



**Faculty of Information and Communication
Technology**

**IDENTIFICATION MODEL FOR HEARING LOSS SYMPTOMS USING
MACHINE LEARNING TECHNIQUES**

Nasiru Garba Noma

Doctor of Philosophy

2014

**IDENTIFICATION MODEL FOR HEARING LOSS SYMPTOMS USING MACHINE
LEARNING TECHNIQUES**

NASIRU GARBA NOMA

A thesis submitted

**In fulfilment of the requirements for the degree of Doctor of Philosophy
in Information and Communication Technology**

Faculty of Information and Communication Technology

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2014

DECLARATION

I declare that this thesis entitled “Identification Model for Hearing Loss Symptoms using Machine Learning Techniques” is the result of my own research except as sited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :

Name :

Date :

DEDICATION

To

My Parents,

My Beloved Wife,

Whom without their Support

The completion of this research wouldn't have been possible

ACKNOWLEDGEMENTS

I will like to show my appreciation to Professor Madya Dr. Mohd Khanapi Abd Ghani for his immense contribution in supervising me throughout the research period. His advice, guidance and encourage is immeasurable. I sincerely thank him for his tolerance and effort in providing the direction of my research. Thank you, I am grateful.

It is in my delight that I express my admiration to the Faculty of Information and Communication Technology for providing me with such great condition during the period of my study and all the staff who assist in one way or the other during this period.

I wish to thank the Department of Otolaryngology, Hospital Sultanah Fatimah, Muar, Johor for their support and cooperation and for making the sample medical audiology records available for this research.

Finally, I am most indebted to my family, especially my father, Alh. Garba Mohd Noma, for taking care of my tuition fees and living expenses. My mother, my wife, Rukayya, my siblings, friends, and well-wishers for their immense support and prayers.

TABLE OF CONTENTS

PAGE

DECLARATION.....	i
DEDICATION.....	ii
AKNOWLEDGEMENTS	iii
LIST OF TABLES	vii
ABBREVIATIONS	xi
LIST OF APPENDICES	xii
ABSTRACT.....	xiii
CHAPTER 1 INTRODUCTION.....	1
1.1 Research Background.....	1
1.2 Problem Statement	1
1.3 Research Objectives	2
1.3.1 To Study the Existing Literature	2
1.3.2 To Design an Identification Model for Hearing loss Symptoms.....	3
1.3.3 To Evaluate the Identification Model.....	3
1.4 Research Questions	3
1.5 Relevance and Contribution of the Research	4
1.6 Organisation of the Thesis.....	5
CHAPTER 2 LITERATURE REVIEW	7
2.1 Background	7
2.2 Prevalence of Hearing Loss.....	7
2.3 Categories of Hearing Loss	9
2.4 Audiogram.....	13
2.5 Hearing Loss Symptoms and Existing Method of Diagnosis	18
2.6 Review of other Approaches for Investigating Hearing Loss	26
2.7 Proposed Technique for Detecting Hearing Loss Symptoms	30
2.7.1 Relationship between Audiometry Thresholds and Patients Data.....	32
2.8 Clinical Decision Support System	36
2.8.1 Impact of Clinical Decision Support System	38
2.9 Summary	42
CHAPTER 3 METHODOLOGY	44
3.1 Background	44

