Tytonidae Tympanometry

Applying Machine Learning to predict hearing loss using wideband tympanometry

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Contents

1 Aim

This project aims to apply machine learning techniques to wideband tympanometry (WBT) data in order to classify ears as either normal, or with conductive conditions such as Otitis Media. These techniques seek to replace the receiver operating characteristic (ROC) analysis that is currently performed, by increasing the performance and improving the interpretability of the results.

2 Background

The ear isn't just the hearing organ. It is a complex system of parts that not only allows humans to hear, but also makes it possible for humans to walk. The middle ear couples sound waves from the low impedance, air-filled outer ear to the high impedance, fluid-filled inner ear. The traditional method (226Hz tympanometry) for testing the function of the middle ear from 7 months old is through using a single tone at 226Hz to measure the acoustic changes in the ear. However, the traditional method has high rates of false positives (11%) and false negatives (25%) when detecting conductive conditions (Zielhuis et al. [4]). To tackle this clinical conundrum, an emerging technology (wideband tympanometry; WBT) has been used to generate data from 250Hz to 8000Hz, giving a more accurate picture of what is present in the middle ear, namely looking for conductive conditions.

The WBT technology measures the proportion of acoustic energy absorbed by the middle ear at the tympanometric peak pressure. Coupled with being measured at more than 60 different pressures, there is a large amount of data to analyse to understand what is happening in the middle ear. This methodology has been available for almost two decades [2] but has seen low uptake due to the limited ability of clinicians to interpret the result. Traditionally, the receiver operating characteristic (ROC) has been used to interpret WBT results, with the measure of success being the sensitivity and specificity metric.

This project seeks to apply machine learning to improve the effectiveness of the analysis by increasing specificity and targeting the interpretability of the results. By taking in the raw WBT data, processing can happen automatically, and the top-performing model can be used to predict the occurrence of conductive conditions. Coupled with simple visualisations and an easy-to-understand output, this would allow clinicians to diagnose different middle ear conditions with high accuracy and reduce unnecessary medical intervention such as surgery. There are approximately 2700 VTI surgeries conducted in WA public hospitals every year, at an estimated annual cost to the health service of $13.7 million. This project seeks to help reduce that number through reducing the false positive rate of conductive conditions in children.

3 Value Proposition

The use of machine learning in analysing the WBT data has the following key benefits:

1. Improving on the performance of existing methods. The current best area under the

ROC results are 77%, which is the target to achieve for the machine learning models. We will also use accuracy as a good classification measure, as well as sensitivity and specificity to fine-tune the models' performance.

2. Increasing the interpretability of the results. The current ROC analysis is often difficult for clinicians to interpret and apply its outputs to their patients. The machine learning models seek to output a clear and simple result to empower their application for the benefit of patients. There is a large amount of data collected, and using feature selection to identify valuable and unnecessary data points would give clinicians greater understanding of what is important.

3. Enable fast and reproduceable analysis. By creating a trained model, machine learning can quickly analyse WBT data from new patients and provide clinicians with an instantaneous classification of their patients' ears for conductive conditions. Coupled with an automated processing pipeline, raw data collected from patients can be directly input into a process that can generate the interpretable results that clinicians require.

4 Deliverables

The deliverables for Tytonidae Tympanometry are as follows:

1. A machine learning solution that takes in the WBT data, and any relevant demographic data, to classify a patient's ears as either normal or with conductive conditions. The output of this solution will not only be the classification, but also a visual analysis of how the prediction was made.

2. A code repository on GitHub which explores different machine learning methods to identify the best performing one, as well as processing steps, that can be used for further or improved analysis. This code repository and any outputs will use Python to generate the results.

3. A report that summarises the data, the processing steps that occurred, the models that were explored, and the results that were achieved by each.

5 Methods

For this project, Python has been selected as the programming language of choice, with Pandas and Scikit-Learn being the key Python libraries for data manipulation and machine learning. These were chosen for their versatility and simplicity, to support the ability to easily interpret the results.

