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Prediction of High-Power Hearing Aid for Audiology Patients Using Data Mining Techniques

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ABSTRACT

Our research examined two of unsupervised Data Mining algorithms for both comparison and prediction to predict the High-Power Hearing Aid for audiology patients who suffer from hearing impairment. These Data Mining techniques are Manifold Learning and Multidimensional Scaling. Both algorithms define specific rules to choose the linear projection of the data. These methods can be effective, but sometimes miss the structure of non-linear data. Our research deals with new specific data set which collects and analyses depends on Audiology information and Patient's diagnosis. Note that the data set selected must be subject to accurate data analysis with pre-processing of data. It should be applicable and authoritative because these factors are very important to obtain the highest degree of prediction possible, as long, some data types are not appropriate for decision tree or some methods of classification. The data set we created consists of seventy-two fields distributed on seventy-one fields for data details and one further for class. All data set fields are categorical, and it contains some of missing values. The fact that our data was subjected to a very accurate analysis (before cleaning) based on the correct medical diagnosis and comprehensive information of the most important points that directly affect the selection of appropriate hearing aid for audiology patient, and via applying data mining techniques, we obtained a prediction of 100% for hearing aid selection, and 98% to determine which power type of hearing aid that those patients should use. To reach our goal, we examined Data Mining techniques utilizing Python for coding and modelling.

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1. INTRODUCTION

Our research purpose is to comprehend the importance that Data Mining (DM) is having when the algorithms and processes have been optimized and improving for healthcare, also how we can utilize data to assist doctor's diagnosis their patients who suffer from hearing problems correctly.
"Data mining is the nontrivial extraction of implicit previously unknown and potentially useful information about data" **[1].**

In the field of healthcare medicine, DM transacts with models of learning to predict the diverse diseases of patients. The applications of DM can assist all parties associated with the industry of healthcare [2]. Clinical resolutions are often based on the intuition of doctors and their expertise instead of the knowledge abundant data hidden within the database. This leads to undesirable biases, mistakes and expensive medical treatments that affect the service quality provided to the patients. Wu, et al suggested that the integration of clinical decision with patient records based on the computer could minimize mistakes, enhance the safety of patient, reduce undesirable practice variation, and it improves the outcome of patient [3].

In our research, we manage the problem which needs to be comprehended more by fundamental factors influencing patients who take advantage from being provided with Hearing Aid (HA). Through diverse techniques of DM, our goal is to examine and discover factors influencing the suitable choice of HA. We have huge audiological data, based on around 75,000 individual records for about 17,300 different patients. In each record, there are structured data like address, age, gender, etc.

There are unstructured data like a free text of specific observations for each case related with the patient and heterogeneous data, like an audiogram (is a graph of different frequencies for hearing ability) [4]. Medical information includes databases which store social data, like patient's records, Through Information Technology advancement, sets of therapeutic data put in the electronic structures such databases include an extensive amount of information [5].

A lot of healthcare organizations competing in the using of data gathered through online organization transaction processing system that is non-integrated for pattern analysis and decision making. It is significant for an effective healthcare organization to authorize the management as well staff for data storage based on knowledge and critical thinking tools for making strategic decisions [3].

The medical big data obtained from the Electronic Healthcare Records (EHRs), thus this organizations will assist in information mining and reports explanation from EHRs using modern techniques, proper tools, and infrastructure.

The data collected are divided into structured or organized and unstructured or un-organized data, it is significant to indicate that the reports of doctors are a type of data involving under the unstructured data category. In fact, the term "Big Data" called on specialized methodologies applications, processes, and techniques which manage large quantities of data sets [6].

