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MULTICLASS CLASSIFICATION OF SOUND HEALING WITH K-NEAREST NEIGHBOR ALGORITHM

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ABSTRACT

Sound healing can be described to the practice of sound vibrations in an individual body directly to bring about a state of harmony and healing. In many ancient countries, sound healing was used as a part of medicine and healing ritual. In this paper, we propose K-Nearest Neighbors (KNN) method to categorize the type of sound healing. The result of this paper could be used to differentiate between sound healing and non-healing sound. Acoustic Sound for Wellbeing (ASW) such as Drums, Gongs, Chimes and Singing Bowls are used as dataset for KNN algorithm. The KNN algorithm is applied to classify the ASW dataset in multi class classification tasks. In our model, KNN gave the best performance measurement for 2 Classes classification. The value of accuracy, precision and recall are higher than 0,87. Meanwhile, the confusion matrix for 3 Classes presented the lowest point from all experimental setting. Furthermore, confusion matrix for 4 Classes showed some anomalies.

Key words: *Sound Healing, Classification method, K-Nearest Neighbor.*

INTRODUCTION

In our environment, the soundscape is an aspect that often failed to notice. Moreover, it is becoming more chaotic in urban area [1] leading to the health complaints for those people in close contact [2]. Vehicles, construction works, loud talks and any other sound can result in conditions such as insomnia, chronic stress and hearing loss [3]. By Definition, The Soundscape is all the audio we hear at a given moment [4]. The soundscape, can involve both acoustic and synthetic-based audio, arranged to load an environment with a particular intention, e.g., for environments which excessive background noise is causing task-distraction.

In spite of the urban Soundscape effect, the ability of sound as healing (sound healing) is well-known [5]. Sound healing can be explained as the practice of sound vibrations to an individual body directly to bring about a state of harmony and healing [6]. In many Countries, sound and healing went together. The Chinese character for music is also the character for medicine. The Indigenous Americans and Africans used singing and chanting as a part of their healing ritual. In ancient Greece, music was used to ease stress, promote sleep, and soothe pain [7]. In term of therapy, a systematic review published in 2011 showed that sound healing as a music intervention may have beneficial effects on pain, mood, anxiety and the quality of life in people with cancer [8]. The Journal of the American Medical Association published in 2013 found that children who listened to music during routine procedure while admitted to the emergency department showed less distress and reported lower pain scores than those who did not listen to music [9]. Another study was evaluated the positive effect of exposure to Al-Quran recitation as a healing on hela cells. The audio murottal Al-Quran provide cytotoxic effects and can be recommended for supporting therapy in treatment of cancer [10].

Acoustic instrumentation is common in many cultures around the world. The application of gongs and drums in altering states of consciousness is prevalent [11]. The meditation Gongs are traditionally known in several places including Indonesia and Burma. It was usually used to increase mental awareness and mental relaxation [12]. Meanwhile the Tibetan singing bowl is also well known as one of the most healing instruments. It is the instrument that usually made from seven holy metal producing a rich and vibrant oscillation when a mallet is continually played around the bowls rim [13].

Data mining is the process of finding information from large databases using several scientific fields that unify techniques from machine learning, pattern recognition, statistics, databases, and visualizations [14]. Moreover, data mining can also be used in several other fields of science such as sound healing. Classification is a datamining function that can be used to assign items in a collection to target categories or classes. the purpose of classification is to predict the target class accurately in dataset. Classification of sound healing might use technology, particularly machine learning, to more easily classify the sound that can be used as a healing.

In this paper, we propose K-Nearest Neighbors (KNN) method to classify the type of sound healing. Acoustic Sound for Wellbeing (ASW) will be used as dataset for KNN algorithm [15]. ASW consist of 88+hrs of audio data, which has been collected form YouTube. ASW dataset consist of several acoustic sound such as Drums, Gongs, Chimes and Singing Bowls. The KNN algorithm will be applied to classify The ASW dataset in multi class classification task. At the end, this paper could be used to differentiate between sound healing and non-healing sound.

