ISSN: 04532198
Volume 62, Issue 08, September, 2020

Device Identifier for Pre-Screening of Depression Assessment

Nor Athirah Muhammad Soffian Wong[1], Siti Fauziah Toha[2], Nik Nur Wahidah Nik Hashim[3*], Rabiatuladawiah Abu Hanifah[4]

Department of Mechatronics Engineering, Faculty of Engineering, International Islamic University Malaysia, Kuala Lumpur, Malaysia[1,2,3,4]

Corresponding author: 3*

ABSTRACT— Current depression pre-screening session is usually completed with a tool such as the Depression, Anxiety, and Stress Scale (DASS21) before proceeding with treatment. Development of a device for depression measurement is hoped to overcome the issues related to time management and paper waste during assessment process. The device may also be useful as an assistance to other assessment method in delivering the final diagnosis. Data input and output of DASS21 has been utilized for the system identification technique where analysis comparison was conducted using ARX and transfer function model. The result shows that the transfer function model of order 2 outperform ARX with best fit of 98.1%. A device identifier was developed in order to assess the level of depression by implementing the transfer function into the Arduino code to predict the result from the user input.

KEYWORDS: ARX, Assessment Device, Mental Health, DASS21, Device Identifier.

1. INTRODUCTION

Mental disorder such as anxiety and depression have a big impact on an individual's lifestyle such as sleep cycle, social life and education life [1]. Depression and anxiety are also one of the main factors of predisposition suicide. The statement is supported by the World Health Organization (WHO) which mentioned that suicidal rate is around 800,000 per year and its' significant contribution is depression. The fact that 322 million people in the world are diagnosed with depression portrays the severity of the illness [2]. With the serious issues highlighted, it is essential to take measurement to prevent further damage towards individual and society. Before proceeding with further treatment, attending pre-screening session is necessary for the patient. Pre-screening is important to determine the severity of depression. However, it does not necessarily involve diagnosing of the illness3. Generally, the session requires some tools to gage the severity of depression and it is normally in the form of questionnaires. Although each tool has its special scoring system, consistent higher score is commonly associated with severe symptoms [3]. Well-known questionnaires or scale that has been used for pre-screening are the Hospital Anxiety and Depression Scale (HADS) [4], Depression, Anxiety and Stress scale (DASS21) [5], Patient Health Questionnaire 9 (PHQ-9) [6], and Hamilton Depression Rating Scale (HDRS) [7]. These scales are self-reported and contain list of questionnaires which will then be analyzed by a trained clinician. For this project, the model for depression will be developed using the system identification technique. System identification is the technique of obtaining mathematical functions of dynamic system based on input and output of the observed system [8]. To fit the data of the model, there are different mathematical functions that are available such as transfer function, state space model, process model, polynomial model, nonlinear model, spectral model, and correlation model9. System identification method includes steps such as model structure selection, parameter estimation and model validation. Model structures such as polynomial and transfer function model have their own characteristics and selected depending on the system characteristics. In this study, ARX model and transfer function model will be used.

2. Methodology

2.1 Depression, Anxiety and Stress Score (DASS21) Database

DASS21 is a shorter version of DASS42 and it is reported to be more stable and distinctive [10]. It has been used widely because the validation is determined and the scale has wider range of user which is suitable for clinical and non-clinical groups. Compared to HADS, it focuses on the clinical group due to its low sensitivity on the opposite group [11]. DASS21 consists of 21 questions that assess depression, anxiety and stress. The database for this study consists of DASS21 sub-scores and total scores were collected from 7,925 subjects. The data was provided by Professor Dr. Ramli Musa from Kulliyyah of Medicine, International Islamic University Malaysia. DASS21 consists of 5 outputs indicating the threshold where normal is 0-8, mild is 10-12, moderate is 14-20, severe is 22-26 and extremely severe is 28-42. The scale has a total 21 items with three sub- scale; depression, anxiety and stress. This study will only focus on the depression aspect. The input for each question in DASS21 will be in range 0 to 3 where 0 means the question is not applicable to the patient while 3 means the question is most applicable to the patient.

2.2 System Identification

System identification is defined as a technique that is used for modelling a dynamic system where it involves obtaining the mathematical description from the input and output data of real plant. System identification is known for its various functions where it is commonly used as a technique for estimation, prediction and simulation. For instances, the technique has been used in the estimation of muscle stiffness during one cycle of pedalling exercises [12], prediction of energy consumption in building [9], simulation of liquid flow process [13] and simulation of a turbine power generator [14]. The existence of various researches on system identification proves its reliability towards these types of applications. Data acquisition is vital because lack of information can lead to failure of result. In this study, only the DASS21 questions related to the depression subscale were chosen for analysis of input/output. The system consists of 7 inputs and 1 output as illustrated in Figure 1. The input will be the scale range from 0 to 3 coming from question number 3,5,10,13,16,17 and 21 of DASS21 scale while the output will range from 0 to 42 representing the severity level of depression.

