A MACHINE LEARNING FOR ENVIRONMENTAL NOISE CLASSIFICATION IN SMART CITIES

YASEEN HADI ALI

A project report submitted in partial fulfilment of the
requirements for the award of the degree of
Master of Engineering (Electronics and Telecommunications)

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

FEBRUARY 2021

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Dr. Rozeha Bt. A. Rashid, for encouragement, guidance, critics and friendship. I am also very thankful to my co-supervisor Mdm. Siti Zaleha Abdul Hamid for her guidance, advices and motivation. Without their continued support and interest, this thesis would not have been the same as presented here.

Many thanks to Universiti Teknologi Malaysia (UTM) for the support. Librarians at UTM, also deserve special thanks for their assistance in supplying the relevant literatures.

My fellow postgraduate students should also be recognised for their support. My sincere appreciation also extends to all my colleagues and others who have provided assistance at various occasions. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family members.

ABSTRACT

Many people may not be aware of the adverse effects of noise pollution on their health which include hearing impairment, negative social behaviour, anxiety, sleep disturbances and intelligibility to understand speech. Machine learning (ML) is the concept of making the machine determines, classifies, and does operations without being explicitly programmed. It is used in many fields such as intelligent transportation system and autonomous driving. Research in audio recognition has traditionally focused on the domains of speech and music. Comparatively, little research was done towards recognizing non-speech environmental sounds. For this reason, this project aims to develop an ML based classifier of sounds originated from the environment and compares the sound levels with the recommended levels by international standards via a created Graphical User Interface (GUI). Noise Capture mobile application will be used to record four sources of environmental noise, that are from highway, railway, lawn mowers and birds. Then, Python programming will be used to simulate the classification model using Scikit-learn. The trained data entered Scikit-learn gathered from Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Bootstrap Aggregation (Bagging) and Random Forest (RF) classifiers, as well as Artificial Neural Network (ANN) algorithm from Keras and TensorFlow libraries for comparative performances in the accuracy test. In addition to ML, a noise pollution survey is conducted to provide qualitative analysis of community perceptions. The findings of ML are presented in terms of confusion matrix, accuracy, precision, recall and F1 score. The results show that the noise classification accuracy for all models exceeded 95%. The best ML models are RF and ANN due to its high accuracy and the least computational time. The findings of survey are also presented, which indicates that there is no correlation between gender, age, location with knowledge of noise pollution and the effect of noise on people. People are bothered by noise regardless of their age and gender.

ABSTRAK

Ramai orang mungkin tidak menyedari kesan buruk pencemaran bunyi terhadap kesihatan mereka yang merangkumi masalah pendengaran, tingkah laku sosial yang negatif, kegelisahan, gangguan tidur dan kesukaran memahami ucapan. Pembelajaran mesin (ML) adalah konsep membuat mesin menentukan, mengklasifikasikan, dan melakukan operasi tanpa diprogram secara eksplisit. Ia digunakan dalam banyak bidang seperti sistem pengangkutan pintar dan pemanduan autonomi. Penyelidikan dalam pengecaman audio secara tradisional memfokuskan pada bidang pertuturan dan muzik. Secara perbandingan, sedikit kajian dilakukan untuk mengenali bunyi persekitaran bukan pertuturan. Atas sebab ini, projek ini bertujuan untuk membangunkan pengkelas berasaskan ML untuk bunyi yang berasal dari persekitaran serta membandingkan tahap bunyi dengan tahap yang disyorkan oleh piawaian antarabangsa melalui perantara muka pengguna grafik (GUI) yang dicipta. Aplikasi mudah alih Noise Capture akan digunakan untuk merakam empat punca bunyi persekitaran, iaitu dari jalan raya, kereta api, mesin pemotong rumput dan burung. Kemudian, pengaturcaraan Python akan digunakan untuk mensimulasikan model klasifikasi menggunakan Scikit-learn. Data terlatih yang dimasukkan ke dalam Scikit-learn dikumpulkan dari pengkelas Mesin Vektor Sokongan (SVM), K-Jiran Terdekat (KNN), Pengumpulan Bootstrap (Bagging) dan Hutan Rawak (RF) dan juga algoritma Rangkaian Saraf Buatan (ANN) dari Keras dan perpustakaan TensorFlow untuk pembandingan prestasi dalam pengujian ketepatan. Selain ML, soal selidik pencemaran bunyi dilakukan untuk mendapatkan analisis kualitatif persepsi masyarakat. Penemuan dari ML dipersembahkan dari segi matrik kekeliruan, ketepatan, kejituan, ingat semula dan skor F1. Hasil kajian menunjukkan bahawa ketepatan klasifikasi bunyi melebihi 95%. Model ML terbaik ialah RF dan ANN yang mempunyai ketepatan tinggi dan masa pengiraan terendah. Penemuan tinjauan juga dibentangkan, di mana menunjukkan tiada hubungan antara jantina, usia, lokasi dengan pengetahuan mengenai pencemaran bunyi dan kesan bunyi kepada orang ramai. Orang ramai terganggu dengan bunyi bising tanpa mengira usia dan jantina mereka.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

