for EEG Eye State Data set

| Method | Fold-1 | Fold-2 | Fold-3 | Fold-4 | Fold-5 | Fold-6 | Fold-7 | Fold-8 | Fold-9 | Fold-10 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Manhattan* | 97,5 (05) | 93,3 (29) | 92,0 (35) | 92,9 (33) | 91,9 (40) | 90,0 (75) | 92,3 (28) | 90,3 (49) | 90,1 (57) | 92,8 (37) | 92,3 |
| *Chebychev* | 89,0 (61) | 90,3 (86) | 91,5 (35) | 89,2 (73) | 90,4 (49) | 88,6 (88) | 89,4 (70) | 89,9 (63) | 96,5(07) | 94,3 (17) | 90,9 |
| *Correlation* | 96,5 (05) | 89,3 (98) | 90,3 (54) | 89,2 (76) | 89,7 (73) | 96,1 (10) | 93,3 (23) | 96,3 (02) | 89,2 (81) | 90,5 (61) | 92,0 |
| *Cosine* | 89,8 (75) | 95,9 (12) | 91,1 (59) | 92,1 (37) | 90,8 (96) | 91,4 (80) | 94,9 (12) | 94,9 (18) | 96,7 (12) | 97,9 (03) | ***93,5*** |
| *Euclidean* | 91,3 (44) | 91,4 (65) | 88,2 (94) | 92,3 (47) | 96,5 (05) | ***98,1*** (04) | 90,3 (63) | 89,6 (75) | 89,6 (60) | 94,8 (21) | 92,2 |
| *Mahalanobis* | 92,3 (25) | 90,7 (93) | 90,7 (71) | 91,1 (56) | 89,1 (85) | 91,2 (62) | 90,1 (94) | 92,5 (25) | 93,7 (30) | 91,5(42) | 91,3 |
| *Minkowski* | 88,4 (74) | 92,1 (51) | 87,9 (99) | 90,7 (60) | 89,8 (80) | 97,9 (05) | 94,0 (11) | 90,9 (53) | 96,5 (02) | 91,8 (53) | 92,0 |
| *Std Euclidean* | 78,4 (57) | 86,7 (01) | 78,9 (57) | 80,6 (29) | 77,6 (86) | 79,2 (91) | 91,9 (01) | 80,3 (23) | 88,0 (25) | 79,5 (42) | 82,1 |
| *Spearman* | 60,4 (58) | 55,0 (10) | 59,6 (44) | 58,4 (38) | 57,7 (26) | 60,3 (40) | 54,7 (17) | 57,7 (37) | 59,7 (54) | 47,6 (03) | ***57,1*** |

neural networks where all the patterns were partitioned for training, validation, and testing with the divisions of 50%, 25%, and 25%, respectively. [9] used PTSVM, RPTSVM, L1LTSVM, L1LPTSVM methods with the standard tenfold cross-validation methodology.

## IV. CONCLUSION

In this paper, we aimed to compare the classification performance of different distance metrics and number of neighbour parameters of k-NN algorithm for eye state prediction. The results demonstrated that different distance metrics highly affect the performance of classification accuracy of k-NN and these parameters must be taken into consideration for more effective learning and classification.

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