The rest of the paper is organized as follows: section 2 introduced a related works, ASW dataset and describes the principle of KNN classifier. Section 3 shows the implementation procedure of ASW dataset in multi class classification tasks and the proposed KNN. Section 4 displays experimental simulation. Finally, conclusions and future work plans are given in Section 5.

RELATED WORKS & THEORY OF KNN

A. Related Works

Over the years, many studies have been proposed to solve classification problem. For instance, the authors [16] used KNN to classify lower back pain into two categories namely normal and abnormal back pain class with 12 Range of Motion (ROM) attributes as the proposed method. The study classified both class using replace missing value and selected attribute method as a preprocessing data. The performance of KNN algorithm is an adequate in terms of accuracy, recall, precision and RMSE with each value of Accuracy about 91.94%, Recall 88.81%, Precision 92.61%. Meanwhile, author [17] suggested KNN algorithm for classification of disk hernia and spondylolisthesis in vertebral column. This research used two from three Classes (Disk Hernia, Spondylolisthesis and Normal) in dataset vertebral column. KNN algorithm is applied to classify disk hernia and spondylolisthesis in vertebral column. The data were then classified into two different but related classification tasks: “normal” and “abnormal”. The results showed that the accuracy of K-NN classifier was 83%.

The authors [18] presented detection of internet traffic using KNN and naïve bayes algorithm. The analysis conducted using statistical features such as interpacket arrival time, time to live and number of packets. The Experiments is conducted using UNSW-NB dataset to obtain highest accuracy in classifying internet traffic on basis of transaction protocol. The results show that KNN algorithm gives accuracy of 85% whereas maximum accuracy is achieved using Naïve Bayes algorithm is 54%.

B. K-Nearest Neighbors Algorithm

KNN Classifier is algorithm that can be used to classify unlabeled data by assigning them to the class that have the most similar labeled example. Variables of Training dan testing dataset are based from their characteristics data [19]. KNN is also known as a supervised learning algorithm. It works on a primary assumption that data points of similar Classes are closer to each other. Supposed there is a classification problem and you have to identify whether a given data point is of class A or class B. For example, grain, fruit and vegetables can be differentiated by their sweetness and crunchiness. To display them in 2 dimensional plot, two characteristics are used. However, in real application there are many variables of characteristics that can be used as predictor. Basically, fruit is much more sweet than vegetables. Meanwhile grain is neither sweet nor crunchy. KNN can categorize those classes based on their characteristics. For instance, KNN algorithm already choose five nearest food as a neighbor for tomatoes (Figure 1). They are grape, rice, carrot, spinach and lettuce. Because the most votes won by vegetables, tomato is assigned to vegetables. This concept makes KNN is easy to understand.

In the above example, two important concept are needed. First, we need to calculate the distance between sweet potatoes and other food. By default, KNN algorithm used euclidean distance which can be computed using equation one.

$$D(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \quad (1)$$

where p and q are variable to be compared with n characteristics. Another method also can be used to calculate distance such as Manhattan distance [20,21]

Another concept of KNN that must be taken into account is the parameter of K. This parameter is responsible to decide how many neighbors will be chosen for KNN algorithm. The more appropriate choice of K, the more significant impact for KNN classification. In one hand, random error can be reduced using a large K. in another hand, important pattern from small data is more suitable using a small K. There is no formula to get the best k. The important key to get best k value is to strike balance between overfitting and underfitting [22]. Some author recommended to set k equal to square root of the number of observations in the training dataset [23].