IOT	-	Internet of Thing
API	-	Application Programming Interface
JSON	-	Java Script Object Notations
ML	-	Machine Learning
KNN	-	K-Nearest Neighbours
SVM	-	Support Vector Machine
RF	-	Random Forest
Bagging	-	Bootstrap aggregation
SPL		Sound Pressure Level
WHO		World Health Organization
LAeq		A-weighted equivalent sound pressure level
Lden		Day-evening-night equivalent sound level
Lnight		Night equivalent sound level
NOISE		Noise Observation and Information Service for Europe
dB		Decibel
dB(A)		A-weighted decibel
END		European Union Directive 2002/49/EC
EU		European Union
GDG		Guideline Development Group

LIST OF SYMBOLS

K	-	The number of nearest neighbors in KNN
dBA	-	A-weighted frequency spectrum in dB

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

With increasing population of 60% by the end of 2030 [1], noise pollution will become a serious issue for many cities around the world. This is due to an increase of noise exposure (unpleasant, unwanted and often loud) for the people who are living in cities. Continuous exposure to high levels of noise may cause psychological and physiological issues e.g. hearing impairment, high blood pressure, heart disease, inconvenience and sleep annoyance [2] . Children who are living in noisy places showed low academic results [3]. Low birth weight of new-born babies is associated with noise exposure in pregnant women [3]. Therefore, there is an essential need not only to raise awareness of the harmful effects of noise pollution, but also to provide them with equipment to monitor their exposure to noise. A professional sound levels meter (SLM) is a standard tool for measuring sound pressure levels (SPL) in dB or dBA (A weighted to account for low human ear's sensitivity at low frequencies). However, these tools are expensive, sensitive, large, and above all, hard to use for non-professionals. With the development of smartphones, all of us carry a powerful mini-computer provided with different sensors, including microphones. These sensors can be used with a set of Application Programming Interfaces (APIs) provided by the smartphone to create applications to measure sound pressure level [4] , coronary heart disease detector [5], earth-quake detector [6], and pathological tremor detector [7]. For these apps to accurately process audio data, it is necessary to calibrate the smartphone microphone to report not only correct sound pressure levels but also correct frequency spectrum. However, it is not just necessary for noise measurement to be carried out, it is also essential to control the level of exposure to noise in critical areas such as schools, hospitals and kindergartens. Hence, there is a need to have a noise pollution measurement data in order to assess the level of noise exposure in certain areas.

1.2 Problem Statement

According to recent review by the World Health Organization (WHO), at least 100 million of people get disturbed by road traffic noise in the European Union and in Western Europe alone, at least 1.6 million years of healthy life have been lost due to traffic noise [8]. Noise pollution can affect people psychologically and physiologically such as hypertension, ischemic heart disease, annoyance, and most importantly, interferes with essential activities such as study, rest, sleep, communication and social activities [9], [10]. The sound at the same decibel (dB) level may be perceived either as annoying noise or as pleasant music by different listeners. Therefore, it is necessary to go beyond the state-of-the-art approaches that measure only the dB level [11][12] and also identifies the type of the sound especially when the sound is recorded using Microphone. The issues need to be addressed here: What was on the captured sound: human sound, animal sounds, or music playing? Is this sound exceeded the recommended levels by international standards? What is the community's perception about noise pollution?

