Preliminary Results on the Use of Classification Trees to Predict Non-suicidal Self-injury with Data Collected through a Mobile App

Chiara Capra[1,2], Pere Marti-Puig[1], Daniel Vega Moreno[3], Laia Llunas[2], Stella Nicolaou[3], Carlos Schmidt[3] and Jordi Solé-Casals[1]

[1]*Data and Signal Processing Research Group, Universitat de Vic-Universitat Central de Catalunya, carrer de la Laura 13, Vic, Spain*

[2]*beHIT, carrer de Mata 1, Barcelona, Spain*

[3]*Department of Psychiatry & Mental Health, Hospital d'Igualada, Fundació Sanitària Igualada, Igualada, Spain*

Keywords: Machine Learning, Digital Mental Health, Non-suicidal Self-injury, Applied AI.

Abstract: Machine learning (ML) integrated with technology has been a breakthrough in mental health, bringing clinical improvements both for the patient and for the clinician. Among these, real-time patient symptoms' tracking through ecological momentary assessment (EMA) data can be a valuable tool to forecast symptomatology at the individual-patient level for specific disorders, among which non suicidal self-injury. We aimed at applying classification trees to predict non-suicidal self-injury (NSSI) with EMA data collected through a mobile app. A database of 40 patients diagnosed with borderline personality disorder (BPD) with NSSI (N=22), and a subclinical group of students with NSSI (N=19) was analysed. EMA data was collected by the Sinjur app. Two classification trees were used as models. For the first tree, training results reported 69,7% of accuracy, whereas test results reported 59,3% of accuracy, 87,5% of sensitivity and 58,78% of specificity. For the second tree, training results reported 67,9% of accuracy, whereas test results reported 65,2% of accuracy, 85% of sensitivity and 64,8% of specificity. We concluded that real-time patient monitoring via a mobile app can be a valuable tool for making technology-based predictions at the individual patient level. This promising data needs to be built upon in future studies and needs major translation in the everyday clinical practice to demonstrate its real-world efficacy and later, to be translated to the enterprise world.

1 INTRODUCTION

The advent of machine learning (ML) integrated with cutting-edge technology has been a breakthrough in mental health, bringing major clinical improvements through the whole patient's journey process, including diagnosis, symptoms and therapy tracking, communication between patient and clinical professional and therapy outcome. Among these, real-time patient monitoring with ecological momentary assessment (EMA) data can be an effective tool to forecast patient's symptomatology for specific disorders, such non-suicidal self-injury (NSSI).

NSSI is defined as the deliberate intention of harming one own's body without wanting to engage in a suicidal act (Zetterqvist, 2015). In the last decade, NSSI has been recognised as a significant psychiatric phenomenon, and it has been inserted in the latest version of the DSM V as a "new condition for further study" as well insa cross-pathology symptom which has increased especially during the COVID-19 pandemic. Literature on NSSI has provided evidence of the key risk factors which predict NSSI, including perceived social support throughout adolescence, depressogenic cognitions (Wolff et al., 2013) and most importantly, emotion dysregulation (Wolff et al., 2019). EMA studies have directly investigated interpersonal functions in individuals with NSS. In this regard, a recent study conducted Briones-Buixassa et al. (2021) utilised EMA data to investigate the associations between decentering as a moderator for NSSI protection and engagement as well as momentary negative affect, captured real-time through EMA data and NSSI.

Although emerging research has provided evidence of relevant variables which contribute to engagement in NSSI, such as the aforementioned linkages between decentring measures, negative affect and NSS; no studies have shown the

Capra, C., Marti-Puig, P., Moreno, D., Llunas, L., Nicolaou, S., Schmidt, C. and Solé-Casals, J.
Preliminary Results on the Use of Classification Trees to Predict Non-suicidal Self-injury with Data Collected through a Mobile App.
DOI: 10.5220/0010978500003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 4: BIOSIGNALS*, pages 278-282
ISBN: 978-989-758-552-4; ISSN: 2184-4305

importance of computational methodologies integrated with ground-breaking technology to forecast relapse in symptomatology in everyday clinical practice. Up to date, no research has applied ML techniques to EMA, in order to predict and prevent real-time NSSI. Thus, we aimed at expanding upon Briones-Buixassa et al. (2021) study and apply classifier analysis to forecast NSSI symptomatology to provide evidence of its implication in everyday clinical practice and the usefulness of digital platforms for specific mental health disorders for remote interventions.