3.2	Theoretical Perspectives and Research Methodologies	44
3.3	Data Collection.....	45
3.3.1	Selecting Data Samples	47
3.3.2	Data Preparation	49
3.3.3	Ethical Considerations.....	50
3.5	Discovering Relationship in Audiometry Dataset.....	50
3.5.1	Small Sample Dataset.....	51
3.5.2	Large Sample Dataset.....	52
3.6	Identifying Relationship with Association Analysis Algorithm	52
3.7	Feature Transformation with FP-Growth Algorithm	63
3.8	Patterns Evaluation.....	65
3.9	Symptoms Identification with Naïve Bayes Algorithm	67
3.10	FP-Growth and Bayesian Classifier	68
3.11	Performance Evaluation and Validation	73
3.12	Summary	74
CHAPTER 4 IDENTIFICATION MODEL FOR HEARING LOSS SYMPTOMS.....		76
4.1	Background	76
4.2	FP-Growth Algorithm	76
4.3	Naïve Bayes Algorithm.....	79
4.3.1	Naïve Bayes Algorithm in Healthcare.....	85
4.4	Proposed Identification Model	89
4.5	Summary	91
CHAPTER 5 RESULTS AND ANALYSIS.....		93
5.1	Background	93
5.2	Results from Association Analysis using Small Sample Dataset	93
5.3	Results from Association Analysis using Large Sample Dataset	101
5.4	Symptoms Prediction and Model Evaluation.....	104
5.5	Discussion	109
5.6	Summary	113
CHAPTER 6 CONCLUSION.....		114
6.1	Background	114
6.2	Summary of the completed Work	114
6.3	Contributions.....	120

6.4 Constraints and Limitations	121
6.5 Future Work	122
6.6 Reflections and Concluding observations	122
List of References.....	124
APPENDICES	138

LIST OF TABLES

TABLE	TITLE	PAGE
2.1	Prevalence of disabling Hearing Loss in Population (15 years and above) Among Regions across the World	8
2.2	Absolute frequencies and assigned labels of the six classes in the Dataset	27
2.3	Expert Systems in Clinical setting	38
3.1	Dataset	54
3.2	Frequent itemsets arranged based on suffixes	62
4.1	Execution Time Based on Dimension of Dataset at support threshold of 5%	78
4.2	Summary of Application of Naïve Bayes Algorithm in Medical Field	87
5.1	Observed Tinnitus association rules from the conditional FP-tree	93
5.2	Summary of Tinnitus association rules from Table 5.1	94
5.3	Observed Vertigo association rules from the conditional FP-tree	96
5.4	Summary of Vertigo association rules from Table 5.3	97
5.5	Observed Tinnitus and Vertigo association rules from the Conditional FP-tree	99
5.6	Summary of Tinnitus and Vertigo association rules from Table 5.5	99
5.7	Observed Giddiness association rules from the Conditional FP-tree	100
5.8	Summary of Giddiness association rules from Table 5.7	100
5.9	Observed Tinnitus/Vertigo association rules from the Conditional FP-tree	100
5.10	Summary of Tinnitus and Vertigo association rules from Table 5.9	101

5.11	Observed Giddiness association rules from the conditional FP-tree	101
5.12	Summary of Tinnitus and Vertigo association rules from Table 5.11	102
5.13	Summary of Results for Multivariate Bernoulli Model with FP-Growth Feature Transformation	104
5.14	Summary of Results for Multivariate Bernoulli Model Without FP-Growth Feature Transformation	105
5.15	Summary of Results for Multinomial Model with FP-Growth Feature Transformation	106
5.16	Summary of Results for Multinomial Model without FP-Growth Feature Transformation	107

LIST OF FIGURES

TABLE	TITLE	PAGE
2.1	Left and Right-Sided Conductive Hearing Loss	12
2.2	Left and Right-Sided Sensorineural Hearing Loss	13
2.3	Frequencies and Hearing Level Measurement	15
2.4	Severities of Hearing Loss	16
2.5	Severities of Hearing Loss in Selected Regions	17
2.6	Investigation protocol for hearing loss	21
2.7	Hearing Loss Symptoms Diagnostic Procedure	23
3.1	Flow Chart of Data Collection	48
3.2	FP-tree Construction after reading TID = 1	54
3.3	FP-tree Construction after reading TID = 2	55
3.4	FP-tree Construction after reading TID = 3	55
3.5	FP-tree Construction after reading TID = 10	56
3.6	Finding frequent itemsets that ends with Otagia, Otorrhea, Giddiness, Vertigo and Tinnitus Path containing Otagia node	58
3.7	Finding frequent itemsets that ends with Otagia, Otorrhea, Giddiness, Vertigo and Tinnitus Path containing Otorrhea node	59
3.8	Finding frequent itemsets that ends with Otagia, Otorrhea, Giddiness, Vertigo and Tinnitus Path containing Giddiness node	60
3.9	Finding frequent itemsets that ends with Otagia, Otorrhea, Giddiness, Vertigo and Tinnitus Path containing Vertigo node	61
3.10	Finding frequent itemsets that ends with Otagia, Otorrhea, Giddiness, Vertigo and Tinnitus Path containing Tinnitus node	62
3.11	Algorithm for Calculating Parameters for the Prior	71