1.3 Research Objectives

The objectives of this research are:

(a) To develop a sound classifier of surrounding environment with WHO recommended level benchmarking.

(b) To provide qualitative analysis of community perceptions based on noise pollution survey.

1.4 Scopes of project

The following are the considered scopes of this project:

(a) The developed model considers only noise pollution.

(b) The focus will be on four kinds of environmental noise originated from highway, railway, Lawn mowers and birds

(c) The measurements will be conducted using smartphone only.

(d) The developed model using python programming only.

(e) The algorithms used are only Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Bootstrap Aggregation (Bagging), Random Forest (RF) and Artificial neural networks (ANN) classifier

1.5 Contribution

The research in audio recognition has traditionally focused on the domains of speech and music. Comparatively, little research was done towards recognizing non-speech environmental sounds. Therefore, this project aims to develop a Machine Learning (ML) sound classification model of sounds originated from the surrounding environment such as sound of birds, vehicles, trains and lawn mowers, as well as comparing the collected noise levels by smartphone with the recommended levels by international standards. A statistical analysis on survey findings is also performed in order to gain a better understanding about the community's perspective on noise pollution and recommend noise mitigation methods.

1.6 Organization of report

This project report consists of five chapters that are organized as below: Chapter 1 consists of a background overview of the project, problem statements, objectives, scopes and contribution of the project. Chapter 2 describes the literature review on topics related to the project. The topics include Smart Cities, Machine learning (ML), Internet of thing (IoT), Cloud platform, fundamental concept of sound, available noise measurement tools, Environmental noise guidelines for the European region, WHO guidelines values for community noise, existing related work and summary with limitation of the previous work. Chapter 3 describes the methodology used in the project by explaining the workflow of the project, tools and software used. Chapter 4 provides the results and discussions of the project. Chapter 5 concludes the report with outcomes and future works of the project.

REFERENCES

[1] A. Almehmadi, “Smart City Architecture for Noise Pollution Mitigation through the Internet of Things,” *Int. J. Comput. Sci. Netw. Secur.*, vol. 18, no. 7, pp. 128–133, 2018.

[2] S. A. Stansfeld and M. P. Matheson, “Noise pollution: non-auditory effects on health,” *Br. Med. Bull.*, vol. 68, no. 1, pp. 243–257, Dec. 2003.

[3] T. Kawada, “The Effect of Noise on the Health of Children,” *J. Nippon Med. Sch.*, vol. 71, no. 1, pp. 5–10, 2004.

[4] R. Navarrete *et al.*, “Software and Hardware to Replace a Sound Level Meter,” *Int. J. Comput. Commun. Eng.*, vol. 1, no. 4, pp. 297–300, 2012.

[5] V. Pareek and R. K. Sharma, “Coronary heart disease detection from voice analysis,” *2016 IEEE Students’ Conf. Electr. Electron. Comput. Sci. SCEECS 2016*, pp. 1–6, 2016.

[6] Q. Kong, Y. W. Kwony, L. Schreierz, S. Allen, R. Allen, and J. Strauss, “Smartphone-based networks for earthquake detection,” *2015 15th Int. Conf. Innov. Community Serv. I4CS 2015*, pp. 0–7, 2015.

[7] J. Daneault, B. Carignan, C. É. Codère, A. F. Sadikot, and C. Duval, “Using a smart phone as a standalone platform for detection and monitoring of pathological tremors,” *Front. Hum. Neurosci.*, 2012.

[8] Z. Jakab, *Environmental Noise Guidelines for the European Region*. 2018.

[9] W. J. Murphy and J. R. Franks, *Revisiting the NIOSH Criteria for a Recommended Standard: Occupational Noise Exposure*, vol. 111, no. 5. 2002.

[10] H. Bloch, *ENVIRONMENT AND HEALTH*, vol. 64, no. 8. Denmark: European Environment Agency, 2008.

[11] M. Goetze, R. Peukert, T. Hutschenreuther, and H. Toepfer, “An open platform for distributed urban noise monitoring,” in *2017 25th Telecommunication Forum (TELFOR)*, 2017, pp. 1–4.