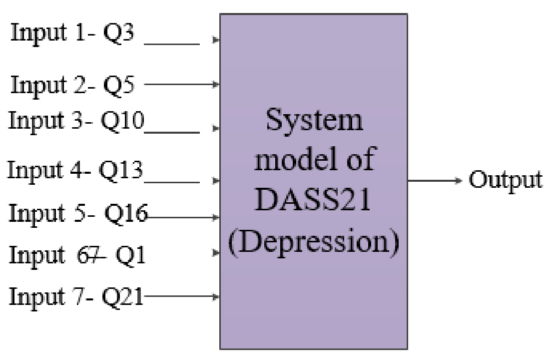


Figure 1. System model of depression based on DASS21

Next step is the model structure selection which is the prerequisite of the parameter estimation. Depending on the characteristic of the system, selection of model can be varied among the candidates such as polynomial model, state-space model and transfer function model. The structures of the polynomial model are ARX, ARMA, ARMAX, Box-Jenkins and output-error model. Upon completion of selecting model structure, the unknown parameters will then be determined. Next, the acquired model with known parameters requires validation in order to achieve high accuracy and reliable result. The validation is done through the process of acquiring best fit and analysis on the quality of the model. For this study, the focus will be on ARX and transfer function model structure with parameter estimation using least square method for ARX model and subspace method for transfer function model. The result will then be validated and analysed based on best fit and correlation test.

2.3 ARX Model

ARX is also known as Auto Regression with eXogenous input. It is the simplest model structure that deals with empirical data in its linear form. Its capability of providing huge practical benefits on estimation and prediction are not deniable since ARX model always produce stable optimal predictors [15]. The advantage of ARX model is that the estimation of ARX helps determine the model order [16]. With the goal to minimize the prediction errors, a set of parameters is identified using system identification steps to structure ARX model where the system is assumed to change slowly over time [17]. In ARX model structure, the model consists of 2 polynomials where the output equation can be written as:

$$y(k) = \frac{B}{A} z^{-1} u(k) + \frac{1}{A} z^{-1} e(k) \tag{1}$$

where $y(k)$ is output of the system, $x(k)$ is input of the system, $e(k)$ is the disturbance and A, B are the polynomials.

The polynomials of A and B can be defined as:

$$A = 1 + a_1 q^{-1} + \cdots + a_n q^{-n} \tag{2}$$

$$B = b_0 + b_1 q^{-1} + \cdots + b_n q^{-n} \tag{3}$$

2.4 Transfer Function Model

Transfer function model is commonly used for handling single input, single output (SISO) and multiple inputs, single output (MISO). With its known ability to handle MISO system, the project will analyse this model to confirm its performance in predicting severity level of depression. The equation describing the model is:

$$y(t) = G(s)u(t) \tag{4}$$

$$y(k) = G(z)u(k) + e(k) \tag{5}$$

where $u(t)$ and $u(k)$ are inputs of the system, $G(s)$ and $G(z)$ are the transfer function between stimulus and response, $y(t)$ and $y(k)$ are the outputs of the system, $e(k)$ is disturbance of the system.

2.5 Least Square Method

The basic equation of model structure can be written as:

$$y(k) = a_1 y\,(k-1) + \cdots + a_n y\,(k-n) = b_1 u\,(k-1) + \cdots + b_m u\,(k-m) \tag{6}$$

Equation (6) can be rewritten into this form:

$$y(k) = -a_1 y\,(k-1) - \cdots - a_n y\,(k-n) + b_1 u\,(k-1) + \cdots + b_m u\,(k-m) \tag{7}$$

Least square estimation (LSE) is a method to estimate the unknown parameter of A and B of the model where the vectors can be represented as:

$$\theta = [a_1 \ldots a_{n\,b1} \;\ldots b_m]^T \tag{8}$$

$$\varphi(k) = [-y\,(k-1) \ldots - y\,(k-n)\; u\,(k-1) \ldots u\,(k-m)]^T \tag{9}$$

The model can also be written as:

$$y(k) = X^T(k)\theta \tag{10}$$

Finally, minimise prediction error square using:

$$\hat{\beta} = (\theta^T\theta)^{-1}\theta^T Y \tag{11}$$

LSE technique offers many advantages which benefit the process of parameter estimation. Since it analyses the whole parameter space, LSE has the highest computational complexity among all estimation techniques. Besides, it also has the highest resolution and capable to estimate the amplitude of the received signal. The important fact is that the increase of signal-to-noise ratio will improve the performance of LSE [18].