2. RELATED WORKS

Some studies have used various statistical methods and machine learning techniques in analyzing and exploring audiometric data as listed below:

- Some studies based on congregating the audiogram graphs into groups of heterogeneous and homogeneous utilizing the K-means clustering and an aim of assisting clinicians about the hearing loss diagnosis in the future [7].
- Workout with Support Vector Machine (SVM) and Multi-Layer Neural Network to classifying disorders of an ear from the data of otoneurologic [8].
- Others employed combinations of neural and statistical techniques on medical records of audiology in the purpose of searching for influencing factors which enable the patients to assistance from using the HA [9].
- Researchers like Nasir G. Noma, Mohd Khanapi Abd Ghani, and Mohamad Khir Abdullah utilized the Naïve Bayes and K-nearest neighbor classification algorithms for determining the accuracy of classification by combining the machine-learned knowledge and expert's knowledge [10].

3. METHODS AND TECHNIQUES

"Big Data" paradigm is introduced in a computer science field to abstract the data size. It indicates to huge data quantities which required specific processes to be compatible with business requirements [6].

To gain accurate information as well as gain knowledge, the professionals should execute intelligent tools along with methodologies in such research areas.

3.1 Data Set Created

After analyzing and cleaning data we obtained hearing thresholds for 230 individual patient records to all ages distributed as less than 18 years, between 18 - 60 years, and greater than 60 years measured at frequencies starting from 125 Hz - 8 KHz of a pure-tone audiogram, these records collected over an 8-years period (2007 to 2014). We also collected other medical record attributes like diagnosis as well as biodata (gender, age, occupation, …etc.) for the patients. Besides, the hearing thresholds were obtained as the first result of the patients' audiometry test from Al-Basrah General Hospital and Al-Nour health clinic for hearing evaluation. Finally, the dataset consists of nominal data, and it includes all patient's information that collected utilizing Microsoft Excel and Access applications, it is saved in such format so that we can make it suitable to be used by the applications of DM. We have a big database containing around 75,000 audiology records for around 17,300 patients. In the process of information mining, we inspect extensive and large observational datasets as well consequently discreet the valuable concealed samples for the end information characterization goal.

Nowadays, information mining started with restorative information and human services. It is the straight result of a critical need for productive methods for identifying ambiguous and useful concealed data within medicinal information [5]. Extraction gainful information within datasets clearly and accurately, has a significant role in the protection and handling a lot of diseases which threat humanity nowadays [11].

3.2 Data Mining Techniques Used

The main goal of DM is the extracted knowledge and disclose the hidden patterns within large databases. Many algorithms are obtainable to accomplish diverse tasks of DM [12]. There are several techniques of DM available for their proportionality depends on an application domain. Statistics supply a strong essential background for evaluation and quantification of outcomes. However, algorithms which build on statistics require to be scaled and adjusted before applied to DM. Now we will describe some classification of DM techniques as well as illustrate their applications in the healthcare system [3].

In our study, we will address two unsupervised DM algorithms for prediction and comparison. These techniques are Manifold Learning (ML) and Multidimensional Scale (MDS).

3.2.1.Manifold Learning (ML)

Big data like characters and images under diverse principal intrinsic features are considered as constituting nonlinear manifolds within the observation of high-dimensional space. In analysis data science, ML consider as most of the widely utilized methods within a high-volume precise clustering of the dataset [11]. The methods of ML mapping dataset of high-dimensional into low-dimensional so that it maintained intrinsic geometry. These techniques are founded on the proposition that the preferred database is near the high-dimensional manifold structure which is mapped in a low dimensional area by algorithms of ML. These methods utilized to identify and extract this manifold [13]. The manifold in mathematics is known as a set for points which locally behave such as Euclidean spaces, which means there is a possibility for attribution of characteristics for these points. After that, and according to a local behavior the manifold corresponds to determined Euclidean spaces.

Obviously, if a manifold is local such as Rm, the dimension defined M. Thus, manifold M dimensional, locally needs for coordinate M into its description. The widely common way for describing the manifold when showing points set in Rn space of Euclidean. This conduct is known as "*embedding manifold into R – space*" [11]. ML techniques are divided into local and global categories. In the global methods, the database mapped of high-dimensional into low-dimensional so that the global properties of the database are preserved. On the other hand, the database of local methods is mapped into low dimensional so that the local properties are preserved [14]. The ML purpose is the allocation of a manifold with a lower dimension of the high dimensional structure database. Hence, the processing of ML in data with high dimensional will be so effective [11]. ML used for visualization of data and calculating new representations of data which then can be utilized for machine learning and signal processing tasks [14].

