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Towards Machine Learning approach for Digital-Health intervention program

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Abstract. Digital-Health intervention (DHI) are used by health care providers to promote engagement within community. Effective assignment of participants into DHI programs helps increasing benefits from the most suitable intervention. A major challenge with the roll-out and implementation of DHI, is in assigning participants into different interventions. The use of biopsychosocial model [18] for this purpose is not wide spread, due to limited personalized interventions formed on evidence-based data-driven models.
Machine learning has changed the way data extraction and interpretation works by involving automatic sets of generic methods that have replaced the traditional statistical techniques. In this paper, we propose to investigate relevance of machine learning for this purpose and is carried out by studying different non-linear classifiers and compare their prediction accuracy to evaluate their suitability. Further, as a novel contribution, real-life biopsychosocial features are used as input in this study. The results help in developing an appropriate predictive classication model to assign participants into the most suitable DHI. We analyze biopsychosocial data generated from a DHI program and study their feature characteristics using scatter plots. While scatter plots are unable to reveal the linear relationships in the data-set, the use of classifiers can successfully identify which features are suitable predictors of *mental ill health*.

Keywords: Biopsychosocial model · Digital-Health interventions · non-linear classifiers · Machine Learning · DASS score · *mental ill health* · mindfulness · physical activity.

1 Introduction

Digital-Health interventions (DHI) are programs that are delivered via digital technologies such as smart phones, websites and text messaging. DHI programs [2] have an enormous potential as scale-able tools to enhance health and health care delivery by improving effectiveness, accessibility, safety and personalization [11]. These programs are increasingly being used to promote mindfulness and physical activity based approaches in health and lifestyle, as part of public health campaigns [13]. The framework of DHI programs enables the easy collection and consolidation of biopsychosocial data. Machine Learning(ML) which refers to an algorithmic framework that can provide insights into data, while facilitating inference and providing a tentative setting to determine functional relationships [16], is being used increasingly to develop different aspects of smart DHI. ML methods for classification have been used in various domains, such as financial trading [7], remote sensing [9] and spam classification [5]. Ludwig and Piovoso [6], describe the comparative performance of three types of ML classifiers for selecting money managers. In the area of biological data, classification problems have been solved on Electroencephalography (EEG) data, survey data on health and drug use, arrhythmia data and many more [3, 4]. ML has been applied extensively on data-sets such as image, text, sound, motion and signal. In health-care, classifiers have been used to classify, predict and assess the risk of hypertension by observing the dynamic changes in pulse waves [19]. In spite of significant applications of ML based classifiers in different domains, there have been very few applications of classifiers on DHI [17]. In health care sector, the first Digital-Health platform (portal.life-guard.dk) with built-in personal coaching uses intelligent algorithm that enables educated coaches to tailor individual plans for exercise, diet and mental well-being [1]. However, to the best of our knowledge, there has been no work reported in the application of ML methods for DHI related application. In this paper we propose to investigate the relevance of ML, study and compare different non-linear classifiers that uses real life biopsychosocial features as input, and compare their prediction accuracy to evaluate their suitability. The results help in developing an appropriate predictive classification model to assign participants into the most suitable DHI.

In this paper we use biopsychosocial real life data which is based on the biopsychosocial model of health and has been generated from a DHI program that assigned participants into the mindfulness and physical activity interventions.

Various input features of the biopsychosocial data are exploited to evaluate different categories of popular classifiers and compare their performance. The study reported paves the way for using historical biopsychosocial features to a-priori determine the suitability of a specific intervention type for an individual participant. The rest of the paper is organized as follows. Section 2 provides an overview of the biopsychosocial model and the biopsychosocial data-set generated from the DHI program. Section 3 describes the method used for the study. Section 4 details the experimental studies carried out using the classifiers. Section 5 presents discussion of results and section 6 provides the conclusion.

2 Biopsychosocial model

The biopsychosocial model of health proposes that illness and health are a result of an interaction between biological, psychological and social factors. This model of health is widely used in research and complex health care interventions, and is the basis of World Health Organizations International Classification of Functioning(WHO ICF) [18]. The progressive understanding of the biopsychosocial model prompted the science of medicine to gradually move away from bio-medical model and evolved to incorporate and integrate the psychological and social components that impact well being [14]. The use of biopsychosocial model in clinical care and especially research remains low, because its framework cannot be defined in a consistent way for an individual patient in the absence of relevant personal historical biopsychosocial data. This makes the biopsychosocial model complicated, for application in a clinical setting [15].

