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A preliminary study of artificial learning algorithms for hearing loss detection in children

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Abstract: This article presents a study carried out applying kNN to a dataset of Brainstem Auditory Evoked Potentials for a timely detection of hearing loss in children. Also a comparative analysis of the MLP and kNN artificial learning algorithms is carried out. The precision between one and the other is evaluated, in order to identify which one is better to solve this kind of problem.

Keywords: Brainstem Auditory Evoked Potential (BAEP), k Nearest Neighbor (kNN), Multilayer Perceptron (MLP).

1. Introduction

Hearing impairment can negatively affect multiple aspects of a person's life when not addressed or identified in a timely manner. Hearing deprivation can diminish the quality of life and access to oral communication, and even hinder the development of speech in children contributing to other forms of impairments. Untreated deafness in early life is associated with poor literacy, as well as reduced employment opportunities later in life [1], [2]. Moreover, children with hearing disabilities are at a higher risk of socioemotional problems [3], making it a priority to identify the type of condition in a timely manner.

Hearing loss in children is a significant concern that can have long-term effects on their development. Detecting hearing loss early is crucial for effective intervention. Machine learning algorithms, such as Multi-Layer Perceptron (MLP) and k-Nearest Neighbors (kNN), have shown promise in various medical applications, including the detection of hearing loss using Brainstem Auditory Evoked Potentials (BAEP) data.

There are different types of disabilities, each with its own characteristics. In this project, we are studying hearing impairment and hearing loss [2]. Over time, technological tools have been aids in the field of medicine. These tools tend to be ideal candidates for close interaction with branches of Artificial Intelligence. Machine Learning can learn from a set of data and carry out prediction processes, facilitating clinical diagnosis [4].

In a previous study, Mosqueda et al. [5] used the Multilayer Perceptron (MLP) algorithm as a tool to interpret BAEP diagnoses. From that study, 11 classes were derived. On the other hand, the k-Nearest Neighbors algorithm (kNN) is simple, interpretable, and surprisingly robust for multi-class classification and regression. This method is very intuitive and has shown effectiveness in the domain of anomalydetection [9].

In this study, a kNN model has been created, and its accuracy is compared against the accuracy obtained by a MLP model. The scenario described in [5] is also used here to identify which one produces better results. The related work, methodology, and results of this research are presented below.

2. Related Work

Electrical response audiometry is a method that quantitatively and qualitatively records the activity generated by the central nervous system. This response is called Brainstem Auditory Evoked Potential (BAEP), which corresponds to voltage fluctuations over time generated in the nervous system in response to an appropriate stimulus. The interpretation of BAEP requires observation by an expert who can distinguish electrical traces of different waves that compose the stages of the auditory pathway. It is mainly used with patients who cannot express themselves verbally [6]. Galarza Parra asserts in their research that auditory diagnosis through BAEP is manually performed by specialists. They propose a method based on symbols and conclude that these results approach manual methods but with less implementation time [7].

In [8] the author explains that the auditory dysfunction is one of the most common deficiencies in newborns. Early auditory screening allows for adjustments to cognitive, speech, and language development. Within the first year of life, direct observation by a doctor and parental recognition have not been significantly successful. Sriraam [8] presents a pilot study on hearing loss detection using electroencephalography (EEG) signals as a key indicator. The effect of BAEP is exploited in EEG by introducing an external stimulus into the subject's auditory channel. Neural network models are configured by varying hidden neurons, and their performance is evaluated in terms of specificity, sensitivity, and classification accuracy as a pilot test for introducing auditory test readings automation.

Absolute values of BAEP, latencies, and amplitudes are the functions used by doctors to assess the severity of various hearing loss conditions. As mentioned, in the study by Mosqueda et al. [5], a multilayer perceptron (MLP) was used for hearing loss detection, but it was not compared against other algorithms. The MLP algorithm classifies the extracted data into eleven groups and provides a four-bit code as output according to the conditions of each group.

The proposed MLP architecture consists of 5 neurons in the input layer to encode a vector that includes age values, latencies, amplitudes, and wavelength lengths. The number of neurons in the hidden layer was chosen based on an experimental test that involved varying the neurons in this hidden layer with 5 neurons per iteration until reaching 25 neurons within a single hidden layer. The output layer consists of 4 neurons. The accuracy for each iteration in the hidden layer ranged from 96.19% to 97.39% [5].

