Prediction of Cochlear Disorders Using Face Tilt Estimation and Audiology Data

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Abstract. Cochlear disorder is an audio impairment issue, which causes difficulty in understanding human speech. These disorders can cause difficulty in speech recognition, communication, and language development. Intelligent approaches are proven to be efficient and novel approaches for performing various challenging tasks in the healthcare industry. The primary objective of this study is to use machine learning and computer vision domain, to create a web-based platform enabling early detection of the disorders. Computer vision with a classification model is used for achieving the objective. The model is trained on the static custom audiology dataset formulated from the UCI machine learning repository. Cross-validation over various classification algorithms like Logistic Regression, Decision Tree, Support Vector Classifier, K-Nearest Neighbors, and Multi-Layer Perceptron is performed and is proven that Multi-Layer Perceptron suits the dataset. Application for the purpose is developed using Python flask and is deployed for validation.

Keywords: Audio impairment · logistic regression · decision tree · KNN · SVM · multi-layer perceptron · prediction

1 Introduction

More than 5% of the total world population, requires hearing loss therapy. According to The World Health Organization, there are approximately 432 million adults and 34 million children who need treatment. It is proposed that by 2050, one out of every 10 people is expected to suffer from various auditory issues such as disabling hearing loss. Diminished sensitivity to sound, such as turning down the level of everything they hear, or reduced clarity, such as garbling everything they hear, are both examples of audio impairments. This is becoming evident due to the continuous usage of earphones during the pandemic and henceforth. The symptoms of cochlear damage often appear before vertigo and are usually overlooked. The goal of this study was to examine the features related to various types of auditory impairments, as well as Meniere's disease, to determine the regularity with which these problems develop. Meniere's disease is an uncommon inner-ear condition that becomes worse over time. The complexity of the

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symptom and its restricted visibility make its diagnosis difficult and it can easily be ignored by the general population. Most people lack access to proper health care or are scared of the exorbitant cost of the consultation to detect any such auditory disorders, while many are just unaware of such a situation persisting in their bodies.

This work aims to develop a product that would attempt to solve the persisting problem of ignorance or unawareness of the auditory disorders (more prominently, cochlear diseases that can be detected with having face tilt as a symptom) present in one's body. Common symptoms such as dizziness, nausea or vomiting, the presence of roaring or ringing sound in the ear, and hereditary disorders related to the ear of the patient are taken as input from the user along with the user's face tilt value, which are the basic requirements for the user's hearing impairment prediction. Early prediction is proposed through the use of a machine learning model trained using a standard dataset. With the rapid advancement of technology and data, the healthcare domain is one of the most crucial study domains in the contemporary era. This paper explains the complete conversion of a dataset from data Pre-processing to Model creation and then to the prediction of output based on user input. Since the dataset was imbalanced oversampling using Random Sampler was implemented. The paper is thus represented as follows. Background and related work is presented in Sect. 2. Section 3 includes the implementation of the project which comprises the objective of the research, proposed work, related algorithms as well as, and research methodology as applied in the study. Section 4 contains results and discussions and the paper is concluded in Sect. 5 with Future works discussed.

2 Background Study

Several people around the world are diagnosed with hearing problems and other cochlear diseases. Many of the affected are afraid to even consult a doctor, while others ignore or overlook the symptoms. In a recent study carried out in Delhi, India; it was found that 25.1% of people had an overall prevalence of hearing loss [1]. Also, less than 16% of adults ages 20–69 who need a hearing aid don't use one. That number almost doubles to 30% for adults over the age of 70 who need a hearing aid but don't use it, according to the National Institute on Deafness and Other Communication Disorders [2]. An estimated 38 million Americans have hearing loss [3]. Using Deep Learning (DL) and Machine Learning (ML) techniques, prediction of a very challenging HA type identification for Audiology Patients (AP) is done by researchers [4]. Many efforts and works have been done in Audiological analysis, where the majority of them focus on one or few efficient model(s) for their dataset. Machine Learning Techniques for Differential Diagnosis of Vertigo and Dizziness: A Review [5] analyses the Audiology dataset with SVM, KNN, Decision Trees, Naïve Bayes, and Genetic Algorithm and presented a comprehensive view of all performance. Hearing aid classification based on audiology data [6] presents a comparative study of two machine learning models namely MLP and Bayesian Networks.