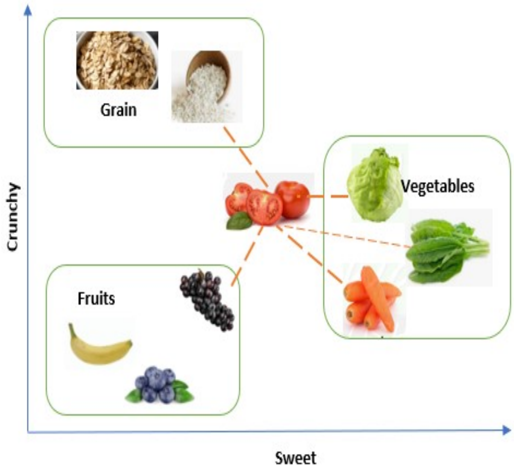

Figure 1. Illustration of How K-Nearest Neighbors' algorithm works

C. Confusion Matrix for Multiclass Classification models

A Confusion matrix is a tabular way to depict our classification models. Each entry in confusion matrix indicates number of prediction made by model. A number of correct and incorrect predictions are summarized in confusion matrix with count values for each class. Each row in a confusion matrix represents an actual class of dataset, meanwhile each column represents a predicted class which had been predicted by an algorithm.

In binary classification problem, confusion matrix classified the classes into correct or incorrect. However, it becomes difficult if we try to classify multiclass classification models. For instance, let's consider we have 3 classes in our multi-class classification problem contains grain, fruit and vegetable. Unlike binary that only have correct or incorrect classes, multi-class tread confusion matrix differently. In order to get accuracy, recall and precision. we need to categorize each sample into 1 of N different classes. The illustration of multiclass confusion matrix can be seen in Figure 2.

		Predicted Class				
		X_1	X_2	X_3	X_4	Recall
Actual Class	X_1	7	0	0	0	1.00
	X_2	3	8	1	2	0.62
	X_3	2	2	9	2	0.56
	X_4	1	0	2	7	0.7
Precision		0.54	0.8	0.69	0.6	

Figure 2. Illustration of Multiclass Confusion Matrix

Construction matrix for multi-class classification is constructed where the number of accurate classifications for each class is revealed by diagonal elements of the matrix, while off-diagonal elements represent miss-classifications recall and precision for each class can be computed separately from the raw of confusion matrix. Recall for each class is calculated by dividing a diagonal element of the matrix by sum of all element in the row. Meanwhile, precision of each class can be derived by dividing a diagonal element of the confusion matrix with the sum of all elements in the corresponding column [24].

MATERIAL & METHODOLOGY

In this section, we explained the materials and methods used in this paper. Figure 3 shows the dataset of ASW. Data is divided into 80% for both training and validation data and the rest 20% for testing data. Before model was created, the data was tested 10 times using the 10-fold-cross validation technique which is divide the data as many as 10 partitions.

A. Data Processing

The ASW dataset is derived from The Acoustic Sounds for Wellbeing Dataset. Authors used 2.200 file (wav) of sound healing with 4 different classes. The duration of each datum is four minutes voice that considered as a sound healing. Since the original data was in WAV format, there were a series of processing steps which applied in order to make the ASW data usable for further computational analysis. Hence, we applied time series in time domain and Fast Fourier Transform (FFT) in frequency domain to convert the audio (WAV) data. Furthermore, to understand the characteristic of ASW data, we used statistic variable such as mean, median, standard deviation and several other Attribute that can be seen in Table 1.

Table 1. Dataset Attribute

	Attribute
Applied in Time and Frequency Domain	Mean
	Median
	Standard Deviation
	Minimum Value
	Maximum Value
	Quartile 1
	Quartile 3
	Interquartile Range

All variable in table 1 was used for both time series and FFT data. Therefore, we have 16 variables that can be used for computational analysis in KNN.

B. The Classes Dataset and Experimental Setting

In ASW dataset, we have 4 classes to be classified. Those classes are Drumming, Singing-Bowl, Gong and wind-Chimes. Table 2 shows Independent partition for Training, validation and Testing data in class distribution of ASW dataset.

As we mentioned in 3.1, the ASW data consists of 2200 sound healing which is divided into a balance 550 data for each class. In order to get the best confusion matrix, K-Fold Cross validation was conducted using training and validation data in a random way. Meanwhile, the last 20% ASW is used for testing data.