2 METHODS

2.1 Participants

A database of 64 adult patients, ranging from 18 and 33 years and diagnosed with borderline personality disorder (BPD) with NSSI (N=22), and a subclinical group of university students with NSSI (N=19) was analysed. The database was comprised of three main groups divided as the following: subjects who reported NSSI (≥ 5 NSSI events in the previous 12 months), including a) a subclinical group of college students (STD group; N = 19) and b) a clinical group of BPD patients (BPD group; N = 22). The subgroup of college students was not undergoing any type of psychological treatment at the time of the study and underwent the Structured Clinical Interview for Axis II personality disorders (SCID-II) to exclude any BPD diagnosis.

2.2 Materials

2.2.1 Sinjur App

The Sinjur app was developed for the purpose of this study. Sinjur app aims to help patients suffering from NSSI through system based on cognitive behavioural therapy. The app collects EMA data based on Experience Sampling Method (ESM), through three main sections, including "emotions", "activity diary" and "self-injuries". The app was configured to send participants reminder notifications 3 times a day to engage in the app and register data.

2.2.2 EMA Data

For this study, we focused on emotions only. More specifically, negative, and positive affect were considered. Participants were asked to provide their emotional states by choosing through a list of emotions presented in the app, including happy, frustrated, guilty, sad, angry, relaxed, and worried. All these emotions are listed in Table 1, together with the code used for each of them in the classification mode. Following to this, participants were also asked to rate their emotions' intensity by choosing between a range from 0 to 100. Figure 1, on the left, shows the screenshot of the application with the list of emotions, while on the right shows a screenshot detailing how to report the patient's chosen emotion rating. For each data registration, number of times of engagement in NSSI was asked, as well as method of NSSI, including burning and cutting. If participants engaged in NSSI they were asked to indicate their emotion after the NSSI and its intensity.

Table 1: List of features collected with the app, together with the code used in the classification trees.

Emotion (*original name in Catalan*)	**Feature code**
Happy (*feliç*)	f_1
Sad (*trista*)	f_2
Embarrassed (*avergonyida*)	f_3
Distressed (*angoixada*)	f_4
Relaxed (*relaxada*)	f_5
Guilty (*culpable*)	f_6
Frustrated (*frustrada*)	f_7
# binge eating	f_8
# self-harm thoughts	f_9
# times taking drugs	f_{10}
# times having sex	f_{11}
# arguments with others	f_{12}

2.3 Procedures

Firstly, all participants underwent a demographical, clinical and NSSI screening. Only subjects who reported more than 5 NSSI acts in the previous 12 months were taken into account to participate in the study, among which 19 out of 180 subjects qualified for the current study. All the participants of the three groups (STD, BPD, and HC groups) were asked to complete both a clinical and a self-report assessment. At the same time, they were given instructions on how to use the Sinjur app and reminded to register relevant data anytime they received a notification, as well as every time they engaged in self-injury.

2.4 Machine Learning Model

Tree-structured classification techniques have been widely used in medical applications. The reason for this is the ease of interpretation and applicability provided by these models. Therefore, the classification model used in this work will be based on a CART tree (Breiman, Friedman, Olshen & Stone, 2017) (Lewis, 2000). A decision tree is a way of representing the knowledge obtained in an inductive learning process. It is a supervised classification method, which means that it uses already labelled data from which knowledge will be extracted. The feature space is subdivided by using a set of conditions, and the resulting structure is the tree.

Figure 1: On the left, a screenshot with the list of emotions to report to the system. On the right, a detail on how to report the grade of the emotion by means of a sliding button (the text in the app is in Catalan).

A tree consists of nodes of two types, internal nodes, and end nodes (also known as leaves). Each internal node contains a question about a particular feature f of the type "Is *f* greater than or equal to a threshold or not?", and provides two children (subdivision), one for each possible answer, depending on whether $f \geq$ threshold or $f <$ threshold. On the other hand, end nodes are those that are assigned to a single class at the bottom of the tree, so there are no further subdivisions from them.

