PREDICTION OF BECK DEPRESSION INVENTORY (BDI-II) SCORE USING ACOUSTIC MEASUREMENTS IN A SAMPLE OF IIUM ENGINEERING STUDENTS

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Abstract. Psychiatrist currently relies on questionnaires and interviews for psychological assessment. These conservative methods often miss true positives and might lead to death, especially in cases where a patient might be experiencing suicidal predisposition but was only diagnosed as major depressive disorder (MDD). With modern technology, an assessment tool might aid psychiatrist with a more accurate diagnosis and thus hope to reduce casualty. This project will explore on the relationship between speech features of spoken audio signal (reading) in Bahasa Malaysia with the Beck Depression Inventory scores. The speech features used in this project were Power Spectral Density (PSD), Mel-frequency Ceptral Coefficients (MFCC), Transition Parameter, formant and pitch. According to analysis, the optimum combination of speech features to predict BDI-II scores include PSD, MFCC and Transition Parameters. The linear regression approach with sequential forward/backward method was used to predict the BDI-II scores using reading speech. The result showed 0.4096 mean absolute error (MAE) for female reading speech. For male, the BDI-II scores successfully predicted 100% less than 1 scores difference with MAE of 0.098437. A prediction system called Depression Severity Evaluator (DSE) was developed. The DSE managed to predict one out of five subjects. Although the prediction rate was low, the system precisely predict the score within the maximum difference of 4.93 for each person. This demonstrates that the scores are not random numbers.

1. Introduction

Based on The National Health and Morbidity Survey on 2015, 29 percent of Malaysians had depression which is 17 percent higher than the statistic in 2011[1]. The percent increment shown by this statistic demonstrated that this issue has become very alarming and shows that this project have very high potential to help this problem. Depression does not only has effect on the individual, it also adds problems to the development of country as each individual has a value to the country.

However, we still having difficulties in solving this problem since it is very challenging for clinician to identify the depression severity of a patient. Researchers have struggled to find a way to identify the severity of depression since long ago, as a result, Aaron T. Beck has published an instrument to measure the severity of depression named Beck Depression Inventory. It is actually a self-report, which contain 21 questionnaires and each one have four options which indicate the score from 0 (not present) to 3 (severe). Each of the item or question have its own category, including sadness, pessimism, past failure, loss of pleasure, suicide thought, crying, agitation, loss of interest, indecisiveness, worthlessness, loss of energy, change in sleep pattern, irritability, change in appetite, concentration...
difficulty, fatigue and loss interest in sex respectively [2]. The severity of depression can be
determined by the rating of overall BDI-II scores as in the Table 1.

**Table 1. Depression indication according to scores range [2]**

| BDI-II Scores | Depression Indication |
|---------------|-----------------------|
| 10 and lower  | Normal                |
| 11 to 16      | Sad                   |
| 17 to 20      | Mild                  |
| 21 to 30      | Moderate              |
| 31 to 40      | Severe                |
| 40 and more   | Need Serious treatment |

Nowadays, the advancement of technologies has changed our daily lives. Many things have been
invented and at the same time encourage researchers to look at new approaches in identifying the
severity of the depression. Some use imaging device like camera to do image processing and some use
audio device to do audio processing and some even do both. This new approach has the goal to accurately
measure the severity of depression instantaneously.

As for this project, we focus on audio processing using the reading speech of the subject. It is
good to review others works related to this project. Based on other research by others [3] [4] [5], most
of them extract Mel-Frequency Cepstral Coefficients (MFCC) speech features, but the approach to
predict the scores were different. They try to predict using Gaussian Mixture Model [3], Gaussian
Staircase Regression [4] and Multiple Linear Regression Model [5]. The best method to apply is using
Linear Regression as it gave the minimum mean absolute error.

2. Data
Data is an important requirement to complete this project as this data are needed to train the prediction
system. The subject need to fill the BDI-II Inventory and then the need to be interviewed and read a
passage which will be recorded using Tascam DR-05 with sample rate at 44.1 kHz. All the recorded
session is done in a closed room. After the whole data collection is done, the subject will receive
RM10.00 as honorarium.