2.6 Subspace Identification Method

Subspace method is one of the techniques used in estimating parameter and it can be applied in many models such as transfer function model and state-model. There are two steps involves in this technique which are by determining the state sequence and/or extended observability matrix and determine state-space model using either state sequence or extended observability [19]. For this project, state sequence method was used to form state- space model. Subspace technique involved several equations which are as followed:
The input-output sequence [20]:

$$Y_f = \Gamma_i X_i + H_i^d U_f + H_i^s M_f + N_f \tag{12}$$

where Y_f and U_f are the output and input of block Hankel Matrices, Γ_i is the extended observability matrix, X_i is the data sequence, H^d and H^s are deterministic and stochastic lower block triangular Toeplitz matrix, and Mf and N_f are Hankel Matrix formed through the process signal and measurement signal [21]. In this equation, 'f' represents future and 'i' represents number of blocks rows;

The output and input of block Hankel Matrices:

$$Y_f = \begin{pmatrix} y_0 & y_1 & \cdots & y_{j-1} \\ y_i & y_2 & \cdots & y_j \\ \cdots & \cdots & \cdots & \cdots \\ y_{i-1} & y_i & \cdots & y_{j+1-2} \end{pmatrix} \tag{13}$$

$$U_f = \begin{pmatrix} u_0 & u_1 & \cdots & u_{j-1} \\ u_i & u_2 & \cdots & u_j \\ \cdots & \cdots & \cdots & \cdots \\ u_{i-1} & u_i & \cdots & u_{j+1-2} \end{pmatrix} \tag{14}$$

The extended observability matrix

$$\Gamma_i = \begin{pmatrix} C \\ CA \\ CA^2 \\ \cdots \\ CA^{i-1} \end{pmatrix} \tag{15}$$

The deterministic lower block triangular Toeplitz matrix:

$$H_i^d = \begin{pmatrix} D & 0 & 0 & \cdots & 0 \\ CB & D & 0 & \cdots & 0 \\ CAB & CB & D & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ CA^{i-2}B & CA^{i-3}B & CA^{i-4}B & \cdots & D \end{pmatrix} \tag{16}$$

The stochastic lower block triangular Toeplitz matrix:

$$H_i^s = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ C & 0 & 0 & \cdots & 0 \\ CA & C & 0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ CA^{i-2} & CA^{i-3} & CA^{i-4} & \cdots & 0 \end{pmatrix} \tag{17}$$

Subspace is also one of the parameter estimation methods used in many researches and it has several advantages that proves its capability. One of the advantages of using subspace method is that the stable and unstable systems are treated equally. It also has no basic complication to be used for transforming from SISO to MIMO. For subspace method, the model is parameterized by full state-space model and identification technique will decide the model order. It also does not undergo any parameterized problem if the system has nonzero initial state21. Each method offers many advantages which can be considered when selecting the model for prediction. These two methods were applied in this research for further analysis.

3. Model Validation

Model validation is necessary to reduce the prediction error of the model. To select the perfect model, best fit formula can be referred to evaluate model accuracy. Best fit represents the smoothness of output model identification following the data of the validation model. Best fit minimizes sum of squares of differences between predicted output and validation output [16]. Higher value of best fit will be chosen as the best model. Best fit formula is written as:

$$Best\ fit = 100\left(1 - \frac{norm(\hat{y}-y)}{norm(y-\bar{y})}\right)\% \tag{18}$$

Validation data is essential to compare the data with the identification model obtained for error minimization purpose. In this research, the data will be divided into two sets for training and validation purposes. The ratio decided is 70:30 where 70% (5548 samples) data of DASS21 is selected as training data while the remaining 30% (2377 samples) data is set as validation data. Other than best fit, correlation test will also be tested for model validation. The result from the tests represent the quality of the model and show whether they are bias to noise. If the correlation value is between the confidence interval, the model can be considered as adequate. There are two types of correlation tests which are the autocorrelation of output residual (whiteness test) and the cross-correlation of residual (independence test).

Autocorrelation of residual is defined as:

$$\theta_{ee}(t) = E[\varepsilon(t-\tau)e(t)] = \delta(\tau) \tag{19}$$

While cross-correlation of residual is defined as:

$$\theta_{ue}(t) = E[u(t-\tau)e(t)] = 0 \quad \forall \tau \tag{20}$$

Correlation function between two sequences is equal by:

$$\hat{\emptyset}_{\psi_1\psi_2}(\tau) = \frac{\sum_{t=1}^{N-\tau}\psi_1(t)\psi_2(t+\tau)}{\sqrt{\sum_{t-1}^{N}\psi_1^{\,2}(t)\sum_{t-1}^{N}\psi_2^{\,2}(t)}} \tag{21}$$