Commonly due to changes in the volume of fluid people suffering from any audio impairment tend to develop imbalance leading to the right or left bend. Usually $< 5°$ is considered to be normally caused to due to slight movements and $5°$ - $20°$ addresses the possibility of audio impairment. The prediction of the auto-Tilt in patients with positional vertigo [7] and Menière's disease [8] by taking inputs i.e. dizziness, nausea, roaring, or ringing or presence of buzzing sound, along with face tilt values from users is discussed in the research works. Computerized dynamic posturography, a method for quantifying balance tests is performed with eyes closed on an unstable surface using a CAPS® system [9]. This indicates the connection between the balance of the body and the audio heard by the person. The authors presented a detailed study about this test and its use in identifying cochlear disease. Detailed research on the importance and need for improvement in technology and research for hearing aid is discussed by researchers [10]. They described the emerging hearing-related artificial intelligence applications and argue for their potential to improve access, precision, and efficiency of hearing healthcare services.

3 Proposed Methodology

The objective of the proposed methodology is to present an efficient framework for predicting the type of cochlear disorder at an early stage based on user input and face tilt values. The proposed methodology followed in the research work is depicted in Fig. 1.

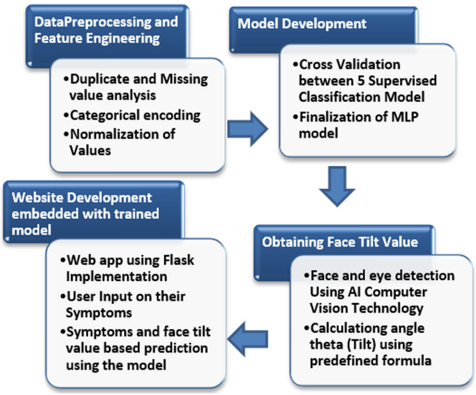

Fig. 1. Proposed Methodology

3.1 Data Preprocessing and Feature Engineering

In this work, an Audiology Dataset having 70 features representing facial values with an output feature representing the abnormality is used. The dataset is analyzed for missing values and then normalized to ensure proper scaling. Linearity between predictor and response variables is analyzed using scatter plots and correlation analysis. Heatmap is used for visualizing the correlation between features. Figure 2–4 represents some sample analysis done using the dataset. Outlier analysis is done for each feature to understand the existence of abnormal values. Boxplot is used for the analysis and such abnormalities are resolved using minimum and maximum values of corresponding features depending on the extremes the outliers lie in. The frequency of values of each feature is analyzed using a histogram plot. Barcharts are used to understand the number of tuples exist for each output class label.

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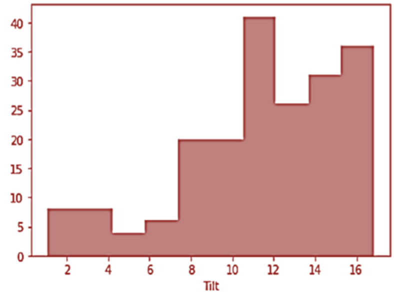

Fig. 2. Face Tilt Value Histogram (Univariate Analysis)

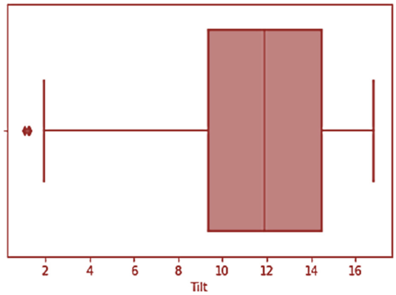

Fig. 3. Face Tilt Boxplot (Univariate Analysis)

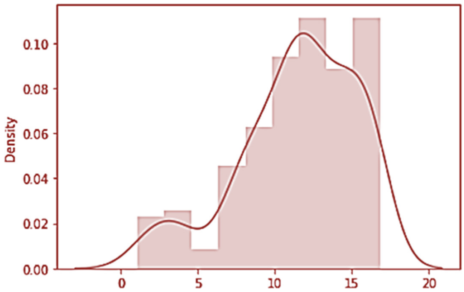

Fig. 4. Face Tilt Distplot (Univariate Analysis)

Feature Engineering was then performed to make the dataset suitable for modeling. First, all categorical variables in the predictor category are replaced with numerical values using ordinal encoding. The dataset is identified as imbalanced using Fig. 5. Cochlear_unknown and cochlear_age are identified to be the dominating or majority classes. Hence Oversampling was done using RandomOverSampler to randomly increase the sample numbers of data with the help of the imbalanced-learn package in python. Hence the sample size increased to 1152 data samples with 48 Class labels each.

3.2 Model Development

The dataset obtained from phase I is divided into training and testing in 80:20 proportion. Since cross-validation is used for validation, proportion alone is fixed. Various machine learning models including logistic regression, multi-layer perceptron, decision tree, support vector machines, and KNN classifier are used for training the dataset. Every model is trained using 80% of the experience and is tested with 20%. To assure uniformity cross-validation using 5 folds is used.