3.12	Algorithm for Calculating Parameters for the Multinomial Likelihood	72
3.13	Algorithm for Calculating Parameters for the Multivariate Bernoulli Likelihood	73
4.1	Naïve Bayes Models Comparison for different Vocabulary Sizes on Yahoo Dataset	82
4.2	Naïve Bayes Models Comparison for different Vocabulary Sizes on Newsgroups Dataset	83
4.3	Naïve Bayes Models Comparison for different Vocabulary Sizes on Industry Sector Dataset	84
4.4	Naïve Bayes Models Comparison different Vocabulary Sizes on WebKB Dataset	85
4.5	Identification Model for Hearing Loss Symptoms	88
5.1	Validation Results using Multivariate Bernoulli Model With FP-Growth Feature transformation	103
5.2	Validation results using Multivariate Bernoulli Model without FP-Growth Feature transformation	105
5.3	Validation results using Multinomial Model with FP-Growth Feature transformation	106
5.4	Validation results using Multinomial Model without FP-Growth Feature transformation	107

ABBREVIATIONS

ADSS	Audiology Decision Support System
EEG	Electroencephalogram
ECG	Electrocardiogram
PPG	Photoplethysmography
WHO	World Health Organization
AC	Air Conduction
BC	Bone Conduction
CDSS	Clinical Decision Support System
VTG	Vertigo
PCA	Principal Component Analysis
ICA	Independent Component Analysis
ART	Acoustic Reflex Threshold
HFA	High Frequency Audiometry
HL	Hearing Loss
NMRR	National Medical Research Register
FP-Growth	Frequent Pattern Growth
TNTS	Tinnitus
TID	Transaction ID
SVM	Support Vector Machine
MLP	Multilayer Perception Neural Network
ENT	Ear Nose and Throat
FP-Growth	Frequent Pattern Growth

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	Source Code	137
B	Expert Validation	145
C	Sample Medical Records	146

ABSTRACT

There is potential knowledge inherent in vast amounts of untapped and possibly valuable data generated by healthcare providers. Clinicians rely in their knowledge and experience and the basic diagnostic procedure to determine the likely symptom of a disease. Sometimes, many stages of diagnosis and longer procedures can leads to longer consultation hours and can consequently results to longer waiting time for other patients that need to be attended to. This can results to stress and anxiety on the part of those patients. This research presents an efficient way to facilitate the hearing loss symptoms diagnosis process by designing a symptoms identification model that efficiently identify hearing loss symptoms based on air and bone conduction pure-tone audiometry data. The model is implemented using both unsupervised and supervised machine learning techniques in the form of Frequent Pattern Growth (FP-Growth) algorithm as feature transformation method and multivariate Bernoulli naïve Bayes classification model as the classifier. In order to find, the correlation that exist between the hearing thresholds and symptoms of hearing loss, FP-Growth and association rule algorithms were first used to experiment with a small sample and large sample datasets. The result of these two experiments showed the existence of this relationship and the performance of the hybrid of the FP-Growth and naïve Bayes algorithms in identifying hearing loss symptoms was found to be efficient with very minimum error rate.