4. Result and discussion

In this project, system identification toolbox is used to perform system identification. Upon the success in obtaining the best model based on their performance, the transfer function will be implemented in Arduino IDE. The graphical-user interface (GUI) is also developed using the software. The complete code is uploaded into Arduino Uno (microcontroller) and Wi-Fi module will be used to transfer data. Thin film transistor liquid-crystal display (TFT LCD) is shielded and connected together to display the GUI and result. The data are applied into system identification toolbox for validation analysis and arranged accordingly based on the output of DASS21. These data are divided into training data and testing data using option in the toolbox before performing data structure selection. 'y1' in the figure represents the output of MISO system while 'u1','u2','u3','u4','u5','u6' and 'u7' represent the 7 inputs from DASS21 questionnaire. The data is first tested using ARX model where the order selection is ranged from 1 to 60. After processing the data, the best fit obtains for several order are shown as in Table 1. From the table, it shows that ARX474043 has the highest best fit (85.48%) among the other models. The model has very high order which is not compromising since higher order does not indicate the accuracy. Thus, this model will be selected for further analysis.

Table 1. List of ARX model and transfer function model with best fit value

Model order	*Best fit (%)*	*Model order*	*Best fit (%)*
ARX1016	54.00	2	98.1
ARX16119	80.46	3	96.5
ARX302035	80.13	4	73.29
ARX33639	78.96	5	91.25
ARX474043	85.48	6	46.03
ARX535052	77.80	7	74.85

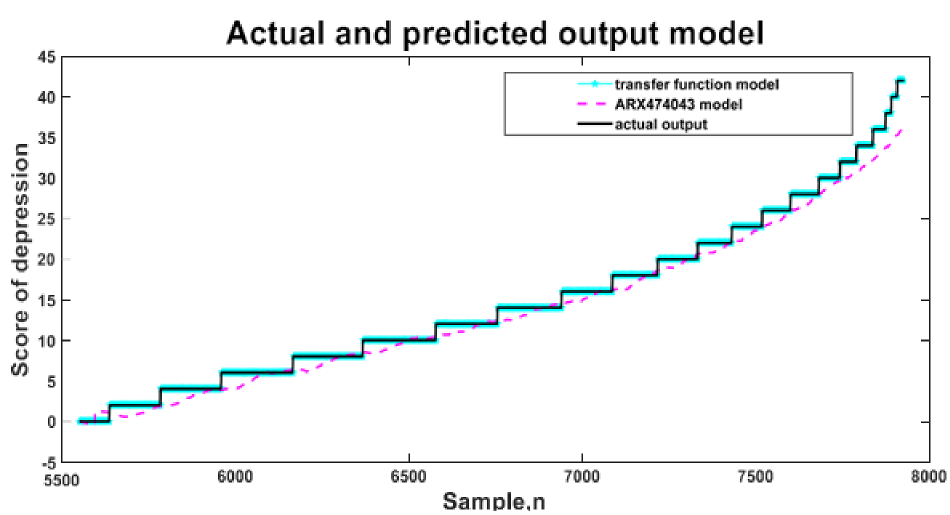


Figure 2. Actual and predicted output model for transfer function and ARX model

The data is also analysed using transfer function model as shown in Table 1 where the model order represents number of poles with number of zeros remaining as 1. The model with order 2 has successfully achieve the best fit with 98.1% which is the highest among other models. The graph on actual output as well as predicted output for both models are shown on Figure 2. As can be seen, transfer function model almost perfectly fit the actual output which indicates the model is well-trained while ARX model were not able to achieve the desired output. The ability to reach steady state is one of the crucial aspect in order for the system to perform as desired. In Figure 3 and Figure 4, show the step response graph for each model where the characteristic of the system model can be analysed. From Figure 3, the graph portrays the steady state of the system that starts at around 200 seconds while transfer function model in Figure 4 achieves steady state at about 2 seconds. The huge different in terms of time taken to achieve steady state shows the transfer function model is a better model compared to ARX model. Step response for ARX model shows no present of overshoot which represents overdamped system while the present of overshoot for transfer function model represent undamped system.