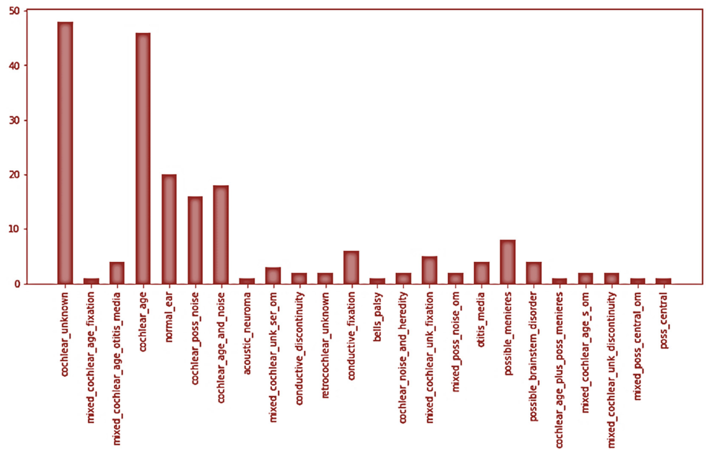

Fig. 5. Bar-chart representing the count of output class

3.3 Face Tilt Value Collection

- With the help of a webcam from the user's end, the patient's face is detected with the help of the haar cascade classifier dataset, and a green-colored box surrounding it is created to show that the system has detected the face.
- Then with the help of another XML haar cascade classifier trained specifically for eye detection, the user's eyes are detected and red-colored boxes are made around each eye.
- The center of the bounding boxes of eyes is also identified and stored for the calculation required for face tilt. A margin of 5°–20° is kept for getting the face tilt value of the patient.
- To compute tilt, angle an assumption that the face is perpendicular to the joining line of eyes is assumed for further calculations.
- Considering (xi, yi) as the center of eyes, where xi is the horizontal axis and yi is the vertical axis, we can get the angle q, which is the angle from the x-axis, thus the tilt value.

$$q = \tan - 1((x2 - x1) / (y2 - y1)) \tag{1}$$

- In the above-mentioned formula (x1, y1) and (x2, y2) are the centers of eyes calculated and stored previously.
- If the angle is positive then the tilt value is considered to be a right tilt and a negative value indicates a left tilt.

3.4 Deployment Procedure

To develop a platform for user Interaction, a python web framework flask was used which helped to create the web application where users can provide their inputs, hence required for detecting the possibility of any audio impairment. HTML and CSS codes were used to create an interactive webpage for users i.e. basically the patients and also the doctors, where doctors from the other end will be responsible to use the model which is better and the one having the highest accuracy. The doctors can analyze our webpage and use the model accordingly which will help in reducing the probability of patients getting misdiagnosed.

Our model was stored in pickle format, a method of serializing objects; machine learning models for saving during run time and loading and deserializing them later for different use. This pickled format of our model was later on passed to the Flask Implementation phase where our web app was developed over this file to give in runtime outputs after giving basic inputs for buzzing, dizziness, etc. Figure 6 represents the method to capture face tilt values. Common symptoms such as dizziness, nausea or vomiting, noise, the presence of roaring or ringing sounds in the ear, and hereditary disorders related to the ear of the patient are taken as input from the user. Along with the above-mentioned inputs we also get the face tilt value which is automatically taken after the user submits the rest of the symptoms from a 10-s live video from their camera. Since the rest of the values required for detection present in our dataset i.e. 59 features cannot be taken from the user as it requires tools and equipment which currently we cannot implement, we take them as random values along with the user input of symptoms and the tilt value. Thus by taking above stated inputs using the created webpage, we predict with the help of the formerly developed model and hence help the patient in detecting their audio impairment.