3.2.2.Multidimensional Scale (MDS)

MDS is defined as an instrument that enables researchers to utilize similarity items sets to gain quantitative valuations. Further officially, MDS indicates the statistical algorithms which utilized for reducing the data set intricacy, permitting the visual estimation for the underlying of relational structures which contained therein [15]. Technically, MDS deals with a set of associated ordination techniques applied in the visualization of information, especially, to show the information which included in the distance matrix, and that is a structure of the reduction non-linear dimensionality [16]. MDS is the classic technique which searches for vectorially representations of data points, by offering the pairwise areas between them. MDS is the fundamental and significant technique of the applications in a vast range of data visualization, social science, artificial intelligence, robotics, network localization, cybernetics, etc. [17]. The typical applications are to approximate the geodesic distances for planar points or mesh points into Euclidean space such that a non-rigid essential structure for shapes gets captured. By given the pairwise areas between N points of data, MDS target at distinguished these data in a space of P dimensional, so that the distances between-object can be possible as well as preserved [18]. To apply MDS, the *'proximity matrix'* required, which is, the similarity collection of valuation between each item pairs in the motivate set. For any set consist of k points:

$$\mathbf{(k*(k-1))/2)} \qquad (1)$$

proximities must be acquired, so that it can compare each item with another one at least once [15]. Classical MDS refers to the dissimilarities over objects set as distances among points in the space of low-dimensional. The goal of these methods of MDS is to discover the relationships among objects and find out the dimensions which awarding rise to space [19].

4. Results and Analyses

We can summarize our work in the following steps:

1. File: Choose dataset file to detect the attributes (71 features, zero meta-attributes, Classification, and categorical class with 3 values: high power HA (h_power_ha), other types of HA (other_ha), and no need for HA (no_ha).
2. Data Table: Downloaded the dataset file after analyses and cleaning data. We obtained 230 instances with 1.3% missing values.
3. Data Sampler: We chose twenty instances as sample data for test and training stages.
4. Select Rows: Determined the condition for data table sample: If ha_power is not no_ha, which means select records with case diagnosis is not normal hearing. In our research for twenty instances rows, there are twelve instances' rows corresponding to this condition and ready for test and training tasks.
5. Applying algorithms: First, we applied the ML algorithm with learning rate = 200 and max iteration = 1000, then applied the MDS algorithm with max iteration = 300 using table selected in step 4.
6. Train Data Table: Extracted the train data table for training data.
7. Predictions: Obtained the final prediction for selecting hearing aid type.
8. Used Python for coding and modeling.

4.1 Predictions and Comparisons

Using the optimum solution with manifold alignment from Laplacian eigenmaps respecting the joint Laplacian. Given *m* datasets:

$$X^{(1)}, \ldots, X^{(m)},$$

They are all located on the same manifold, the similarity function (sometimes called as distance function), S, which returns the similarity for any pair of instances from one dataset with regard to geodesic distance over all the manifold (possibly $S = e^{-||x-y||}$), and some given symmetry information that present in the form of similarities instances pairs from various datasets, this algorithm act as follows:

a) Find the nearby (within reach) matrices:

$$W^{(1)}, \ldots, W^{(m)},$$

of every dataset using S, including only a weight between two sets when one of them is within the k-nearest neighbors' distance of the other.

b) Construct the Laplacian joint, *L*.

c) Find the smallest d eigenvectors nonzero of:

$$\mathrm{L}f = \lambda \mathrm{D}f \qquad (3)$$

d) The rows:

$$1 + \sum_{l=0}^{g-1} nl,\ 2+ \sum_{l=0}^{g-1} nl,\ \ldots,\ n_g + \sum_{l=0}^{g-1} nl \qquad (4)$$

of $\boldsymbol{f}$ are the latest coordinates for $X^{(g)}$.