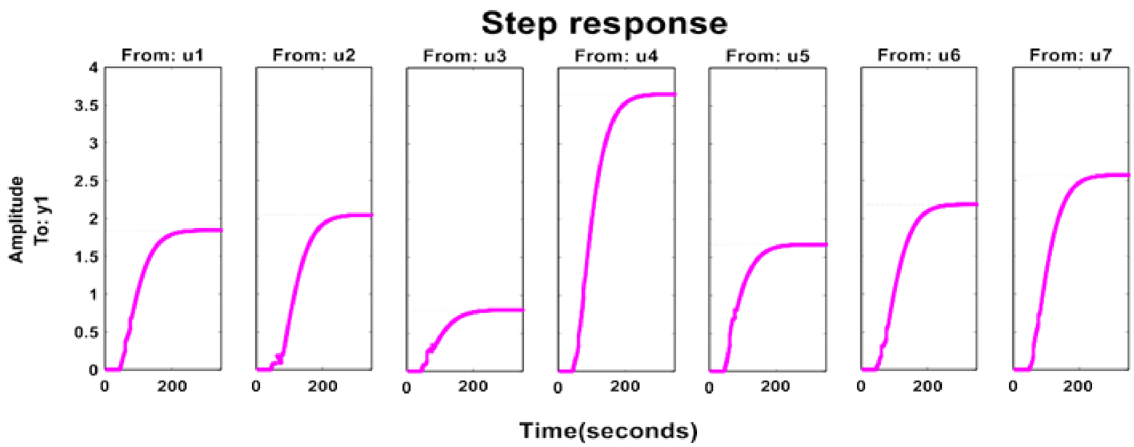


Figure 3. Step response for ARX474043 model.

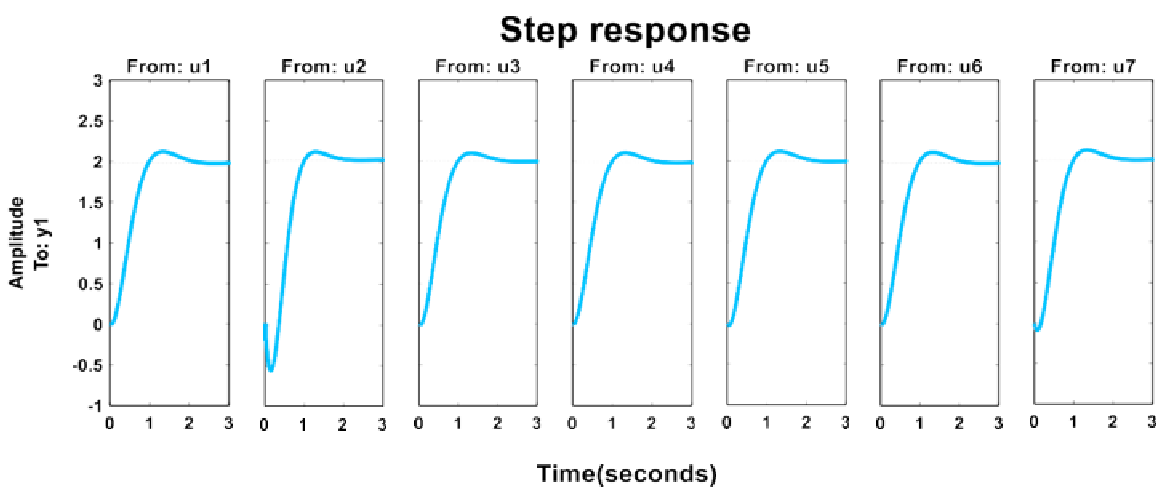


Figure 4. Step response for transfer function model of order 2.

So far, transfer function shows a good behavior as a prediction model. Since transfer function model achieves highest best fit among the models and the model performs well in terms of achieving steady-state, further test was conducted on this model in order to analyses its performance. The observation on correlation test in Figure 5 shows that the result of autocorrelation of residual (Whiteness test) values lie inside the confidence interval. Thus, this concludes that the residual has no significant correlation. The model is not overfitting as shown by the model's error not following the pattern. Figure 6 represents the independence test where cross correlation values are slightly over the confidence level. Since the value is not very significant and considered weak, the result is still acceptable. Each figure shows almost similar behavior. Therefore, it can be concluded that transfer function model of order 2 is enough to declare that it is adequate.

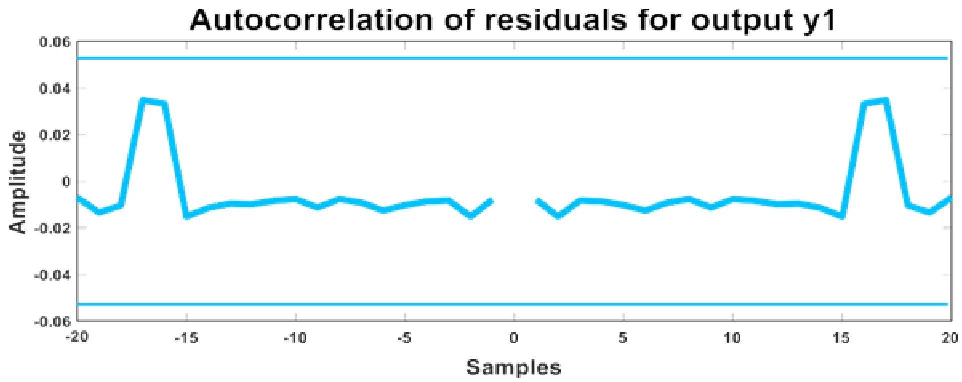
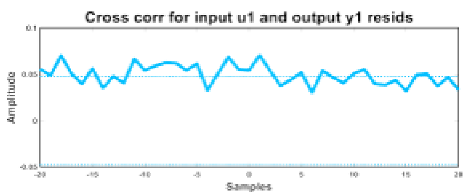
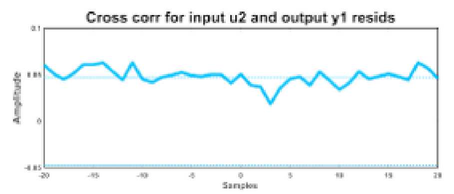