2.1 Digital- Health Interventions (DHI)

The biopsychosocial data-set, as part of DHI program, has been generated in a research environment, by the Faculty of Health (FOH); at Federation University Australia in 2015. Local Australian volunteers, aged between 19 to 59 participated in this experiment. The goal of this program is to investigate which of the participants among the intervention groups, benefit from the interventions conducted. We analyze the data-set generated from DHI and identify which biopsychosocial features are suitable predictors of *mental ill health* described by the Depression Anxiety and Stress Scale (DASS). The use of DASS to describe *mental ill health* is elaborated in the subsequent section. The participants were randomly assigned to one of the two interventions in the experimental group or to the control wait-list group. The participants in mindfulness or physical activity interventions undertook activities which were relevant to that group, during the experiment period that lasted up-to 12 weeks. The participants in both the intervention programs were examined for biological, psychological and social conditions as part of various tests.

At the start of the intervention, the participants are given biological tests, neuro-cognitive test and survey questions that enable in assessing their levels of emotions, negative feelings, optimism and perceived psychological stress level. Scales, namely, Perceived Stress Scale(PSS), DASS (Depression Anxiety and Stress Scale), Kessler scale (K6), Difficulty in Emotion Regulation scale (DERS), Mental Health Continuum scale (MHC) and Life Orientation Test (LOT), encapsulate the test level values. At the end of the intervention, all the above mentioned tests are repeated, and the test level values are captured again.

2.2 Feature categories

The biopsychosocial features used in this study are divided into 5 main categories:

1. *Demographic data* : consists of features such as age and gender obtained during screening and demographic survey. The features - employment area and income were excluded from the study.
2. *Self reported levels* : includes features such as social support, religiousness, physical health, mental health and quality of life. Each of these features were self reported values supplied by the participants on a Likert scale prior to the start of DHI. The self reported measure of medication was excluded from study.
3. *Test scale levels* : consists of the features such as:
   (a) DASS level : measures distress along 3 axes of depression, anxiety and stress and equated them to clinical levels. DASS has been used to describe the measure of *mental ill health*
   (b) K6 level : measures general psychological distress
   (c) DERS level : measures how people managed their emotions
   (d) MAAS level : measures how mindful the person is

   (e) MHC level and LOT level : measures well-being and optimism.
4. *Psychological test levels* : consists of features such as PEBL [10] Go/No-Go test mean accuracy, trail test total time and stroop test total errors for each participant. These features are derived from the computerized neuro-cognitive tests that were conducted to measure cognitive flexibility, selective attention and response inhibition.
5. *Biological test levels* : consists of the cortisol level (cortisol is a hormone, which is mainly released at times of stress and manages many important body functions) and blood proteins (BDNF, iL-6) level, recorded at the start of the intervention during week 1. Blood proteins data was not used due to missing data values.

For the present study, the levels of all the biopsychosocial features were recorded at the start of the intervention period. The DASS level measured the negative affect states which included stress, depressive and anxiety symptoms (*mental ill health*). The DASS level was recorded at the start and at the end of the intervention period. DASS label *Improvement* was used if the DASS level at the end of intervention was less than the DASS level recorded at the start of the intervention. DASS label *No Improvement* was used if the DASS level at the end of intervention remained same or was greater than the DASS level recorded at the start of the intervention.

3 The Method

The biopsychosocial features are derived from the biopsychosocial data-set. We propose to apply a score to each biopsychosocial feature during analysis to enable:

1. applying a single biological score to a set of four cortisol level readings recorded on a single day that changed over time
2. regularizing the scores for the different biopsychosocial features to make them consistent; so that they can be used within classifiers as input features
3. computing correlation coefficient on a 2 dimensional scale.

The output DASS score and the input biopsychosocial features are applied for comparing the ten classifiers mentioned below. Following are the salient factors related to the proposed approach for DHI data analysis.