[12] Y. Tsao, B. Su, C. Lee, and C. Wu, “An implementation of a distributed sound sensing system to visualize the noise pollution,” in *2017 International Conference on Applied System Innovation (ICASI)*, 2017, pp. 625–628.

[13] U. N. Publications, *World Urbanization Prospects: The 2018 Revision*. UN,

2019.

[14] H. Chourabi *et al.*, “Understanding Smart Cities: An Integrative Framework,” in *2012 45th Hawaii International Conference on System Sciences*, 2012, pp. 2289–2297.

[15] R. Giffinger, G. Haindlmaier, H. Kramar, and F. Strohmayer, “european smart cities 4.0,” 2015.

[16] P. Bhavsar, I. Safro, N. Bouaynaya, R. Polikar, and D. Dera, “Chapter 12 - Machine Learning in Transportation Data Analytics,” M. Chowdhury, A. Apon, and K. B. T.-D. A. for I. T. S. Dey, Eds. Elsevier, 2017, pp. 283–307.

[17] A. L. Samuel, “Some Studies in Machine Learning Using the Game of Checkers,” *IBM J. Res. Dev.*, vol. 3, no. 3, pp. 210–229, 1959.

[18] “Machine Learning Tutorial - Javatpoint.” [Online]. Available: https://www.javatpoint.com/machine-learning.

[19] “Applications of Machine Learning - Javatpoint.” [Online]. Available: https://www.javatpoint.com/applications-of-machine-learning.

[20] “Life cycle of Machine Learning - Javatpoint.” [Online]. Available: https://www.javatpoint.com/machine-learning-life-cycle.

[21] “Machine Learning in MATLAB - MATLAB & Simulink - MathWorks.” [Online]. Available: https://in.mathworks.com/help/stats/machine-learning-in-matlab.html?w.mathworks.com.

[22] D. Dwivedi, “Machine Learning For Beginners |Towards Data Science,” 2018. [Online]. Available: https://towardsdatascience.com/machine-learning-for-beginners-d247a9420dab.

[23] “Supervised Machine learning - Javatpoint.” [Online]. Available: https://www.javatpoint.com/supervised-machine-learning.

[24] Y. Alsouda, “An IoT Solution for Urban Noise Identification in Smart Cities: Noise Measurement and Classification.” 2019.

[25] “Unsupervised Machine learning - Javatpoint.” [Online]. Available: https://www.javatpoint.com/unsupervised-machine-learning.

[26] W. H. Organization, *Hearing loss due to recreational exposure to loud sounds: a review*. Geneva PP - Geneva: World Health Organization, 2015.

[27] A. Kern, C. Heid, W.-H. Steeb, N. Stoop, and R. Stoop, “Biophysical parameters modification could overcome essential hearing gaps,” *PLoS Comput Biol*, vol. 4, no. 8, p. e1000161, 2008.

[28] B. Berglund, T. Lindvall, D. H. Schwela, and W. H. O. O. and E. H. Team, “Guidelines for community noise.” World Health Organization, Geneva PP - Geneva, 2000.

[29] J. E. Noriega-Linares and J. M. Navarro Ruiz, “On the application of the raspberry pi as an advanced acoustic sensor network for noise monitoring,” *Electron.*, vol. 5, no. 4, 2016.

[30] H. Fletcher and W. A. Munson, “Loudness, its definition, measurement and calculation.,” *J. Acoust. Soc. Am.*, vol. 5, pp. 82–108, 1933.

[31] Y.-H. Kim, *Sound propagation: an impedance based approach*. John Wiley & Sons, 2010.

[32] “IEC 61672-1:2013. Electroacoustics – sound level meters – Part 1,” *Specifications. Stand. Int. Electrotech. Comm.*, 2013.

[33] S. Garg, K. M. Lim, and H. P. Lee, “An averaging method for accurately calibrating smartphone microphones for environmental noise measurement,” *Appl. Acoust.*, vol. 143, pp. 222–228, 2019.

[34] N. Audio, “Fast, Slow, Impulse Time Weighting - What do they mean?” [Online]. Available: https://www.nti-audio.com/en/support/know-how/fast-slow-impulse-time-weighting-what-do-they-mean. [Accessed: 29-Sep-2020].