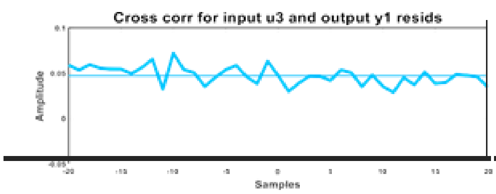
Figure 5. Autocorrelation for output of transfer function model.



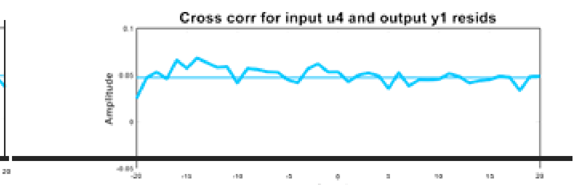
a) Cross correlation for transfer function model of input (u1) and output.



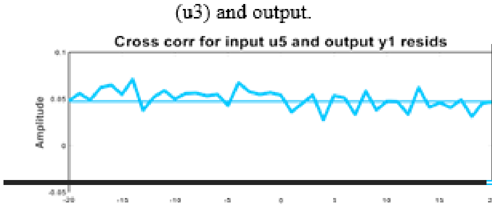
b) Cross correlation for transfer function model of input (u2) and output.



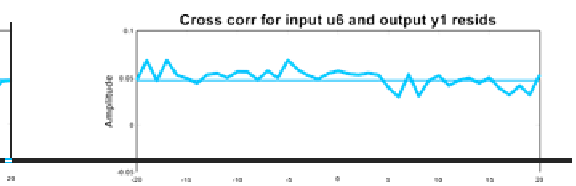
c) Cross correlation for transfer function model of input (u3) and output.



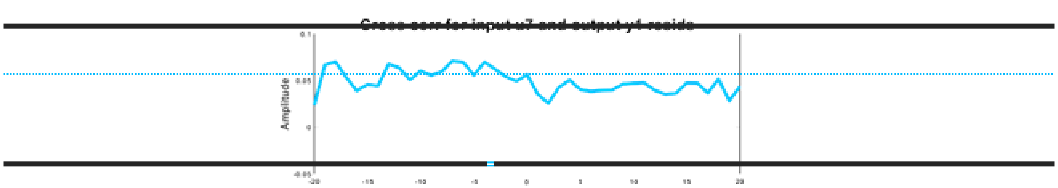
d) Cross correlation for transfer function model of input (u4) and output.



e) Cross correlation for transfer function model of input (u5) and output.



f) Cross correlation for transfer function model of input (u6) and output.



g) Cross correlation for transfer function model of input (u7) and output.

Figure 6. (a)-(g) is the cross correlation of input (u1 - u7) and output for the transfer function model.

Analysis result of transfer function model portrays satisfying performances in predicting severity level of depression based on DASS21 data with best fit of 98.1%. The value is considered well enough for predicting severity level of depression. After going through the process of model order selection and parameter estimation of best model, the transfer function is successfully obtained for each input to output where the block diagram for the whole model is depicted in Figure 7. The algorithm is useful and can be implemented in many ways. The final step after obtaining the model is to implement the transfer function in Arduino code in order to predict result directly from user input. Arduino Uno is chosen as a microcontroller for the device while GUI of the device is displayed on TFT LCD which connected to microcontroller. All the data of the user will be transferred into computer via Wi-Fi using Wi-Fi module in order to be assessed by the doctor. The architecture of the device can be seen in Figure 8.