3.1 Computation of cortisol level score

Cortisol is a steroid hormone that regulates a wide range of processes throughout the body including metabolism, immune response and also helps the body to respond to stress. The drool method (method used to collect oral fluid for biological testing) was used for data collection of cortisol levels. The cortisol readings obtained at the start of the intervention (during week 1) has been used for this study. The 4 readings denoted by S1 (20 mins after wake), S2 (60 mins after wake), S3 (mid day) and S4 (evening) were recorded. We propose to use the AUC_G [8] method to compute the single cortisol score from the set of 4 readings.

3.2 Feature scaling

The biopsychosocial data-set contains 18 features. We propose to apply a feature score by normalizing and re-scaling the data value for each feature. Each feature value (excluding gender and age) will be normalized by linearly re-scaling the data values using the observed minimum and maximum values for that feature, into a new arbitrary range of 0 to 1. The formula used for scaling is given by:

$$\frac{(featVal - min(featVal_1 : featVal_n))}{(max(featVal_1 : featVal_n) - min(featVal_1 : featVal_n))}$$

where *featVal* refers to the feature value, *min* is minimum observed value of the feature and *max* is the maximum observed value of the feature.

3.3 Trail test reaction time

The trail test reaction time data was generated from PEBL [10] tests. In our earlier research [12], we had established that neurocognitive reaction time data is best represented by Gamma distribution. In our study, we propose to use the Gamma 'Cumulative Distribution Function (CDF)', for the analysis of trail test reaction time data.

3.4 Correlation between features

The biopsychosocial data used for this study is rich in variety, and with high dimensionality (consisting of 18 input features). However, the number of samples that could be used for the study was limited owing to missing data. Given the nature of the data-set, imputation of missing biopsychosocial data is very challenging, and it can result in inaccurate imputed values. The correlation between the three biopsychosocial disciplines will be analyzed using the Pearson correlation coefficient. In order to compute the correlation coefficient, the large set of 18 feature scores will be reduced to 3 feature scores; one for each discipline(i.e. biology, psychology and social). A single mean score for each discipline of the biopsychosocial data-set will be computed using the simple average of the features scores. The mean scores for each of the biopsychosocial dimensions will be used to explore the linear relationship between them and the DASS result at the end of the mindfulness intervention.

3.5 Classification

We propose to evaluate ten popular classifiers to ascertain which set or subset of biopsychosocial features affect the *mental ill health* of the participant measured as the DASS score; at the end of the DHI program. These classifiers are: Support Vector Machines(SVM), decision trees, random forests, logistic regression, Naïve Bayes, stochastic gradient descent, linear discriminant analysis, extra tree classifier, bagging classifier and neural net. The choice of these classifiers are based on their robustness to small data-sets. The following are key considerations for modeling the classifiers:

1. *Classifier parameter optimization* : We propose to use the grid search function to scan the data-set to configure optimal parameters for the classifier. The Python GridSearchCV function will be used for classifiers - SVM, decision trees, random forests and neural net.
2. *Number of hidden layers and nodes in neural network* : We propose to use one hidden layer to keep the classifier model simple and enable the data points to be separated non-linearly. We will use the same number of nodes for the neural net classifier as the number of input features. This decision is made based on test runs carried out on the neural network classifier with different number of nodes on the hidden layer. In the test runs, the highest prediction accuracy was seen when the number of nodes are the same as the number of input features.

4 Experimental studies

In this section, we first carry out the scatter plot analysis to examine if a linear relationship exists between the different biopsychosocial features. Subsequently, we apply the ten popular classifiers to the biopsychosocial data-set for their comparative evaluation.

4.1 Data-set

The following table describes the participant data-set used for this study. The data-set of 18 participants (11 from mindfulness program and 7 from physical activity program) was expanded to 90 samples, using data augmentation by introducing noise around each feature data point.

Table 1. Data summary

	Mindfulness program	**Physical activity program**
Number of participants	11	7
Number of features	18	18
Binary classification group - 1	Improvement in DASS	Improvement in DASS
Binary classification group - 2	No Improvement in DASS	No Improvement in DASS

4.2 Scatter plot analysis

The correlation between the mean scores in each of the biopsychosocial dimensions was described using scatter plots. The Pearson correlation coefficient value r was computed. The correlation scores for the different dimensions of the biopsychosocial data-set are summarized in Table 2.

