# CLASSIFICATION OF STRESS LEVEL BASED ON SPEECH FEATURES

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# CLASSIFICATION OF STRESS LEVEL BASED ON SPEECH FEATURES

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# **Abstrak**

Kehidupan kontemporari adalah penuh dengan cabaran, gangguan, tarikh akhir, kekecewaan dan permintaan yang tidak berkesudahan. Ini boleh mengakibatkan sesorang itu stres. Stres telah menjadi satu fenomena global yang dialami dalam kehidupan moden harian kita. Stres mungkin memainkan peranan penting dalam gangguan psikologi dan tingkah laku seperti kebimbangan atau kemurungan. Oleh itu, pengesanan awal tanda-tanda dan gejala stres merupakan penawar ke arah mengurangkan kesan buruk dan kos yang tinggi dalam pengurusan stres. Usaha penyelidikan yang dibentangkan ini merangkumi teknik Pengenalan Percakapan Automatik (ASR) untuk mengesan stres sebagai alternatif yang lebih baik berbanding pendekatan yang lain seperti analisis kimia, kekonduksian kulit, elektrokardiogram yang mahal dan mempunyai kesan halangan dan gangguan. Dua set data suara direkodkan daripada sepuluh orang pelajar Arab di Universiti Utara Malaysia (UUM) iaitu dalam mod rehat dan stress. Ciri-ciri percakapan seperti frekuensi asas  $(f_0)$ ; formants (F1, F2, dan F3), tenaga dan Pekali Frekuensi Cepstral Mel (MFCC) ini diekstrak dan dikelaskan menggunakan jiran K-terdekat, Analisisa Diskriminan Linear dan Rangkaian Neural Buatan. Keputusan dari nilai purata frekuensi asas mendedahkan bahawa peningkatan stres adalah berkait rapat dengan pertambahan nilai frekuensi asas. Daripada tiga metod pengkelasifan, prestasi jiran K-terdekat (KNN) adalah terbaik diikuti oleh analisisa diskriminan linear (LDA) manakala rangkaian neural buatan (ANN) menunjukkan prestasi yg paling rendah. Klasifikasi tahap stres rendah, sederhana dan tinggi telah dilakukan berdasarkan keputusan klasifikasi daripada KNN. Kajian ini menunjukkan kebolehgunaan maju ASR sebagai cara yang lebih baik pengesanan stres dan pengkelasan.

# **Abstract**

Contemporary life is filled with challenges, hassles, deadlines, disappointments, and endless demands. The consequent of which might be stress. Stress has become a global phenomenon that is been experienced in our modern daily lives. Stress might play a significant role in psychological and/or behavioural disorders like anxiety or depression. Hence early detection of the signs and symptoms of stress is an antidote towards reducing its harmful effects and high cost of stress management efforts. This research work thereby presented Automatic Speech Recognition (ASR) technique to stress detection as a better alternative to other approaches such as chemical analysis, skin conductance, electrocardiograms that are obtrusive, intrusive, and also costly. Two set of voice data was recorded from ten Arabs students at Universiti Utara Malaysia (UUM) in neural and stressed mode. Speech features of fundamental, frequency  $(f_0)$ ; formants (F1, F2, and F3), energy and Mel-Frequency Cepstral Coefficients (MFCC) were extracted and classified by K-nearest neighbour, Linear Discriminant Analysis and Artificial Neural Network. Result from average value of fundamental frequency reveals that stress is highly correlated with increase in fundamental frequency value. Of the three classifiers, K-nearest neighbor (KNN) performance is best followed by linear discriminant analysis (LDA) while artificial neural network (ANN) shows the least performance. Stress level classification into low, medium and high was done based of the classification result of KNN. This research shows the viability of ASR as better means of stress detection and classification.

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# **List of Acronyms**

A Age of the speakers

**ANN** Artificial Neural Network

ANS Automatic Nervous System

**ASR** Automatic Speech Recognition

**BN** Bayesian Network

**BPNN** Back-propagation Neural Network

**BVP** Blood Volume Pressure

**CB** Critical Band

**CRs** Classification Rates

**CV** Consonant-Vowel

**DFT** Discrete Fourier Transform

**DTW** Discrete Wavelet Transform

*f0* Fundamental Frequency

**F1, F2, F3** First, Second and Third Formants

**F, M** Female, Male

**FFT** Fast Fourier Transform

**FM** Frequency Modulation

**FS, FN** Female Stress, Female Neutral

**GMM** Gaussian Mixture Model

**GSR** Galvanic Skin Response

**HCI** Human- Computer Interaction

**HCNN** Hidden Control Neural Network

**HMM** Hidden Markov Model

**HR** Current Heart Rate

**KNN** K-Nearest Neighbor

*l* Exertion level

**LDA** Linear Discriminant Analysis

LM Levenberg-Marquardt back propagation

**LPC** Linear Predictive Coding

MAP Maximum A Posteriori

MFCC Mel-Frequency Cepstral Coefficient

MHR Maximum Heart Rate

MLP Multi-Layer Perceptron

MS, MN Male Stress, Male Neutral

NN Neural Network

**PAD** Pitch, Amplitude, Duration

**PLP** Perceptual Linear Prediction

**RHR** Normal Heart Rate

**RNN** Recurrent Neural Network

**ROS** Rate of Speech

**SLM** Sound Level Meter

**ST** Skin Temperature

**STT** Speech to Text

SUSAS Speech under Simulated and Actual Stress

**SVM** Support Vector Machine

**TEO** Teager Energy Operator

**VQ** Vector Quantization

WER World Error Rate

# **CHAPTER ONE**

### INTRODUCTION

### 1.0 Introduction

This section serves as a broad introduction to the study. It contains the background of the study, motivation, and problem statement. In addition, it also presents research questions and the objectives of the research, the scope and significance of the study.

# 1.1 Background

Contemporary life is filled with challenges, hassles, deadlines, frustrations, disappointments, and endless demands. The consequent of which might be stress. Stress has become a global phenomenon that is been experienced in our modern daily lives (Lu et al., 2012). For many people, stress is so commonplace – in traffic, markets, schools, or at work that it has become a way of life so much that ability to cope with stress is seen as a plus quality. While to some stress is a nightmare. Stress is not always bad, in small doses, it can help propel and motivate an individual under pressure to do better (Dhole & Gurjar, 2013). But being constantly running in emergency mode (stressed), the body and mind might pay the price. Affirming this is the studies report that stress might play a significant role in psychological and/or behavioural disorders like anxiety or depression (Dhole & Gurjar, 2013; Lu et al., 2012). Early detection of the signs and symptoms of stress is an antidote towards reducing its harmful effects and high cost of stress management efforts. Ability to detect stress and the level can be of use vital in applications that are stress sensitive such as

# The contents of the thesis is for internal user only

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