Table 1. illustrates the train data table with final predictions for choosing high power HA (h_power_ha), other HAs (other_ha), and no need for HA (no_ha) by applying ML algorithm.

Table 1. Predictions of Need for Hearing Aid Rresults using ML algorithm

Data sample Info.	HA type	Need for Hearing Aid	C0
20 instances, 1 feature (no missing values), 12 instances correspond condition for select rows,	h_power_ha	Yes	2055.964
	other_ha	Yes	198.803
	h_power_ha	Yes	-2192.685
	h_power_ha	Yes	1285.252
	no_ha	No	-1095.346
	no_ha	No	-10.754
	h_power_ha	Yes	-648.811
	other_ha	Yes	836.776

Discrete class with 3 values (no missing values)	h_power_ha	Yes	-869.529
	other_ha	Yes	-1584.853
	h_power_ha	Yes	1777.276
	h_power_ha	Yes	-1862.679
	no_ha	No	-220.849
	no_ha	No	408.902
	no_ha	No	-433.292
	no_ha	No	1523.577
	other_ha	Yes	1057.408
	no_ha	No	-1332.190
	h_power_ha	Yes	621.297
	no_ha	No	2391.143

Despite MDS is usually applied as a dissimilarity measurement, MDS capable technically to measure the **similarity** as well. The **dissimilarity** between points ***r*** and ***s*** is indicated as: $\boldsymbol{\delta_{rs}}$ and **similarity** is indicated as: $\mathbf{s_{rs}}$. Small δ_{rs} denote to the values which are close together while larger values denote values which are farther away from each other (more dissimilar). Furthermore, the opposite is with similarity values: small s_{rs} denotes values which are farther away from each other; larger values indicate more similarity (values that are nearer together). The measures of similarity are simply converted from one to another via routine decreasing transformation.

NCSS (n.d.) leads to the transformation formula as follow:

$$d_{rs} = \sqrt{(S_{rr} + S_{ss} - 2S_{rs})} \tag{5}$$

Where:

- d_{rs}: Indicates the dissimilarity.
- s_{rs}: Indicates the similarity.

Other symbols like:

- *i* and *j*: Sometimes used instead of s and r referring to the points of primary and secondary, respectively.
- d_{rs}: The distance between the points r and s (The meaning is independent of its counterpart d_{rs} in the previous equation above).
- X: The coordinate values matrix in the lower-dimensional area.

The MDS can divided into sub-types which are differ in the dissimilarities δ_{rs} are transformed to distances d_{rs}: $d_{rs} = f(;\delta_{rs})$.

Table 2. illustrates the train data table with last predictions for choosing high power HA (h_power_ha), other Has (other_ha), and no need for HA (no_ha) by applying MDS algorithm.

Note that the x axis of MDS (mds-x) represents repetitiveness in texture, and the y axis of MDS (mds-y) represents a combination of directionality and contrast.

For more clarification, we can identify the HA types depend on the hearing cases in three steps and illustrate the probabilities of all these categorical using ML algorithm as shown in Figure (1).

1) High-power HAs using for patients who suffer from hearing loss with the following levels:
   a) Moderate b) Severe c) Profound.
2) Other HAs (mild power) for cases of mild hearing loss.
3) No need for any type of HAs in the case of normal hearing.