Table 2. Correlation scores (Note: Figures in **bold** indicate significant values)

DASS label	Dimensions compared count	Pearson correlation r
Improvement	bio and psycho	**0.55783**
No improvement	bio and psycho	0.3880
Improvement	psycho and social	0.4079
No improvement	psycho and social	0.4580
Improvement	bio and social	0.4079
No improvement	bio and social	0.4580

The following conclusions were drawn from the scatter plots:

1. There is a moderate positive correlation (see Figure 1) between mean biological and mean psychological scores to indicate *Improvement* in the DASS score for the participants at the end of the mindfulness intervention. The correlation coefficient is given by r=0.55783
2. No linear correlation exists between mean biological, psychological and social scores of the biopsychosocial data-set to indicate any DASS score *Improvement* or *No Improvement* (see Figure 2).

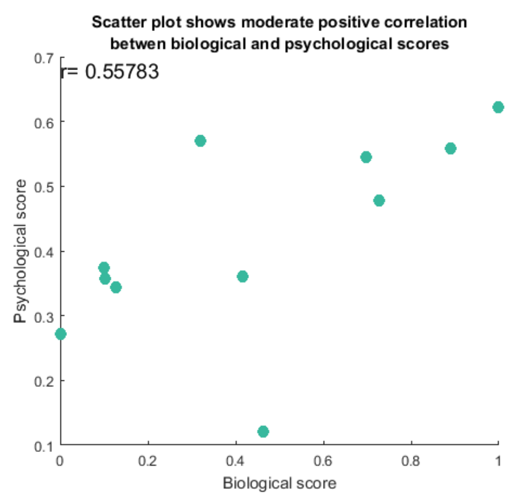

Fig. 1. Correlation between biological and psychological features to indicate *improvement* in DASS score

Although scatter plots are a good tool to statically visualize linear relationships, they cannot reveal the non-linear relationships between features in multiple dimensions. In our pursuit to study the undercurrent influence of the biopsychosocial factors to assign participants into effective DHI in future, we compared different non-linear classifiers to ascertain which set or subset of these biopsychosocial features affect *mental ill health* of the participant, measured by the DASS score. The prediction accuracy of these classifiers has been compared based on predicted output DASS score and the input biopsychosocial features.

4.3 Comparison of classifiers

We compared 10 non-linear classifiers to determine the underlying relationship between the biopsychosocial features. The application of machine learning methods on the real-life biopsychosocial data-set has not been done before and is unique to this study. The biopsychosocial data in this study was gathered using a structured DHI program and this adds credibility to this unique data-set. The present study used the biopsychosocial data of 18 participants assigned to mindfulness program and the target label used was - *Improvement* or *No Improvement* in DASS score. The data-set of 18 participants was expanded to 90, using data augmentation by introducing noise around each