3. Materials and Methods

For this study, preliminary research was reviewed, such as the works of N. Sriraam [8] and Mosqueda et al. [5], both mentioned previously and related to the detection of hearing loss through automated tools for BAEP diagnosis. The next step was to select a classification algorithm in this case, kNN, as it is a popular model in statistics and ranks in the top 10 of the best algorithms in data mining [9] to train, utilize, evaluate, and compare it with an algorithm already used for the same purpose.

Due to the difficulty of obtaining real BAEP test data due to patient confidentiality issues, synthetic datasets generated by authors of previous articles [5] were utilized. The kNN algorithm was trained using these synthetic datasets, and its accuracy was compared with that obtained from MLP to observe cases where each algorithm achieves higher accuracy, which one is more efficient, and in which scenarios one we choose between the two.

Table 1. Classification of auditory diagnoses according to the MLP model [5].

Classification	Diagnosis
0	Normal values
1	Prolonged latency in wave I
2	Prolonged latency between peaks I-III
3	Prolonged latency between peaks III-V
4	Prolonged latency between peaks IV-V and III-V
5	Absent wave III with presence of I and V
6	Absent wave V with presence of I and III
7	Absent wave V with normal values of I and III
8	Absence of waves
9	Excessive amplitude in V/I
10	Absence of waves except for I and possibly II

3.1 Synthetic Data

To implement a classification framework for BAEP signals based on an MLP approach, a dataset for training and testing is required. Unfortunately, data collection represents obstacles, such as the availability of relevant samples or legal restrictions on patient data collection and handling. A temporary solution to this issue has been generating synthetic data for training and testing [5].

Once these amplitudes are obtained, latencies are extracted using the temporal differences between different peaks or waves (IV, I-III, III-V). The generated dataset simulates a time-domain-sampled BAEP signal with the aim of training and testing algorithms. Subsequently, they were used by a Multilayer Perceptron, where a classification was assigned to identify the type of problem the patient might have, as shown in Table 1.

As previously mentioned, the dataset used in this study is the same as that used in [5], which contains information from a thousand patients, 800 samples were taken for training kNN and 200 for testing. The dataset includes variables like age, wave values, and the converted binary-to-decimal classification classes.

Table 2 displays some predictors and anomalies, with these values being manually adjusted, assuming that the first number is an integer and the following numbers belong to the decimal part. Figure 1 depicts the distribution of the utilized data, split into four graphs. The first graph shows the age in months of the patients, ranging from 0 to 24 months. The subsequent four graphs illustrate the range of values for latencies I-V, I-III, III-V, and wave I. The graph titled "Final Classification" reflects the number of patients grouped under each classification, where the classification 4 is null for this dataset. The label represents the classification, and the predictors are age, latency, and waves.

Table 2. Differences in Output between MLP and kNN.

Age (months)	I	I-V	I-III	III-V	MLP	kNN
6	1.35	4.74	44714	2.28	0	2
6	44621	4.77	3.19	2.31	2	3
6	1.46	4.82	44683	2.92	3	2
12	1.31	4.63	2.38	44714	3	2
12	1.36	44716	3.19	2.23	2	0
18	1.48	4.57	2.39	44714	0	1
18	1.36	4.59	2.41	44775	0	1
18	1.86	44716	44622	44594	1	3
18	1.41	44655	3.18	44594	2	0
18	1.45	4.46	44622	2.889	3	0