Looking at previous work done with wideband absorbance data and machine learning by Grais et al. [1] and Sundgaard et al. [3], there appears to be a preference for more complicated black-box models such as deep learning and convolutional neural networks (CNN). These may provide better results, but they conflict with the requirement to be explainable to clinicians. With this in mind (and still aiming for the best performance), the following machine learning techniques have been selected for the initial analysis:

1. Logistic Regression - LR is a statistical technique that looks at the probability of a

record (a patient in this situation) belonging to either the positive class (with a conductive condition) or the negative class (without a conductive condition - a normal middle ear). As logistic regression is a simple model compared to the others, it provides a baseline result upon which to compare the other results with data that has gone through the same processing steps.

2. Support Vector Machine - SVM is a supervised learning technique that performs classification by creating a division between the different classes present in the data. The wider this division, and the less data that falls on the wrong side, the better the classification results. SVM is effective in high-dimensional space, which is useful for WBT data as it is collected across 16 frequencies, plus the additional demographic features that are added in.

3. Decision Tree - DT is one of the most explainable machine learning techniques, where the model is made up of branches and leaf nodes. Each branch represents a test, and each leaf node is the resulting class that is being predicted. This allows a logic flow to be followed down the tree, seeing which features are contributing to the prediction of the class. The features that have a greater effect of the prediction, the higher they are up in the tree, which will give insights to clinicians as to why the model is providing a certain result.

4. Random Forest - RF is a ensemble model that incorporates many decision trees and averages out the results of each individual tree. As this incorporates multiple trees, it inherently takes longer than a single tree, but a wisdom-of-the-crowd approach results in a decrease in variance of the results. Even though each tree is easily interpretable, the overall forest loses this due to the nature of averaging across a large number of trees.

All of these models will be compared across a range of metrics, and with the existing ROC results, to see which is the best performing model for incorporation into an automated process. The data that is being passed into these models will incorporate different levels of feature selection to identify those features which add predictive value to the model, as well as one of the following record selection methods:

1. All data - this will incorporate all of the WBT data across all pressures to see if there is any predictive power in any of the data that was collected.

2. Matching Pressures - only the records where the pressure recorded matches the tympanometric peak pressure which is recorded as the Adult Absorbance feature in the data.

Additional models such as K-Means Clustering or Neural Networks may be explored given the time constraints and the performance of the above four models in order to deliver the best results.

6 Project Management

This project will be completed over twelve weeks which is divided into three Phases (Processing, Modelling, and Reporting). The six team members will each contribute approximately 8 hours per week in Phase One and Phase Three, and 4 hours per week in Phase Two. This results in 480 hours spent over the 12 weeks. With an estimated cost of $40 per hour, this project is worth $19,200. The distribution of work amongst the team and across the Phases can be found in the Gantt Charts in Appendix A.

References

[1] E. M. Grais, X. Wang, J. Wang, F. Zhao, W. Jiang, Y. Cai, L. Zhang, Q. Lin, and H. Yang. Analysing wideband absorbance immittance in normal and ears with otitis media with effusion using machine learning. *Scientific Reports*, 11(1):1–12, 2021.

[2] M. K. Park. Clinical applications of wideband tympanometry. *Korean Journal of Otorhinolaryngology-Head and Neck Surgery*, 60(8):375–380, 2017.

[3] J. V. Sundgaard, J. Harte, P. Bray, S. Laugesen, Y. Kamide, C. Tanaka, R. R. Paulsen, and A. N. Christensen. Deep metric learning for otitis media classification. *Medical Image Analysis*, 71:102034, 2021.

[4] G. Zielhuis, G. Rach, and P. Van Den Broek. Screening for otitis media with effusion in preschool children. *The Lancet*, 333(8633):311–314, 1989.