[35] B. Zhong *et al.*, “An automatic calibration system for frequency weighting functions of sound level meter,” in *2010 IEEE International Conference on Mechatronics and Automation*, 2010, pp. 401–405.

[36] W. Zamora, C. T. Calafate, J. C. Cano, and P. Manzoni, “Accurate ambient noise assessment using smartphones,” *Sensors (Switzerland)*, vol. 17, no. 4, pp. 1–18, 2017.

[37] P. Patil, “Smart IoT Based System For Vehicle Noise And Pollution Monitoring,” *Int. Conf. Trends Electron. Informatics*, pp. 322–326, 2017.

[38] E. Kanjo, “NoiseSPY: A Real-Time Mobile Phone Platform for Urban Noise Monitoring and Mapping,” *Mob. Networks Appl.*, vol. 15, pp. 562–574, Aug. 2010.

[39] N. Maisonneuve, M. Stevens, M. Niessen, and L. Steels, *NoiseTube: Measuring and mapping noise pollution with mobile phones*. 2009.

[40] J. Picaut, N. Fortin, E. Bocher, G. Petit, P. Aumond, and G. Guillaume, “An open-science crowdsourcing approach for producing community noise maps using smartphones,” *Build. Environ.*, vol. 148, no. October 2018, pp. 20–33,

2019.

[41] T. B. de Souza, K. C. Alberto, and S. A. Barbosa, “Evaluation of noise pollution related to human perception in a university campus in Brazil,” *Appl. Acoust.*, vol. 157, p. 107023, 2020.

[42] H. P. Lee, S. Garg, and K. M. Lim, “Crowdsourcing of environmental noise map using calibrated smartphones,” *Appl. Acoust.*, vol. 160, p. 107130, 2020.

[43] J. A. Mariscal-Ramirez, J. A. Fernandez-Prieto, J. Canada-Bago, and M. A. Gadeo-Martos, “A new algorithm to monitor noise pollution adapted to resource-constrained devices,” *Multimed. Tools Appl.*, vol. 74, no. 21, pp. 9175–9189, 2015.

[44] P. W. Wessels and T. G. H. Basten, “Design aspects of acoustic sensor networks for environmental noise monitoring,” *Appl. Acoust.*, vol. 110, pp. 227–234, 2016.

[45] F. T. Espinoza and G. B. Gavilanes, “Sound Noise Levels Calibration with Smart-phones,” in *European Wireless 2017; 23th European Wireless Conference*, 2017, pp. 1–6.

[46] I. Kirillov and V. Bulkin, “The mobile system of urban area noise pollution monitoring,” in *2015 Second International Scientific-Practical Conference Problems of Infocommunications Science and Technology (PIC S&T)*, 2015, pp. 200–203.

[47] Y. Alsouda, S. Pllana, and A. Kurti, “A Machine Learning Driven IoT Solution for Noise Classification in Smart Cities,” in *21st Euromicro Conference on Digital System Design (DSD 2018)*, 2018.

[48] V. Bountourakis, L. Vrysis, and G. Papanikolaou, “Machine learning algorithms for environmental sound recognition: Towards soundscape semantics,” in *Proceedings of the Audio Mostly 2015 on Interaction With Sound*, 2015, pp. 1–7.

[49] C. Sparke, “Environmental Noise Classification through Machine Learning,” in *Proceedings of ACOUSTICS*, 2018, vol. 7, no. 9.

[50] D. Nast, W. Speer, and C. Le Prell, “Sound level measurements using smartphone ‘apps’: Useful or inaccurate?,” *Noise Health*, vol. 16, no. 72, pp. 251–256, Sep. 2014.

[51] C. Kardous and P. Shaw, “Evaluation of smartphone sound measurement applications,” *J. Acoust. Soc. Am.*, vol. 135, Mar. 2014.

[52] T. McLennon, S. Patel, A. Behar, and M. Abdoli-Eramaki, “Evaluation of smartphone sound level meter applications as a reliable tool for noise monitoring,” *J. Occup. Environ. Hyg.*, vol. 16, no. 9, pp. 620–627, Sep. 2019.