Table 2. Independent Partition of Dataset

Type of Sound	Number of Dataset			
	Train	Validate	Test	∑
Singing Bowl	396	44	110	550
Gong	396	44	110	550
Drum	396	44	110	550
Chimes	396	44	110	550
∑	1.584	176	440	**2.200**

In Addition to dataset attribute, another experimental setting is presented. Figure 3 shows detailed information of our experimental setup. based on Figure 3, we can observe that both training and validation data were used in 10-K Fold Cross validation process. Otherwise, the testing data is stored for prediction analysis. In terms of cross validation process, the data was tested 10 times in order to get optimal K-value for KNN data testing.

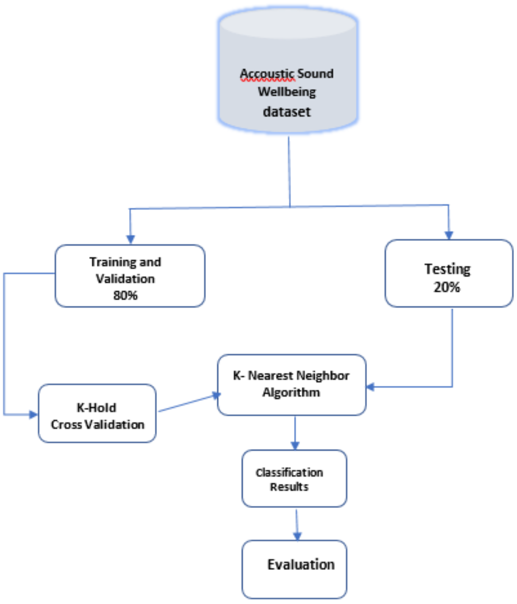

Figure 3. Illustration of Multiclass Confusion Matrix

Due to analysis of the classes in ASW dataset, we constructed a series of baseline classification using three experiment setting:

1). **2 Classes:** Gong (gon) Vs Singing Bowl (sb). We used both classes for first experiment due to their similarity of these two instruments such as the common use of materials (i.e.,often precious metal). This combination is used to take a closer look at the difference in the data sources for these two classes

2). **3 Classes:** Chimes (chi), Drum (dru), Gong. opposed to the 2 classes task, we took this combination because of their intrinsic acoustic difference.

3). **4 Classes:** Chimes, Drum, Gong, Singing bowl. In this experiment we used combination of the ASW dataset together to see the performance of KNN classification algorithm.

C. Performance Evaluation

Evaluation of classification model is extremely important due to limitation of each model. In order to obtain performance evaluation of KNN, we used confusion matrix to visualize the different output and to calculate Precision, Recall and Accuracy.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

(TP= True Positive, TN= True Negative, FP= False Positive and FN= False Negative).

C. Classification Approach

For our experiments, we use a K-Nearest Neighbor (KNN) with Pandas and NumPy library in Python programming. During the development phase, we trained a series of KNN models using K parameter (K=3 to K=21) to get the best number of neighbors that will be used for testing dataset.

RESULT AND DISCUSSION

To give a performance evaluation of the proposed method, we measure the accuracy, precision and recall. as we explained in 3.2, 10-K Fold Cross validation process is conducted for training and validation data to get the best K value for data testing in KNN.

The line graph in Figure 4 illustrate the confusion matrix of 2 Classes in term of Accuracy, Precision and recall from K=3 to K=21. Furthermore, The K value is generally an odd number to create deciding factor.

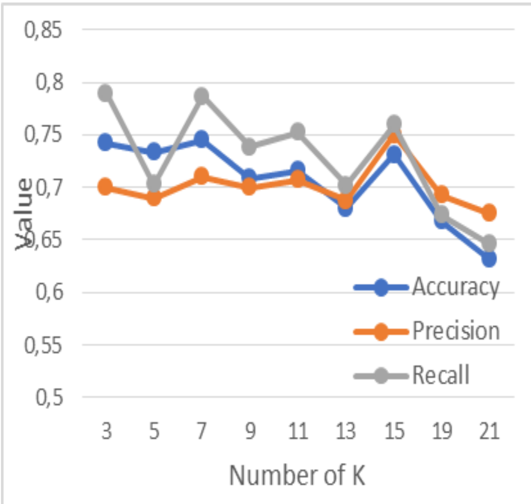

Figure 4. Confusion matrix of 2 Classes

It is clear that the confusion matrix of all three line experienced a downward trend and fluctuated over the K value. Furthermore, the recall of KNN algorithm remain higher than the other performance measurement. In reference to the K value, K=3 consistently give a better result than the other value.