Table 2. Predictions of Need for Hearing Aid results using MDS algorithm

Data sample Info.	HA type	Need for Hearing Aid	mds-x	mds-y
20 instances 71 features (1.3% missing values), 12 instances correspond condition for select rows, Discrete class with 3 values (no missing values)	h_power_ha	Yes	-3.015	2.531
	other_ha	Yes	2.908	-3.820
	h_power_ha	Yes	-2.753	0.659
	h_power_ha	Yes	-1.476	-2.139
	no_ha	No	1.186	-1.822
	no_ha	No	1.194	0.903
	h_power_ha	Yes	-3.870	-2.968
	other_ha	Yes	0.258	-2.983
	h_power_ha	Yes	-3.015	2.531
	other_ha	Yes	-0.945	-3.823
	h_power_ha	Yes	-0.330	4.108
	h_power_ha	Yes	-3.727	-0.930

	no_ha	No	1.333	-0.435
	no_ha	No	2.957	0.547
	no_ha	No	2.444	1.696
	no_ha	No	3.887	-0.353
	other_ha	Yes	1.446	3.818
	no_ha	No	2.305	-1.178
	h_power_ha	Yes	-0.830	3.129
	nzo_ha	No	0.046	0.529

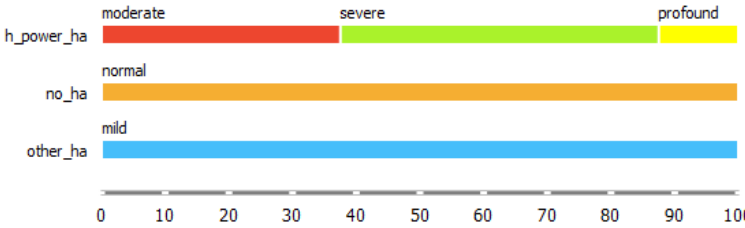

Figure 1. The probability of all three categorical of hearing using ML algorithm

Figures (2), (3) show the probability of prediction we gained for HA choosing at given `mds-x and mds-y respectively using MDS algorithm. Finally, we reached 1.0 as a prediction result using ML and 0.98 applying MDS, since the sample of data selected for the training and learning phases was free of missing values as shown in Table 1.

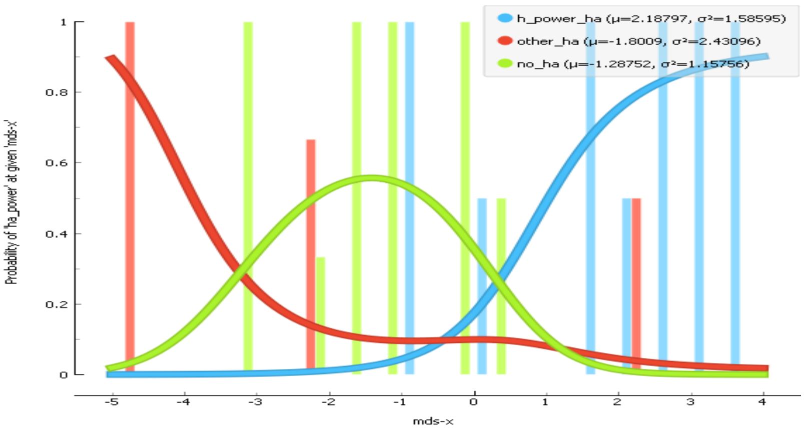

Figure 2. The probability of prediction for hearing aid choosing at `mds-x'

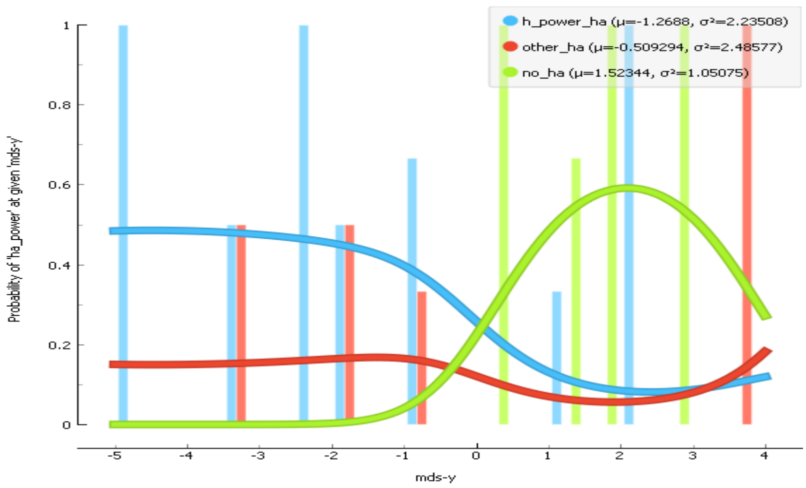

Figure 3. The probability of prediction for hearing aid choosing at `mds-y'

5. CONCLUSION

DM applications signify all parties concerned in the industry of healthcare. For instance, DM can assist healthcare insurers to detect abuse and fraud.