The subjects were male and female with the age range 18-29 which are engineering students at
International Islamic University Malaysia (IIUM). All of the subjects do not have any respiratory
problem and not under the influence of alcohol. The recording session was done in a closed room, but
not fully soundproof to make sure the robustness of the system.

During the recording session the subject reads a passage. The passage should be a rainbow
passage, but since there is no Bahasa Malaysia passage that is equivalent to the rainbow passage, we
decided to go with any controlled passage.

3. Speech Features
Several types of speech were collected to be tested to identify the best combination of speech features
to be implemented in DSE system. The speech features include 3 Power Spectral Densities (PSD), 13
MFCC, 6 Transition Matrix (TM), 2 formant, maximum and minimum pitch which in total of 26
features. This system, however only applies PSD, MFCC and TM since the best combination of speech
features only contain these 3 types of speech features.
3.1. Power spectral Density (PSD).
Three features are collect from PSD. PSD is actually a power intensity of a signal in frequency or for a sound waves it is loudness. Most energy in a speech of an adult contain in a rage 0 to 2000Hz. To minimize the number of features, the range of 0Hz to 2000Hz is divided into 4 segments with equal width. Thus, the first band would be 0Hz to 500Hz and the second band from 500Hz to 1000Hz and the third band would be 1000Hz to 1500Hz. Only the first three bands are collected as the fourth band can be predicted by the first three bands.

3.2. Transition Matrix.
This feature is a set of probability of state transition as shown in figure 1. Each block represent 0.04 second segment and categorized into number 1, 2 and 3 which represent voiced, unvoiced and silence respectively. The unvoiced speech segments are basically a noise like signal which have high frequency components. Whereas the voiced signal have low frequency components. Butterworth Filter was used to categorize this signal. However, silence speech sound wave also has low frequency components like voice speech sound wave. In order to categorize between them, threshold is needed. [6]

Figure 1. Graphical representation of state transition [5]

3.3. Mel-Frequency Cepstral Coefficients (MFCC)
Mel-Frequency Cepstral Coefficients are quite popular speech features and commonly used for speech analysis. MFCC represents the logarithmic perception of the human auditory system. MFCC also can represent the spectrum of an audio signal in the Mel scale. It acts like human hearing system.

4. Methodologies
The system development was divided into two parts which are identifying the best speech features for part 1 to achieve the first two objectives and develop Depression Severity Evaluator (DSE) to achieve the third objective.

In part 1 the flowchart is shown in Figure 2. This process is very important in order to continue to part 2. The goal of this process is to find the combination of speech features that give the lowest mean absolute error in predicting the BDI-II score using the data that have collected. Too many features may result in high error, so the Sequential Forward Selection (SFS) method was used with linear regression to find the predicted scores. Each feature was selected one-by-one and evaluated using linear regression until all features are evaluated. Feature that gives the least mean sum of absolute error was selected and add it to the empty set one at a time.

Jackknife method also used in this process to train the system. The implementation of the jackknife method in this process is on the basis of leave-one-out. The process involves discarding out one student’s score data from the data set and develops a training data set with the remaining N-1 students. The excluded data is then tested. This process is repeated by excluding the next students from the overall set of data until all students have been chosen to be excluded as testing data.

The combination of speech features that give the least mean absolute error were selected as the best and used to find the model coefficient, a using the formula of linear regression $b = D \times a$ where $b$ is the column vector of the actual value of BDI-II scores, $D$ is the input vectors (combination of speech features). Note that the model coefficient, $a$, is in matrix form.
Figure 2. Flowchart of identifying best combination of Speech Features for BDI prediction.

Once we have the model coefficient, \( a \), from the best combination of speech features, we can continue to part 2 to build the Graphical User Interface (GUI) of the DSE. The simple block diagram of DSE is shown in figure 3.