The line graph in Figure 5 shows performance measurement of confusion matrix for 3 Classes. Similar to the Figure 4, the effectiveness of the model is measured to give a visualization of the performance of an algorithm between K=3 and K=21. The K value each model is also generally an odd number to create deciding factor.

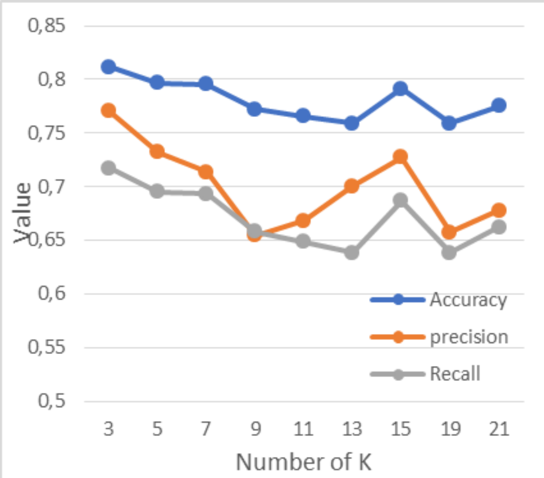

Figure 5. Confusion matrix of 3 Classes

Overall, the confusion matrix of all three performances measurement experienced a decreased over the K value. It is different from confusion matrix of 2 Classes in figure 2, The Accuracy in 3 Classes of KNN algorithm took the highest value of performance measurement. in term of the K value, K=3 create a better result than any other value.

The line graph in Figure 6 is also give an information about performance measurement of confusion matrix for 4 Classes from K=3 to K=21. Likewise in previous Figure, evaluation of confusion matrix is conducted to get the best K value that can be used in testing data.

The confusion matrix of all three performances measurement declined over the K value. Similar in the figure 5, the accuracy in 4 Classes of KNN algorithm took the highest value of performance measurement. In reference to the K value, value of K=5 gave a great result than the other value.

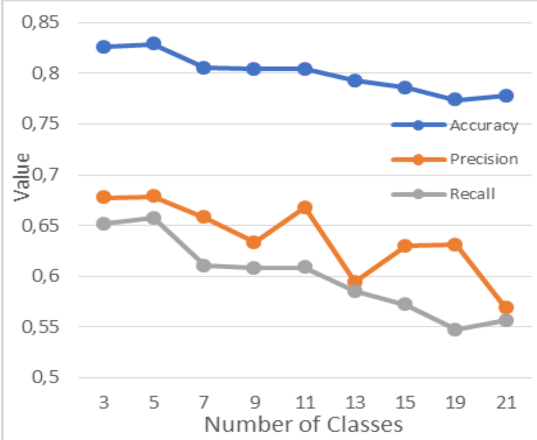

Figure 6. Confusion matrix of 4 Classes

Regarding training and validation process, we concluded that the best K of each Classes have a different value. Table 3 shows the K value paired with its own Classes.

Table 3. Dataset Attribute

Number of Classes	The K value
2	7
3	3
4	5

The result of K value from Training and validation process is used for next measurement. As we explained in Table 2, 20% of ASW data is used for Testing data.

The bar chart in Figure 7 provides information about the value of confusion matrix for multiclass classification using KNN algorithm from 2 to 4 number of class.

Overall, the confusion matrix of all performance measurement showed some fluctuation trend throughout all classes. K value for K=7 gave the best performances in 2 Classes, meanwhile 3 Classes with K=3 took the lowest point regarding its performance in confusion matrix.