ABSTRAK

Terdapat sejumlah besar pengetahuan yang dihasilkan daripada penyedia penjagaan kesihatan yang masih belum diterokai dan sangat berharga. Kebiasaanya, para pengamal perubatan menggunakan pengetahuan, pengalaman dan prosedur diagnosa untuk mengenalpasti simptom bagi sesuatu penyakit. Kadangkala, proses diagnosa yang rumit dan prosedur yang banyak mengakibatkan masa menunggu dan jangkamasa konsultasi mengambil masa yang panjang dan lama. Senario sebegini boleh mendatangkan rasa stres dan kebimbangan kepada pesakit. Penyelidikan ini membentangkan kajian kaedah yang cekap dan memudahkan proses diagnosa bagi mengecam simptom kehilangan pendengaran melalui kaedah rekabentuk model pengenalpastian simptom yang cekap berdasarkan data “*on air and bone conduction pure-tone audiometry*”. Model yang dicadangkan menggunakan kedua-dua kaedah pembelajaran mesin yang diselia dan tidak diselia. Kaedah pembelajaran mesin yang digunapakai adalah dengan menggunakan algorithma “*Frequent Pattern Growth (FP-Growth)*” yang bertindak menggunakan kelebihan kaedah transformasi dan model klasifikasi “*multivariate Bernoulli naïve Bayes*” sebagai pengkelasan. Untuk mencari hubungan yang wujud di antara ambang pendengaran dan simptom kehilangan pendengaran, algorithma *FP-Growth* dan peraturan bersekutu akan digunakan di peringkat awal bagi proses ujikaji dengan menggunakan sampel data yang kecil dan juga dataset yang besar. Hasil kedua-dua ujikaji yang dijalankan menunjukkan wujudnya hubungan dan gabungan prestasi algorithma *FP-Growth* dan *naïve Bayes* di dalam proses mengenalpasti simptom kehilangan pendengaran. Hasil ujikaji juga menunjukkan keputusan yang baik dan kadar kesilapan yang sangat minima.

CHAPTER 1

INTRODUCTION

1.1 Research Background

The overall aim of the research is to efficiently identify hearing loss symptoms from pure-tone air and bone conduction audiometry thresholds in order to facilitate the procedure for investigating hearing loss symptoms.

The process involves finding relationship that exist between pure-tone audiometry thresholds and symptoms and other attributes in patient's medical audiology datasets and utilizing these relationships in identifying hearing loss symptoms. The symptoms can be accurately predicted with the aid of an identification model that employs hybrid machine learning techniques that can predict a class or label of a given input air and bone conduction pure-tone audiometry data.

1.2 Problem Statement

Statistics have shown the prevalence of disabling hearing loss to be very high in Asia pacific; a region which Malaysia is part of (WHO | Estimates, 2012). In Malaysia alone, about 31,000 cases of hearing loss were recorded in 1980 (Gallaudet encyclopedia, 1987). In 2005, statistics from National Survey Disorder shows prevalence of 17.4% within the population and about 3,962,879 cases were recorded during this period. This has made hearing loss as one of the top 10 reported disease by the Ministry of Health Malaysia (Mohd Hashim & Gazali, 2011). Hearing loss is one of the most common conditions that affect children, younger and elderly adults, which if not diagnosed and treated on time can leads to disability.

An otorhinolaryngology specialist classifies the hearing loss symptoms of a patient on the basis of their knowledge and after going through the basic hearing loss symptom diagnostic procedures. These procedures include 5 stages that are followed according to order. They include collection of patient case history, Otoscopy, Audiometric hearing tests, Tympanometry and Acoustic reflex. Considering the number of patients that usually visits ENT department of various hospitals for consultation with the otorhinolaryngology specialist in order to get their hearing problem diagnosed, the number of procedures and the time it takes for each procedure to be completed, these stages can significant delay the process and leave many patients waiting in a queue for many hours. On the part of the patients that were on the queue, longer waiting time can cause stress and anxiety. This can taint the patients' perception of the health system. Therefore, possible solutions are needed to reduce average patients waiting time in order to decrease the relative cost of consultation to the hearing loss patients.