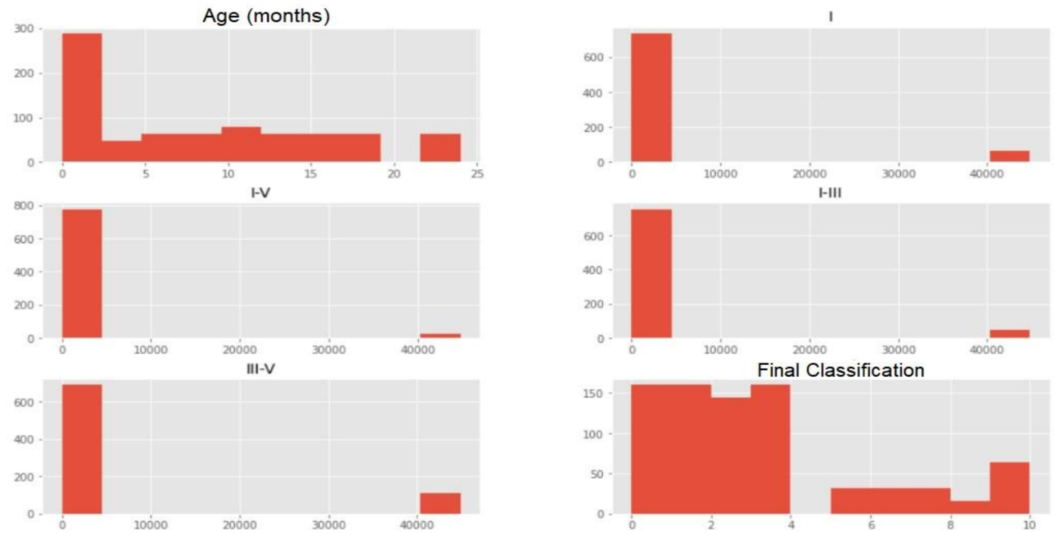

Fig. 1. Graphs of Label and Predictors in the Dataset.

3.2 K-Nearest Neighbor

Due to its simple implementation and significant classification performance, the kNN method is highly popular in data mining and statistics and has been voted as one of the top ten data mining algorithms [9]. The nearest neighbor rule states that for all sample instances in the set E, if y is the nearest neighbor instance of x, then the category of y is the decision outcome. Let X be a sample of unknown category, the specific decision process is [10]:

$$g_j(X) = \min g_i(X) \qquad i = 1, 2, 3, \ldots, C \tag{1}$$

It is commonly based on the Euclidean distance between test data and specific trainingdata [11]. The k-nearest neighbor algorithm (kNN) is a scalable and efficient learning algorithm that has been successfully used in real applications [11]. kNN performs clustering by first calculating the distance between the test data model and all training data to obtain their nearest neighbors and then performs classification, which is obtained by assigning labels to the test data that seeks the nearest similar labels. This distance is denoted as k, and for the implementation of the model, it is important to find an optimal value for all test data [9].

For this project, the kNN model was executed using synthetic training data from 800 patients and 200 test data points. To determine the value of k, a process was carried out which yielded to the information shown in Figure 2. This figure depicts a graph with k values on the x-axis and the corresponding accuracy for each k on the y-axis. This means that the highest point corresponds to the k value with the highest accuracy, in this case, the best value is k = 1.

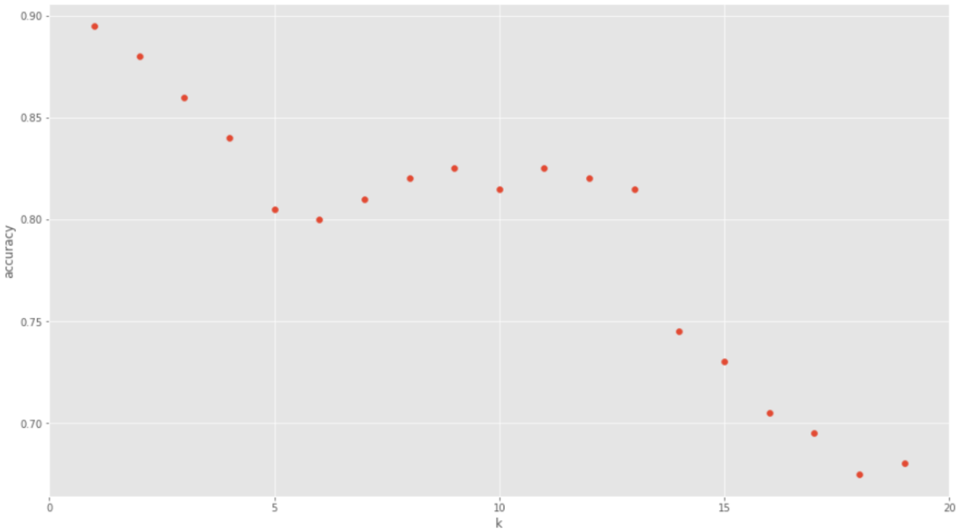

Fig. 2. Accuracy obtained for various values of k.

The model uses the k distance to classify the aforementioned datasets, resulting in eleven possible groupings. This model requires a label and its predictors; for this case, the label is the classification, and the predictors are age and wave latency.

4. Results

The kNN and MLP algorithms for 199 test data obtained 10 cases where the classification differed between the two for the same dataset. In this case, the percentage of different results was 5.03%, while 94.97% coincided in that when evaluating the same dataset, the resulting grouping was the same in both models.