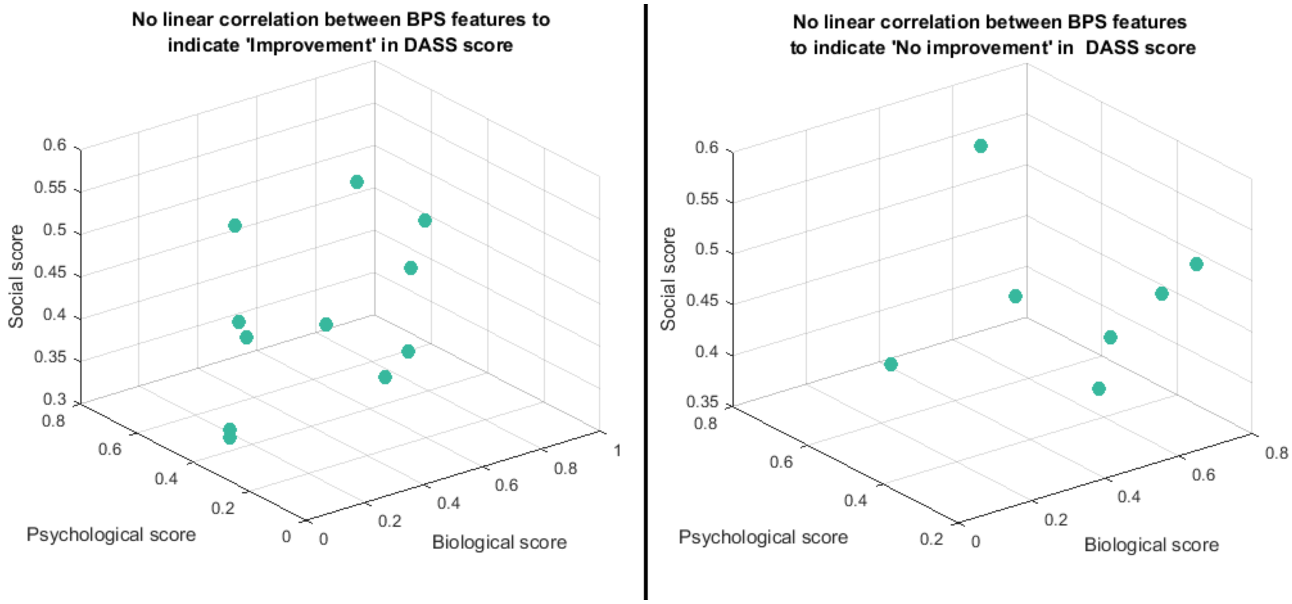

Fig. 2. No linear correlation between biological, psychological and social features to indicate DASS *Improvement* or *No Improvement*. The values on axes are from 0 to 1 (normalized and re-scaled).

feature data point. Each data point was surrounded with 4 noise data points by adding and subtracting 10 % and 20% to the original data value. The classifiers were trained on the training set of 90 records (known observations - biopsychosocial feature set of the mindfulness group); using the Leave One Out (LOO) method. Thereafter the classifiers were tested on the unseen set of 16 records (biopsychosocial feature set of the physical activity group), to determine the classifiers prediction accuracy. The classifiers used different combinations of input features from the biopsychosocial data-set to enable a comparative study of their prediction accuracy. A comparative study of the classifier prediction accuracy is provided in the following tables. Classifier prediction accuracy has been described as the ratio of the number of correct predictions to the total number of input samples. The classifiers classified the given set of samples into two groups: Binary classification group - 1 that described the improvement in DASS and Binary classification group - 2 that described no improvement in DASS. Interesting influences of the biopsychosocial features on the classifiers are described below.

Table 3. Classifiers using 18 biopsychosocial features as input and their prediction accuracy.

Classifier	**Feature count**	**Prediction accuracy Physical activity group**	**Prediction accuracy Mindfulness group**
Neural net	18	0.4375	0.38889
Bagging classifier	18	0.4375	**0.55556**
Extra test classifier	18	**0.625**	**0.55556**
Linear discriminant analysis	18	**0.625**	0.44444
Stochastic gradient descent	18	**0.5625**	0.5
Naïve Bayes	18	0.4375	0.38889
Logistic regression	18	**0.5625**	**0.55556**
Random forest	18	0.375	**0.5**
Decision trees	18	**0.5625**	**0.61111**
SVM	18	**0.5625**	**0.61111**

1. Table 3 shows that majority of classifiers perform better than a random prediction accuracy of 50%; when all the biopsychosocial features are used for training the classifier. Extra tree classifier and linear discriminant analysis show high prediction accuracy for mindfulness intervention (at 62.5%). Decision trees and SVM show high prediction accuracy for the physical activity intervention (at 61.1%).

Table 4. Classifiers using 3 biological features as input and their prediction accuracy.

Classifier	**Feature count**	**Prediction accuracy Physical activity group**
Neural net	3	**0.5625**
Bagging classifier	3	**0.5625**
Extra test classifier	3	0.4375
Linear discriminant analysis	3	0.5
Stochastic gradient descent	3	0.3125
Naïve Bayes	3	0.4375
Logistic regression	3	0.5
Random forest	3	0.5
Decision trees	3	0.4375
SVM	3	0.4375

Table 5. Classifiers using 5 psychological features as input and their prediction accuracy.

Classifier	**Feature count**	**Prediction accuracy Physical activity group**
Neural net	5	0.5
Bagging classifier	5	0.5
Extra test classifier	5	**0.5625**
Linear discriminant analysis	5	0.5
Stochastic gradient descent	5	**0.5625**
Naïve Bayes	5	0.5
Logistic regression	5	0.5
Random forest	5	**0.5625**
Decision trees	5	**0.5625**
SVM	5	**0.5625**

Table 6. Classifiers using 14 social features as input and their prediction accuracy.