Healthcare organizations enable management decisions of customers relationship and effective treatments that identify by physicians as well as best diagnosis.

Medically, a substantial quantity of the latest data is constantly created, and the quantity of data created is frequently higher than the quantity of produced knowledge. Hence, large increases in data production require a rapid transfer into knowledge. To acquire this, clustering tests the data items groups which are similar or dissimilar [20].

The tool modified will be appropriate for data held in most hospitals, making us conduct DM surveys on the national scale then HA users will answer the online satisfaction survey with their HAs in diverse situations every day. This data availability will expose new DM opportunities and assist us into our consequent goal for accurate predicting or otherwise for the HA fitting [4].

By analyzing the cases of healthcare, the healthcare Decision Support System (DSS) can produce the input features description detailed with the unique healthcare conditions of characteristic [1].

Current research is a complementary to our previous work [2] through which we would like to compare the supervised and unsupervised algorithms so we can evaluate the efficiency of dealing with the audiology data set and its effectiveness in the development of accurate prediction for any category of this data set to provide the greatest possible benefit for audiology patients.

The organizations of health care are return value and strategic applications of mining the patient data generally and society data particularly.

While significant profits can be gained and noted in the analysis of organizational level, a lot of attention is given to an individual, where focal points centered on the security and privacy of patient's data. While privacy argumentation is a prominent issue, DM offers wide community-based profits which improve and enable healthcare analyses, forecasting, and visualization.

This research studied some cases where DM has been utilized to mine patient's data to create decisions concerning patients as well as investigates how DM can be helpful in the healthcare system context.

"Any computer program that helps experts in making healthcare decision comes under the domain of healthcare decision support system" [1]. DM is the step into processing journey of knowledge acquisition, it is applying discovery algorithms and data analysis, which should convey data collections which widespread growth [20].

The analysis of big data is predicted to detect the structure of knowledge which guides to the making decisions [21].

As a conclusion, big data concerns real-time data, the management of healthcare follows three significant and main steps, the first step presents data collection, and this data might come from hospitals or billing clinical systems, imaging, and lab systems, or may come from data devoted with patients. The second step is extracting and cleaning useful data such as the technology of data warehouse, and the last step is knowledge and management step which lies in data analysis utilizing the techniques of DM.

The perspective of data scientists in the target of big data analysis, is analyzing and retaining a lot of data and maintaining the speed of increasing analysis, as well publishing accurate results with least cost. Finally, in healthcare, the analysis of *"Big Data"* will offer a lot to the knowledge structure.

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REFERENCES

[1] S. S. R. Monali Dey, "Study and Analysis of Data mining Algorithms for," *International Journal of Computer Science and Information Technologies (IJCSIT),* vol. 5, no. 1, pp. 470-477, 2014.

[2] M. A. H. A. Sefer Kurnaz, "Predict the type of hearing aid of audiology patients using data mining techniques," in *Association for Computing Machinery*, Istanbul, Turkey, 2018.

[3] K. B. R. D. A.Govrdhan, "Applications of Data Mining Techniques in Healthcare and Prediction of Heart Attacks," *(IJCSE) International Journal on Computer Science and Engineering,* vol. 02, no. 02, pp. 250-255, 2010.

[4] M. O. S. W. a. M. H. Shaun Cox, "AudioMine: Medical Data Mining in Heterogeneous Audiology Records," *INTERNATIONAL JOURNAL OF COMPUTATIONAL INTELLIGENCE ,* vol. 1, no. 1, pp. 1-12, 2004 .