Figure 3. Simple Block Diagram of DSE
Graphical User Interface (GUI)

![Graphical User Interface](image.png)

**Figure 4.** Depression Severity Evaluator (DSE) GUI

![Depression Severity Evaluator (DSE) operational flowchart](image.png)

**Figure 5.** Depression Severity Evaluator (DSE) operational flowchart.

The process of this system almost the same with the process in part 1. Only few changes were done on the feature extraction. The major changes in this system compare to part 1 is on
evaluating process. Where the model coefficient, \( a \), in part 1 were used to multiply with the best combination of speech features which shown in table 2 for male and female.

**Table 2.** Best speech features combinations

| Number of features | Male: List of features | Female: List of features |
|--------------------|------------------------|--------------------------|
| 6                  | mfcc7, mfcc1, tm9, mfcc9, mfcc11, tm1 | 6 | mfcc2, mfcc11, mfcc8, mfcc7, mfcc10, psd3 |

5. Result and discussion

For part 1, the result was in term of mean absolute error (MAE). As the process depended on gender separately same goes on the result. For male reading, it can be seen that (SFS) method give the most minimum MAE which is 0.098437 with 6 features selected. The minimum MAE for (SBS) method, however could not outperform the SFS method with MAE of 1.95651 with 8 features left.

For female reading, again, the Sequential Forward Selection method gives the lowest mean absolute error with also 6 speech features. The mean absolute error is quite low which at 0.4096. Whereas, the MEA for SBS method is 4.261898 with 7 features left.

Thus, the best combination of speech features for male reading are mfcc7, mfcc1, tm9, mfcc9, mfcc11, tm1 whereas for female reading mfcc2, mfcc11, mfcc8, mfcc7, mfcc10, psd3. Quite interesting that the remaining best features are MFCC, PSD and TM. MFCC and PSD are a spectrum based measure where spectrum based, in a sense that it involves the energy information, whereas for Transition Matrix, more like speech pattern.

As for part 2, the DSE GUI was tested by using the train data to validate the system as few changes have been made. The result was pretty good, we can say that the system can predict the score accurately within the trained data. Then, the system was tested on a new subject where the subject need to fill BDI-II survey as an actual score and read a passage two times to get scores using DSE as predicted scores. All the result were evaluated and tabulated in table 3. The percentage error were calculated by using actual score and the average of test score 1 and 2. Whereas, the test score difference shows the different between test score 1 and 2. Despite the unsatisfactory on percentage error, the test score difference shows the potential of DSE.

**Table 3.** DSE analysis result

| Subject         | Test1 | Test2 | Test3 | Test4 | Test5 |
|-----------------|-------|-------|-------|-------|-------|
| Actual Score    | 17    | 13    | 4     | 13    | 34    |
| Test Score 1    | 4.29  | 4.25  | 25.36 | 27.63 | 40    |
| Test Score 2    | 5.36  | 2.87  | 28.03 | 26.96 | 35.07 |
| % Error         | 71.62 | 72.62 | 567.38| 107.35| 37.53 |
| Test Score Difference | 1.07 | 1.38  | 2.67  | 1.35  | 4.93  |

6. Conclusion

As a conclusion, the relevant speech features from Bahasa Malaysia’s speech were obtained. The combination of speech features for BDI-II score prediction also managed to be evaluated and the prediction system Depression Severity Evaluator has developed. Even though the DSE could not accurately measure the severity of depression, the score is not just a random numbers which have
potential to be improved. Thus, it highlights the potential of this project in identifying the severity of depression.

7. References
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In the Acknowledgements section, the following text appears:

“This work is part of the ongoing project on the development of BDI-II score prediction system funded by the Department of Mechatronics Engineering, International Islamic University Malaysia.”

This should read:

“This work is part of the ongoing project on the development of BDI-II score prediction system funded by the Department of Mechatronics Engineering, International Islamic University Malaysia. This research is supported by the Research Acculturation Grant Scheme (RAGS 14-040-0103) by the Ministry of Higher Education Malaysia.”