Classifier	**Feature count**	**Prediction accuracy Physical activity group**
Neural net	14	**0.5625**
Bagging classifier	14	**0.5625**
Extra test classifier	14	0.5
Linear discriminant analysis	14	0.4375
Stochastic gradient descent	14	0.375
Naïve Bayes	14	0.375
Logistic regression	14	0.4375
Random forest	14	0.5
Decision trees	14	0.5
SVM	14	**0.5625**

2. Table 4 and Table 6 show that fewer classifiers perform fairly when only the biological features or only social features are used for training the classifier.
3. Table 5 shows that more number of classifier (5 out of 10), perform fairly when only psychological features are used for training. However the prediction accuracy of these classifiers are lower (at 56.25%), compared to the case where all the biopsychosocial features are used for training the classifier.
4. Table 7 shows that other combinations of biopsychosocial features used for training the classifiers, do not result in higher prediction accuracy compared to what is achieved by using all the biopsychosocial features for training the classifier.

Table 7. Classifiers using combinations of biopsychosocial features as input and their prediction accuracy on unseen test set (physical activity group).

Classifier	Bio and Psycho	Psycho and Social	Social and Bio
Neural net	**0.5625**	**0.5625**	**0.5625**
Bagging classifier	**0.5625**	0.375	0.3125
Extra test classifier	0.4375	**0.5625**	0.4375
Linear discriminant analysis	**0.5625**	0.5	0.4375
Stochastic gradient descent	0.5	0.5	0.4375
Naïve Bayes	0.375	0.4375	0.4375
Logistic regression	0.5	0.3125	0.375
Random forest	0.375	0.43755	0.4375
Decision trees	0.375	0.4375	0.4375
SVM	**0.5625**	**0.5625**	**0.5625**

5 Discussion

The addition of data points using noise enabled us to effectively apply the classifiers thereby reducing over-fitting and avoid poor performance. The additional data points make the input space smoother and easier for training. Although the biological data - cortisol level, was clinically obtained and was of good quality, the feature values of social data, in the form of self reported scores is subjective and only as good as the interest level of the participant. The prediction accuracy of the classification model affected by the sparsity of the biopsychosocial data-set and the quality of the feature values in the data-set, can be further improved by improvements in field data collection techniques. The biopsychosocial data-set used for this study, being from an earlier conducted DHI program, its objective was different to the proposed research. In this study, we have used the DASS to measure *mental ill health* and examined the prediction accuracy of the ML methods to predict which intervention is more suitable, based on the underlying biopsychosocial features. Realizing that most/all the participants were not clinical, it is possible that little changes can occur during the intervention period. The framework of DHI program that conducted the biopsychosocial tests partly focused on the DASS variables as part of the social data that was collected in the form of *Test scale levels*. More integrated tests spanning the three dimensions of the biopsychosocial model within the framework of DHI program will enable use of the data-set more productively.

6 Conclusion

DHI programs have an enormous potential to improve health-care. These programs are at the intersection of technology and health-care. Machine learning has changed the way data extraction and interpretation works by involving automatic sets of generic methods that have replaced the traditional statistical techniques. In this paper, we used ML and non-linear classifiers on real-life biopsychosocial features, compared their prediction accuracy and evaluated their suitability to a DHI. DASS score has been identified as a successful metric for indication of *mental ill health*. The experimental studies indicate while the methods such as scatter plots were unable to reveal the linear relationship between the features of the biopsychosocial data- set, the ML approach has been successful in identifying which features are appropriate as predictors of *mental ill health*. Prediction accuracy of classification models was seen to improve when all biopsychosocial features are considered as input features compared to using features from just one or two domains. Classifiers such as extra tree classifier and linear discriminant analysis showed high prediction accuracy (at 62.5%) in the mindfulness group and decision trees and SVM showed high prediction accuracy (at 61.1%) in the physical activity group. While the research work focused on establishing the relevance of ML approach for DHI, the prediction accuracy can, indeed, be improved further by improved classifier design and data collection. The work in this paper opens up avenues for further research in using classification models for patient assignment into DHI programs.

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