[5] R. S. B. K. Anusha N, "A Survey on Medical Data by using Data Mining Techniques," *International Journal of Science, Engineering and Technology Research (IJSETR),* vol. 7, no. 1, p. 14, January 2018.

[6] D. A. AbdulAmeer, "Medical Data Mining: Health Care Knowledge Discovery Framework Based On Clinical Big Data Analysis," *International Journal of Scientific and Research Publications,* vol. 5, no. 7, p. 6, 1 July 2015 .

[7] J.-H. H.-J. H. &.-C. L. Cheng-Yung Lee, "Using cluster analysis to classify audiogram shapes," *International Journal of Audiology,* vol. 49, no. 9, pp. 628-633, 2010.

[8] M. D. M. A. M. M. A. Mahsa Moein, "Classifying Ear Disorders Using Support Vector Machines," in *Second International Conference on Computational Intelligence and Natural Computing (CINC)*, Wuhan, China, 2010.

[9] M. P. O. Muhammad N Anwar, "Data mining of audiology patient records: factors influencing the choice of hearing aid type," *BMC Medical Informatics and Decision Making,* vol. 12, no. 1, p. 8, 2012.

[10] M. K. A. G. M. K. A. Nasir G. Noma, "Identifying Relationship between Hearing loss Symptoms and Pure-tone Audiometry Thresholds with FP-Growth Algorithm," *International Journal of Computer Applications (0975 – 8887),* vol. 65, no. 21, pp. 24-29, March 2013.

[11] E. G. a. K. Maghooli, "Overview of Manifold Learning and Its Application in Medical Data set," *International journal of Biomedical Engineering and Science (IJBES),* vol. 1, no. 2, pp. 23-33, July 2014.

[12] a. A. P. Murchhana Tripathy, "A Study of Algorithm Selection in Data Mining using Meta-Learning," *Journal of Engineering Science and Technology ,* vol. 10, no. 2, pp. 51- 64, 2017.

[13] X. H. J. Y. Binbin Lin, "A geometric viewpoint of manifold learning," *Applied Informatics,* vol. 2, no. 3, pp. 1-12, 2015.

[14] G. M. Philippos Mordohai, "Dimensionality Estimation, Manifold Learning and Function Approximation using Tensor Voting," *Journal of Machine Learning Research () 411-450,* vol. 11, no. 1, pp. 411-450, 1 October 2010.

[15] M. H. P. S. D. G. Michael C. Hout, "Multidimensional scaling," *WIREs Cognitive Science,* vol. 4, no. 1, pp. 93-103, January/February 2013.

[16] P. M. Jan de Leeuw, "Multidimensional Scaling Using Majorization: SMACOF in R," *Journal of Statistical Software,* vol. 31, no. 3, August 2009 .

[17] X. B. L. J. L. Q. T. Song Bai, "Multidimensional Scaling on Multiple Input Distance Matrices," in *Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)*, 2017.

[18] Y. Sahillioğlu, "A shape deformation algorithm for constrained multidimensional scaling," *ELSEVIER/ Computers & Graphics,* vol. 53, no. 1, pp. 156-165, 23 October 2015.

[19] S. O. R. E. D. P.J.F. Groenen, "I-Scal: Multidimensional scaling of interval dissimilarities," *ELSEVIER/ Computational Statistics & Data Analysis,* vol. 51, no. 1, p. 360 – 378, 2 May 2006.

[20] M. P. O. S. W. S. H. Muhammad Naveed Anwar, "Clustering Audiology Data," in *Proceedings of the 19th Machine Learning conference of Belgium and The Netherlands*, 2010.

[21] S. K. MAALIM A. ALJABERY, "Applying Datamining Techniques to Predict Hearing Aid Type for Audiology Patients," *JOURNAL OF INFORMATION SCIENCE AND ENGINEERING,* vol. 36, no. 2, pp. 205-215, March 2020.