7 Appendix - Gantt Charts

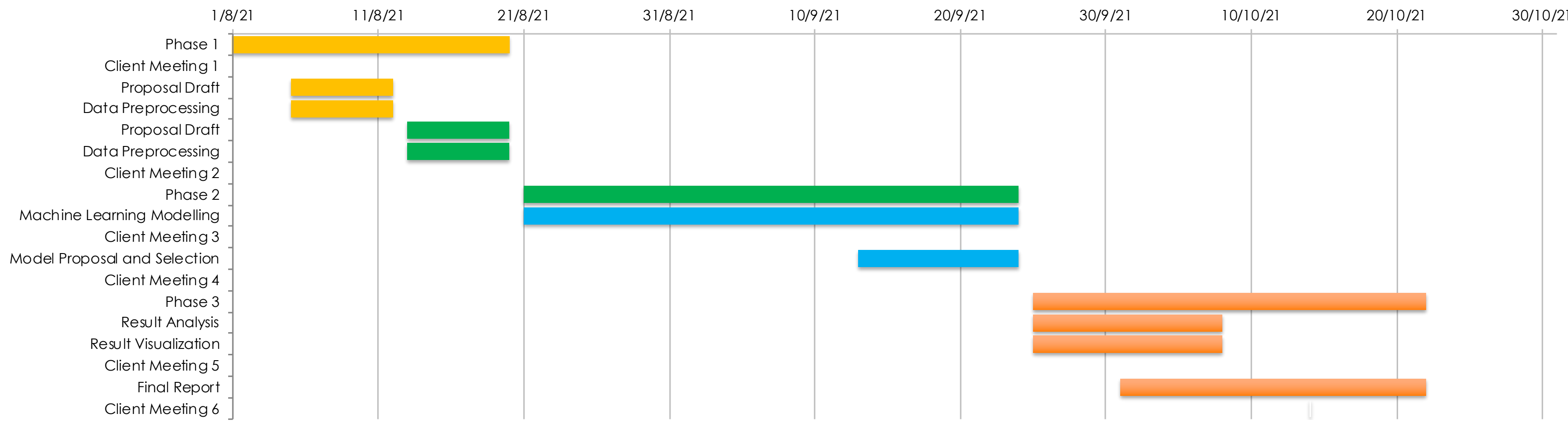
PROJECT NAME	PROJECT SUPERVISOR	START DATE	END DATE
Tytonidae Tympanometry	Robyn Choi	26-Jul	22-Oct

OVERALL PROGRESS
23%

PROJECT DELIVERABLE	1. ML Tool 2. Code 3. Final Report
TEAM MEMBERS	Daniel Chegwidden, Cheng Nian, Karan Rebello, Aminul Islam, Anitha Raghupathy, Di Yao

TASK NAME	RESPONSIBLE	START	FINISH	DURATION (DAYS)	STATUS	COMMENTS
Phase 1		26/7/21	20/8/21	25	In Progress	Team A - Karan, Di, Anitha Team B - Daniel, Cheng, Aminul Team Leader - Daniel
Client Meeting 1	Team Leader	28/7/21	28/7/21	0	Completed	
Proposal Draft	Team A	5/8/21	12/8/21	7	Completed	
Data Preprocessing	Team B	5/8/21	12/8/21	7	Completed	
Proposal Draft	Team B	13/8/21	20/8/21	7	Complete	
Data Preprocessing	Team A	13/8/21	20/8/21	7	In Progress	
Client Meeting 2	Team Leader	19/8/21	19/8/21	0	Complete	
Phase 2		**21/8/21**	**24/9/21**	**34**	Not Started	
Machine Learning Modelling	Entire Team	21/8/21	24/9/21	34	Not Started	
Client Meeting 3	Team Leader	2/9/21	2/9/21	0	Not Started	
Model Proposal and Selection	Entire Team	13/9/21	24/9/21	11	Not Started	
Client Meeting 4	Team Leader	16/9/21	16/9/21	0	Not Started	
Phase 3		**25/9/21**	**22/10/21**	**27**	Not Started	
Result Analysis	Team C	25/9/21	8/10/21	13	Not Started	
Result Visualization	Team D	25/9/21	8/10/21	13	Not Started	
Client Meeting 5	Team Leader	30/9/21	30/9/21	0	Not Started	
Final Report	Team E	1/10/21	22/10/21	21	Not Started	
Client Meeting 6	Team Leader	14/10/21	14/10/21	0	Not Started	

STATUS
Complete
Overdue
In Progress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Phase 1
Client Meeting 1
Proposal Draft
Data Preprocessing
Proposal Draft
Data Preprocessing
Client Meeting 2
Phase 2
Machine Learning Modelling
Client Meeting 3
Model Proposal and Selection
Client Meeting 4
Phase 3
Result Analysis
Result Visualization
Client Meeting 5
Final Report
Client Meeting 6