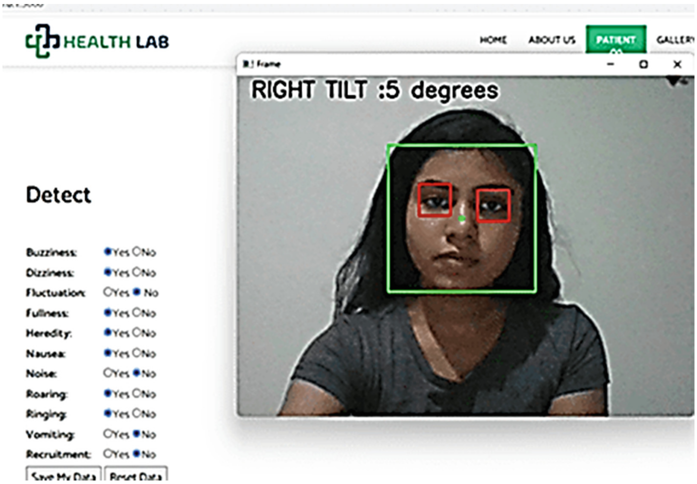

Fig. 6. Face Tilt value capturing

4 Results and Discussion

The user interactive web application developed was successfully able to predict the cochlear disorder user is suffering from, with the help of all the user input of symptoms and face tilt value. The developed models are validated using test datasets and through cross-validation procedures. Various metrics like Recall, Precision, and F1-score are used for validation. The values of these metrics are calculated using a confusion matrix computed for each model. Table 1 represents the comparison of these metrics for various machine-learning models. Upon analysis, it is found that Multilayer perceptron performs better than other models when tested separately and using 5-fold cross-validation. Thus with the current dataset and model developed we were able to correctly predict the audio impairment issue of the user with the average highest accuracy of 82.5%.

Table 1. Comparison of various models.

Model	precision	recall	f1-score	accuracy
SVC	0.98	0.97	0.97	0.968
MLP	0.99	0.99	0.98	0.9852
KNN	0.97	0.97	0.97	0.9661
Logistic Regression	0.98	0.98	0.97	0.9756
Decision Tree	0.99	0.99	0.98	0.9852

5 Conclusion and Future Works

The developed project is a website embedded with A.I. and a machine-learning model developed for the Audiology dataset. This project had a vision of making a product; a website making predictions if a person has audiology defects based on the face tilt value captured using computer vision implementation. Machine learning application was implemented using sci-kit learn library for classification of the data set and model training. The final model chosen was MLP and the model trained was converted to a pickle file and used with Flask to make the website. Using the ideas from this paper on advancing technology added work to the project can help in improving the output with better results. Considering the future, a lot of development can be done for the given project. The “curse of dimensionality” is well-represented in this dataset. Extensive Dimensionality reduction techniques like PCA and other methods can be used to handle the data more efficiently. Also, a thorough survey can be conducted and more prominent data sources can be gathered; as this dataset only contained 200 experiences (rows), so that could be taken care of with the survey. Deep Learning models could also be explored for the given dataset to improve the accuracy and efficiency of the model.

References

1. Garg, S., Kohli, C., Mangla, V., Chadha, S., Singh, M.M., Dahiya, N.: An epidemiological study on burden of hearing loss and its associated factors in Delhi, India. Ann. Otol. Rhinol. Laryngol. **127**(9), 614–619 (2018). https://doi.org/10.1177/0003489418781968
2. https://www.nidcd.nih.gov/health/statistics/use-hearing-aids-adults-hearing-loss

3. Glassman, J., Jordan, T., Sheu, J.-J., Pakulski, L., Thompson, A.: Health status of adults with hearing loss in the United States. Audiol. Res. **11**(1), 100–111 (2021). https://doi.org/10.3390/audiolres11010011
4. Aljabery, M., Kurnaz, S.: Applying datamining techniques to predict hearing aid type for audiology patients. J. Inf. Sci. Eng. **36**, 205–215 (2020). https://doi.org/10.6688/JISE.202003_36(2).0002
5. Kabade, V., et al.: Machine learning techniques for differential diagnosis of vertigo and dizziness: a review. Sensors **21**(22), 7565 (2021). https://doi.org/10.3390/s21227565
6. Panchev, C., Anwar, M.N., Oakes, M.: Hearing aid classification based on audiology data. In: Mladenov, V., Koprinkova-Hristova, P., Palm, G., Villa, A.E.P., Appollini, B., Kasabov, N. (eds.) ICANN 2013. LNCS, vol. 8131, pp. 375–380. Springer, Heidelberg (2013). https://doi.org/10.1007/978-3-642-40728-4_47
7. https://curve.carleton.ca/873548bb-f077-49d4-a5a6-9a69fddf1284
8. Futaki, T., Ikeda, T.: The auto-tilt test in patients with positional vertigo and Menière's disease. Am J Otol. **10**(4), 289–292 (1989). https://doi.org/10.1097/00129492-198907000-00010. PMID: 2801893
9. Pagnacco, G., Klotzek, A.S., Carrick, F.R., Wright, C.H., Oggero, E.: Effect of tone-based sound stimulation on balance performance of normal subjects: preliminary investigation. Biomed Sci Instrum. **51**, 54–61 (2015). PMID: 25996699
10. Wasmann, J.-W.A., et al.: Computational audiology: new approaches to advance hearing health care in the digital age. Ear Hearing **42**(6), 1499–1507 (2021). https://doi.org/10.1097/AUD.0000000000001041