1.3 Research Objectives

The research objectives of this research are summarised as follows:

1.3.1 To Study the Existing Literature

The first objective of this research is to study the existing basic method of investigating hearing loss symptoms in patients and to find the problems associated with the method. And also, to study the existing body of literatures that show the existence of relationship or connection between hearing loss patient's pure-tone audiometry data and any attribute in the medical record.

1.3.2 To Design an Identification Model for Hearing loss Symptoms

The second objective is to design an identification model for identifying hearing loss symptoms that employs hybrid machine learning technique to efficiently detect hearing loss symptoms given pure-tone audiometry thresholds. The model will be made up of both unsupervised and supervised learning techniques that detect the symptoms with high accuracy. FP-Growth algorithm is used as the unsupervised learning algorithm and naïve Bayes classification algorithm will be used as the supervised learning algorithm.

1.3.3 To Evaluate the Identification Model

The third objective is to evaluate the efficiency of the identification model using both expert validation and a statistical validation technique. The statistical technique to be used is the random repeated sub-sampling cross validation technique. It is a statistical method for evaluating learning algorithms by partitioning the data into training and validation sets. It will be used to estimate the accuracy of the model in identifying hearing loss symptoms given both air and bone conduction pure-tone audiometry data.

1.4 Research Questions

After the survey of various literatures on pure-tone audiometry, hearing loss etiologies and attributes in medical audiology records of hearing loss patients. Those studies that indicate a connection between patient's audiogram thresholds and their age, gender or disease have motivated raising the question of whether there is a relationship or connection between patients audiogram configuration and the diagnosed symptoms. This has also led to the question of whether the existence of relationship between audiogram thresholds and diagnosed symptoms could help in predicting hearing loss symptoms. Based on this the two research questions are:

Research Question 1

Is there any relationship between patient's pure-tone audiometry thresholds and hearing loss symptoms?

As earlier mention this question was brought about due to the engagement with relevant body of literature. It depicts possible connection between two variables that are to be tested. Gray (2009) pointed out that a good research question should describe potential relationships between and among variables that are to be tested.

Research Question 2

Can patterns that describe the relationship between pure-tone audiometry thresholds and hearing loss symptoms be used to predict symptoms?

This research question is dependent on the first research question. It is only applicable if those extracted patterns from the computational algorithm employed show any relationship. That is if patients audiogram configuration had any effect on the symptoms, otherwise it will not be applicable. For this research it is applicable because those patterns generated by FP-Growth algorithm have revealed relationship between pure-tone audiometry and hearing loss symptoms.

1.5 Relevance and Contribution of the Research

There is large amount of data that pervade the healthcare industry (Mowerman, 2007). This data needs to be utilized using the proper techniques in order to realize the value and the knowledge that may be inherent in it. With the advancement in information technology and the wide adoption of health information system (HIS) healthcare providers can no longer be complacent regarding embracing techniques to enable quality health services.

The healthcare worker goes through multi-spectral data and various information sources when diagnosing a disease in order to decide on the appropriate treatment strategy. This research can help in the discovery of new and useful patterns in audiometry datasets of patients. The computational algorithm can be used to implement an audiology decision support system (ADSS) that learns from past experiences and predicts likely symptoms with high accuracy and minimal error rate. The clinician can use both his knowledge and the system to make a better analysis of patient hearing test results and make more informed and better decisions than either he or the ADSS could make.

This work contributes to the existing body of knowledge by providing an efficient approach to feature transformation that can enhance the accuracy of text classification algorithms. The current findings of this research can also add to a growing body of literature on the connection between patient's audiogram configurations and structured data like age and gender and free text data such as diagnosis and medical history in patients' medical records.

1.6 Organisation of the Thesis

The thesis is structured in this order: Chapter 1 starts with the Research background which is 1.1, then Problem statement and Research objectives in sections 1.2 and 1.3 respectively. Research questions are in section 1.4, Relevance and contribution of the research in section 1.5 and Organization of the thesis on section 1.6.