In Table 2, the "Age" column displays the patient's age in months, columns 2 to 5 contain the values corresponding to each wave obtained from the synthetic dataset, and finally, the result obtained from both the MLP and kNN algorithms is shown. The data shown in Table 2 are cases where the kNN and MLP models did not match, meaning that one algorithm grouped the data from a BAEP test into a different classification than the other algorithm.

We can say that the groupings of hearing impairment characteristics range from 0 for a healthy ear to 11 for the most severe classification. In Table 2, for example, in the first entry, the MLP classifies that sample as 0, while kNN classifies it as 2. It is also observed that in cases where MLP did not find an alteration, kNN did (first sample).

The confusion matrix counts the similarity between the grouped characteristics of a classification [12]. Table 3 shows the confusion matrix obtained from the kNN model created for this project. The diagonal of this matrix contains the quantities corresponding to well-classified samples, and the cells not included in the diagonal correspond to confusions or errors due to omissions and commissions [12].

It can be observed that the first 4 groupings (0, 1, 2, and 3) contain data off the diagonal of well-classified samples, while all the subsequent ones are within the diagonal, classified correctly.

For the specific case of kNN, we were allowed to observe the performance of a BAEP test on an infant at a specialist hearing clinic. The test is typically performed by a doctor on a preferably sleeping patient, who is fitted with headphones playing a clicking sound at various decibels. Electrodes on the head, connected to a device, record values such as wave latency and amplitudes of sound waves, which are then printed on a computer.

Thanks to this, the model was tested with data from a real patient, a 24-month-old infant. A specialist doctor in the field provided their diagnosis, allowing it to be processed with kNN and compared to the results. The input data are shown in Table 4.

Intuitively, one could say that their classification belongs to 0 since their values are within the normal range for their age, with classification 0 encompassing healthy ears. When processed with kNN, it yielded the classification 0. For the final diagnosis, the doctor considered other factors based on their experience, which aligned with kNN's result. The diagnosis was:

The presence of wave V at an intensity of 50 dB HL. Absolute latencies and interwave intervals are obtained at 100 dB, appropriate according to the patient's age range. Presents normal morphology. No significant inter-ear difference.

Table 3. kNN Confusion matrix.

Observation \ Prediction	1	2	3	4	5	6	7	8	9	10
1-	39	2	1	1	0	0	0	0	0	0
2-	3	35	0	1	0	0	0	0	0	0
3-	2	2	28	0	0	0	0	0	0	0
4-	5	2	2	31	0	0	0	0	0	0
5-	0	0	0	0	8	0	0	0	0	0
6-	0	0	0	0	0	10	0	0	0	0
7-	0	0	0	0	0	0	9	0	0	0
8-	0	0	0	0	0	0	0	6	0	0
9-	0	0	0	0	0	0	0	0	5	0
10-	0	0	0	0	0	0	0	0	0	8

Conclusions

Technology plays a crucial role as a medical aid, and automating the diagnosis of BAEP test readings through artificial learning is a clear example of its potential. Both the kNN and MLP algorithms demonstrated practical performance in development, as they yielded accurate and realistic results. The kNN model is effective for classifying synthetic BAEP test values. Despite slightly lower accuracy in some groups within this dataset, it proved efficient when compared to a real diagnosis by a specialist doctor.

Table 4. Input data and BAEP outcome.

Age (months)	I	I-V	I-III	III-V	kNN Classification
24	1.36	4.63	2.35	2.28	0

The classification obtained from a prior study served as a basis for implementing the kNN and MLP algorithms to study their precision. These models produced consistent results for the majority of the data. However, in 5.03% of cases where they didn't agree, the kNN algorithm achieved 90% accuracy, while MLP reached 96%. The instances where they didn't align were within classifications 0, 1, 2, and 3.Both models achieved acceptable performance in controlled tests with synthetic data. In this case, the kNN algorithm was tested with some real data, and the resulting grouping diagnosis was compared to the diagnosis provided by a specialist. The agreement between the model's output and the specialist's diagnosis was satisfactory.

Although attempts were made to collaborate with specialized hearing clinics to obtain real datasets, it was limited due to confidentiality concerns. It's worth emphasizing that having access to real data is crucial for future research. Therefore, as a future endeavor, it's planned to evaluate the accuracy of both algorithms trained with authentic BAEP test results.

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