The accuracy of Confusion matrix was about 0.89 for 2 classes, being higher 0.013 than recall and 0.19 lower than precision at the same classes. furthermore, the accuracy slightly fluctuated in the 3 and 4 classes respectively. It can be figured out that the ratio of correctly predicted observation for all different scenario is relevant. Since we used a symmetric dataset, the accuracy of our model by using KNN is an ideal for ASW dataset.

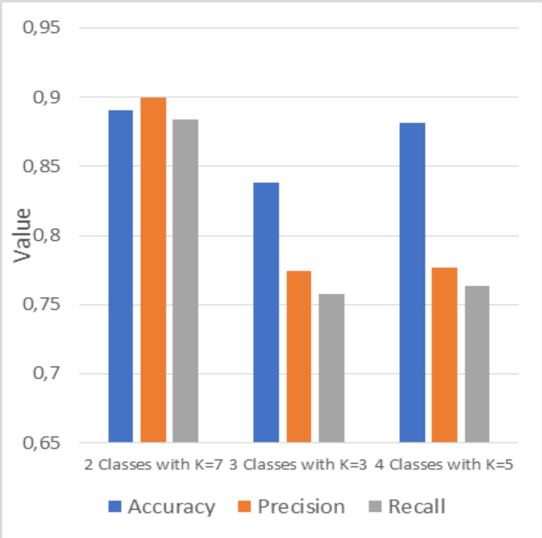

Figure 7. Confusion matrix of Testing Data

The recall performance measurement of confusion matrix was about 0.883 for 2 Classes. It was the highest value of recall performance measurement from all classes, however the recall value significantly decreased for 3 Classes to about 0.7575 and rose steadily to about 0.7636 for 4 Classes.

The recall performance examined very well for two Classes. It means that the ratio of correctly predicted positive observations in actual class is adequate for two Classes. Yet the recall performances significantly decreased for 3 Classes and rose steady for the last 4 Classes. Therefore, it can be explained that the number of classes can affect the ratio of data in actual class.

The precision of confusion matrix also showed some fluctuations over all Classes. at the beginning, the precision was about 0.9 for 2 Classes. It is the highest value from all confusion matrix. However, the value dramatically decreased 0.126 point to 0.774 for 3 Classes and rose steadily 0.003 to 0.777 for 4 Classes. in another words, the proportion of relevant results in the list of all returned search for 2 Classes give the best value in KNN algorithm.

CONCLUSION

This paper presented the implementation of K-Nearest Neighbor algorithm to classify 4 classes in ASW dataset. The 10-Fold Cross validation technique used to get the optimal K-value for data testing. In addition, to evaluate the performances of our model we also used confusion matrix as a visualization of precision, recall and accuracy.

Using different K-value, KNN gave the best performance measurement for 2 Classes classification. The value of Accuracy, Precision and recall are higher than 0.87. It can be concluded that the data points of similar classes (Gong and Singing Bowl) are closer to each other. Meanwhile, the confusion matrix for 3 Classes (Chimes, Drum and Gong) presented the lowest point from all experimental setting. The value of all measurement in 3 classes significantly decreased. The lowest point touched 0.7575 for the recall. It is different from the recall value for 2 classes that reached 0.8839 point.

Assessment of how the performance measurement in 3 Classes significantly decreased is affected by the outliers of data points in each class. The more outlier data points in each class, the less value of confusion matrix in each class. Furthermore, performance evaluation of confusion matrix for 4 Classes (Chimes, Drum, Gong and Singing bowl) showed some anomalies. Even though the number of classes increased, the value of confusion matrix rose steadily. The only reason why such a thing occurred is that data point of singing bowl's class is so closer to each other. It makes the accuracy of confusion matrix grow significantly though the number of classes expanded.

At the end, the result of this paper could be used to differentiate between sound healing and non-healing sound. Using feature extraction concept, other kinds of sound can be simply assigned as a new sound healing.

FUTURE WORK

In the future work it is planned to implement the Pseudo Nearest Neighbor (PNN) to overcome the outliers problem. Also, feature selection will be implemented to reduce a number of variables in ASW dataset to reduce computational problem and increased its performances.

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