Chapter 2 introduces the main components that make up the research. Literatures relating to each of these components are reviewed. Problems that are presented in Chapter 1 are also highlighted.

Chapter 3 summarises the theoretical research perspective adopted for the research. It also presents the research methodology used and data collection methods; the ones that were adopted for this research and why they were adopted.

Chapter 4 discusses the proposed identification models for hearing loss symptoms that help in accomplishing the research objective. Detailed explanation of the proposed solution is provided.

Chapter 5 depicts the results in tabular form and bar graph and discusses the findings from experiments carried out in the research.

Chapter 6 concludes the thesis by restating the aims and objectives of the research. The research contribution is discussed. It summarises the research findings and their significance. The limitations of the research are also explained.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

The overall aim of this chapter is to discuss the prevalence of hearing loss in selected regions with focus on Asia Pacific and Malaysia in particular, the categories, severities and symptoms of hearing loss and the existing method of investigating hearing loss symptoms. Then, identify the problem with the existing method. Most part of the chapter reviewed the current approaches or techniques proposed by other literatures in order to improve the process of investigating hearing loss. The chapter critically evaluate these different methods and the problems associated with them. The chapter also introduce the proposed appropriate technique for detecting hearing loss symptoms in patient; a technique which also addresses the research questions for this research. This chapter provide some review of literatures indicating relationship between audiometry configuration and some hearing loss patients attributes. It ends with discussing the meaning and impact of clinical decision support system and the contribution of researchers in this area.

2.2 Prevalence of Hearing Loss

It was estimated, about of 360 million people around the world are affected with hearing impairment (WHO, 2013). That is approximately 5.3% of the world's population. The prevalence of hearing loss has been found to be the highest in Sub-Saharan Africa, South Asia and Asia pacific (WHO | Estimates, 2012). In Malaysia, about 31,000 cases of hearing loss were recorded in 1980 (Gallaudet encyclopedia, 1987). In 2005, statistics from National Survey Disorder shows prevalence of 17.4% within the population and about 3,962,879 cases were recorded. This has made hearing loss as one of the top 10

reported disease by the Ministry of Health Malaysia (Mohd Hashim & Gazali, 2011). According to the World Health Organization (WHO), disabling hearing loss or deafness is a type of hearing loss that is greater than 40 decibels (db) in adults and greater than 30 decibels in children between the ages of 0 – 14 years (WHO Estimates, 2012).

Table 2.1 Prevalence of disabling Hearing Loss in Population (15 years and above)

Among Regions across the World

Source: Adapted from (WHO Estimates, 2012)

Selected Regions	Adults Over 65 years All Both sexes		Adults between 15 to 64 years Both sexes		Adults (15 years or older) Both sexes	
	Millions	Prevalence (%)	Millions	Prevalence (%)	Millions	Prevalence (%)
High-income	28.1	18.4%	9.1	1.4%	37.2	4.7%
Central/Eastern Europe and Central Asia	18.4	36.1%	11.3	4.0%	29.6	8.9%
Sub-Saharan Africa	11.3	44.1%	19.1	4.3%	30.3	6.4%
Middle East and North Africa	5.2	26.3%	5.5	1.9%	10.7	3.5%
South Asia	34.4	48.1%	53.8	5.4%	88.1	8.3%
Asia Pacific	14.8	43.5%	18.6	4.7%	33.4	7.7%
Latin America and Caribbean	14.8	38.6%	13.2	3.5%	28.0	6.8%
East Asia	37.6	34.4%	33.6	3.4%	71.2	6.5%

From table 2.1, it can be observed, within the population of people with hearing loss, the percentage of aged people that are over 65 years with disabling hearing loss years is higher in Sub-Saharan Africa, South Asia and Asia Pacific. It is highest in South Asia with 48.1% out of 34.4 million people with hearing loss. This is followed by Sub-Saharan Africa with