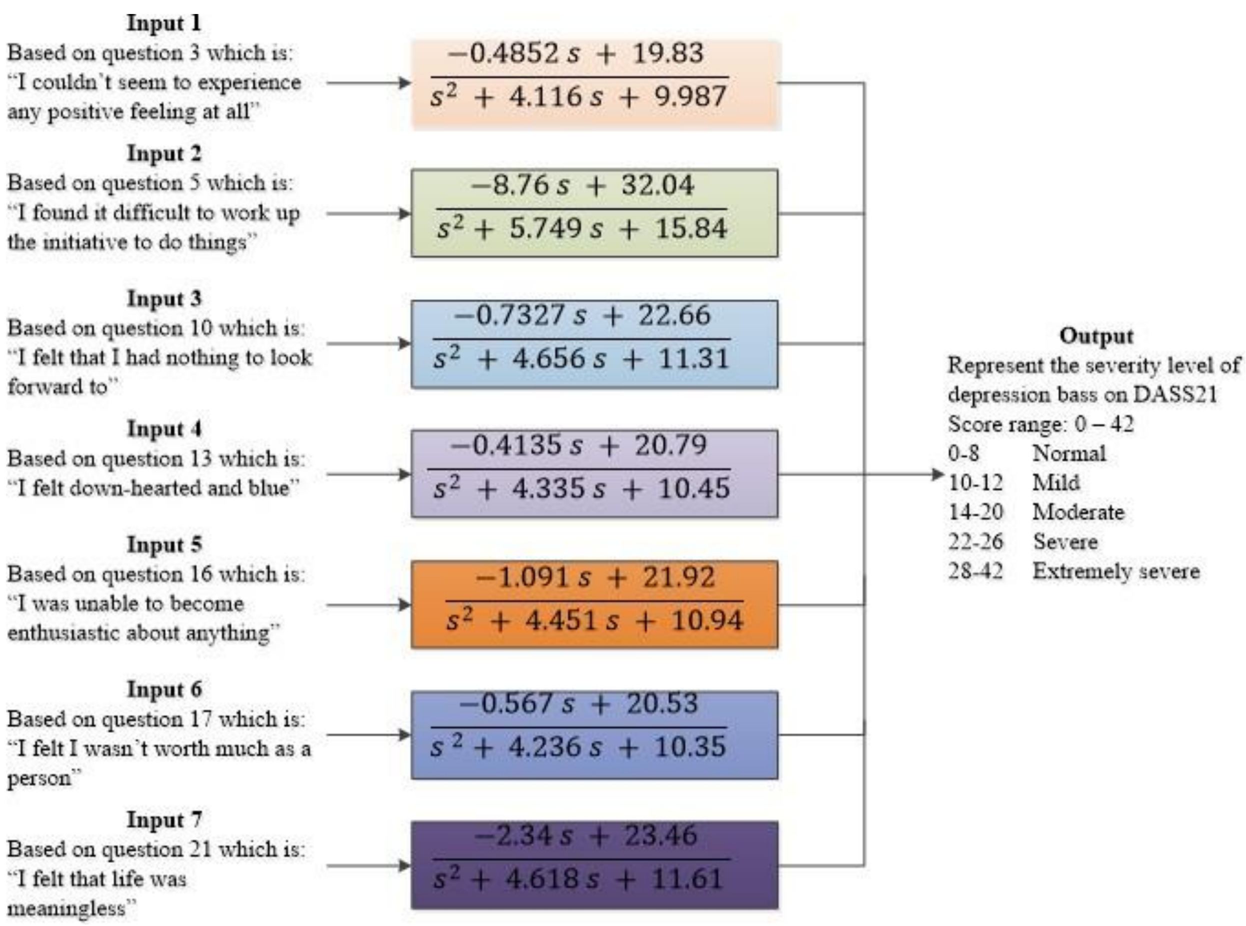


Figure 7. Block diagram for transfer function model.

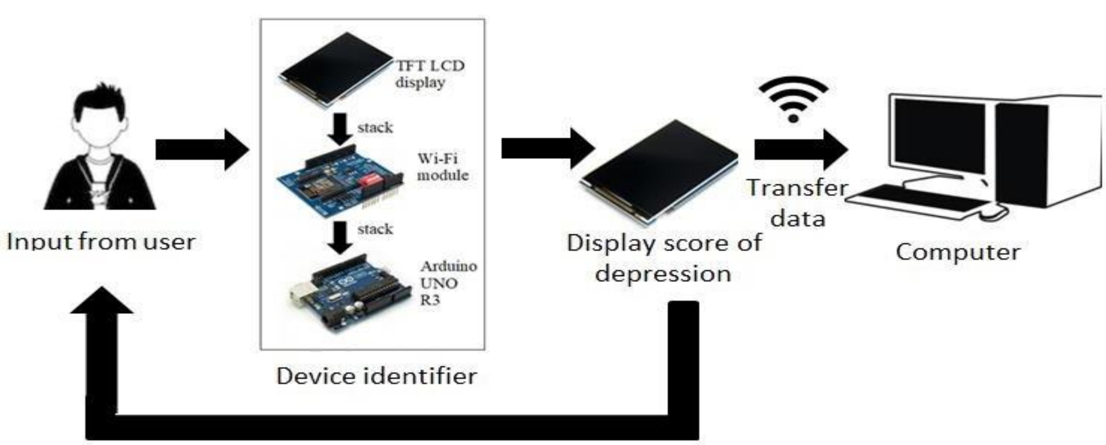


Figure 8. Architecture of device identifier for depression based on DASS21.

5. Conclusion

The project has successfully achieved the entire objectives including development of device identifier for depression. With the device, pre-screening session will have better process. It may also help to assist researcher on the assessment of depression. With system identification technique, ARX and transfer function model has successfully been obtained and analyse in terms of accuracy and quality of model. From the analysis, transfer function is concluded to be a better model than ARX because it is capable to predict the severity level of depression accurately.

6. Acknowledgement

The author would like to acknowledge financial assistance from the International Islamic University Malaysia under the FRGS Grant FRGS17-031-0597: Gait Identification Modelling for a hybrid amphi- underwater robot with exponential momentum ant colony algorithm.

8. References

[1] Nguyen, D. T., Dedding, C., Pham, T. T., Wright, P., & Bunders, J. Depression, anxiety, and suicidal ideation among Vietnamese secondary school students and proposed solutions: a cross-sectional study. BMC public health, 13(1), pg. 1195, 2013.

[2] Health Organization. Depression and other common mental disorders: global health estimates, 2017.

[3] Sharp, L. K., & Lipsky, M. S. Screening for depression across the lifespan. Am Fam Physician, 66, 1001-1008, 2012.

[4] Zigmond, A. S., & Snaith, R. P. The hospital anxiety and depression scale. Acta psychiatrica scandinavica, 67(6), 361-370, 1983.

[5] Lovibond, S., & Lovibond, P. (1995). Manual for the Depression Anxiety Stress Scales. Sydney: Psychology Foundation. Google Schola, 1995.

[6] Spitzer, R., Williams, J., & Kroenke, K. Instruction manual: instructions for Patient Health Questionnaire (PHQ) and GAD-7 measures, 1999.

[7] Hamilton, M. A rating scale for depression. Journal of neurology, neurosurgery, and psychiatry, 23(1), 56, 1960.

[8] Pillonetto, G., Dinuzzo, F., Chen, T., De Nicolao, G., & Ljung, L. Kernel methods in system identification, machine learning and function estimation: A survey. Automatica, 50(3), 657-682, 2014.

[9] Long, D., Nassif, N., & Ours, A. S. Prediction of energy consumption in buildings by system identification. Paper presented at the Future Technologies Conference (FTC), 2016.

[10] Szabó, M. The short version of the Depression Anxiety Stress Scales (DASS-21): Factor structure in a young adolescent sample. Journal of adolescence, 33(1), 1-8, 2010.

[11] Musa, R., Ramli, R., Abdullah, K., & Sarkarsi, R. Concurrent validity of the depression and anxiety components in the Bahasa Malaysia version of the Depression Anxiety and Stress Scales (DASS). ASEAN Journal of Psychiatry, 12(1), 2011.

[12] Saito, K., & Uchiyama, T. Estimation of muscle stiffness during one cycle of pedaling exercises using

system identification. Transactions of Japanese Society for Medical and Biological Engineering, 54(Proc), P2-C06-01- P02-C06-02, 2016.

[13] Araydah, W., Tutunji, T. A., & Al-Naimi, I. System identification for a liquid flow process., Paper presented at the 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), 2017.

[14] Mohamed, O., Khalil, A., Limhabrash, M., & Wang, J. The application of system identification via canonical variate algorithm to north benghazi gas turbine power generation system. Paper presented at the 2015 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), 2015.

[15] Diversi, R., Guidorzi, R., & Soverini, U. Identification of ARX and ARARX models in the presence of input and output noises. European Journal of Control, 16(3), 242-255, 2010.

[16] Ljung, L. System Identification Toolbox for use with MATLAB (Vol. 21). 2011.

[17] Huang, K. Y., & Jane, C.-J. A hybrid model for stock market forecasting and portfolio selection based on ARX, grey system and RS theories. Expert systems with applications, 36(3), 5387-5392, 2009.

[18] Gehlot, S., & Singh, R. Trajectory estimation of a moving charged particle: An application of least square estimation (LSE) approach. Paper presented at the 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), 2014.

[19] Miranda, S., & Garcia, C. Subspace closed loop identification using the integration of MOESP and N4SID methods. IFAC Proceedings Volumes, 42(11), 476-481, 2009.

[20] De Moor, B. Mathematical concepts and techniques for modelling of static and dynamic systems. Ph. D. dissertation, Dep. of Elect. Eng., Katholieke Univ., 1988.

[21] Favoreel, W., De Moor, B., & Van Overschee, P. Subspace state space system identification for industrial processes. Journal of process control, 10(2-3), 149-155, 2000.