The construction of a tree is the learning stage of the method and consists in analysing a set of available features ($f_1, f_2, \ldots, f_n$) and obtaining logical rules adapted to the already available labelled examples. In our case, the features are a set of 12 feelings or answers to simple questions, as explained in Section 2.2.2, and the following classes: class 1 (corresponding to positive NSSI) and class zero (corresponding to negative NSSI).

The construction process is recursive and starts by considering all possible partitions and taking the one with the best separation. Then the optimal partitioning is applied, and the previous step is repeated to all the internal nodes. A key point in this process is how the best separation is defined. In a general way, the best separation is the one that divides the data into groups such that there is a dominant class. To measure that, the algorithm in our experiments uses the Gini diversity index, which is one of the possible impurity measures (Yuan, Wu & Zhang, 2021). The Gini diversity index is a measure of how often a randomly chosen item from a set would be incorrectly labelled if it were randomly labelled according to the distribution of labels in the subset. The Gini impurity can be calculated by summing the probability of each item being chosen multiplied by the probability of an error in the categorization of that item (1). It reaches its minimum (zero) when all cases in the node correspond to a single target category.

$$G(f_{ij}) = P(f_i < j)G(c|f_i < j) + P(f_i \geq j) \tag{1}$$

where:

$$\begin{aligned} &G(c|f_{ij}) \\ &= P(c = 1|f_{ij})P(c \neq 1|f_{ij}) \\ &+ P(c = -1|f_{ij})P(c \neq -1|f_{ij}) \\ &= 1 - \sum_{c_k} P(c_k|f_{ij})^2 \end{aligned} \tag{2}$$

Thus, the importance of the characteristics is established. The first-level characteristics are the most important. Similarly, the lower-level features are the less important ones. If the algorithm keeps some of the available features out of the tree definition, it means that these features are irrelevant to the classification model. And this is one of the most interesting capabilities of trees, because it means that the model can be interpreted in terms of the features used in it and the features discarded by it. Hence, by analysing the structure of the tree we can infer the interest of each of the chosen explanatory variables.

3 RESULTS

Two different experiments were carried out. In the first case, a very small tree was used to elucidate the most important features. Then, a second, larger tree was used to improve the previous result without losing the interpretability of the model. In all cases, the database was balanced by dividing the positive class into two halves, one for the training step and one for the test step. Then, for the negative class, the same number of examples as the positive class were randomly taken to train the model, while all remaining samples were used in the testing step. Therefore, the training was performed with 50% of the samples from one class and 50% of the samples from the other class.

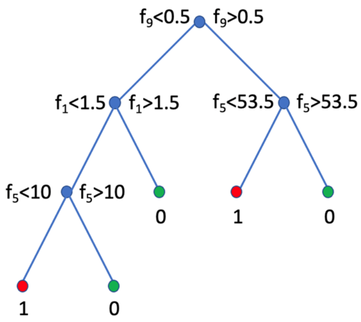

Figure 2: Coarse classification tree. The algorithm only selected three different features to model the data. See Appendix 1 for the coding of the features.

However, all the remaining samples from both classes were used in the test, so it contained many more samples from the negative class.

3.1 Coarse Tree

The coarse tree was defined to have a maximum number of 4 splits, and the split criterion to be the Gini's diversity index. The accuracy for the training step was 67.9%, and for the test step, 59.3%. Figure 2 depicts the final tree derived from the model.

The confusion matrix is shown in Table 2. From it we can calculate the sensitivity or true positive rate, and the specificity or true negative rate, which are 87.5% and 58.78% respectively

Table 2: Confusion matrix for test step of the coarse tree.

True class	Predicted class 0	Predicted class 1
0	1185	831
1	5	35

3.2 Larger Tree

The second tree was defined to have a maximum number of 20 splits. Again, the split criterion was the Gini's diversity index. The accuracy for the training step remained the same, at 67.9%, but for the test step, it increased to 65.2%.

The confusion matrix is shown in Table 3. The new values of sensitivity and specificity are 85% and 64.8% respectively, and the obtained tree is depicted in Figure 3.

Table 3: Confusion matrix for test step of the larger tree.

True class	Predicted class 0	Predicted class 1
0	1307	709
1	6	34

4 DISCUSSION

The two models selected the number of NSSI thoughts (f_9) as the most important feature to predict non-suicidal self-injury. This is something expected but also confirmed by our experiments. When not having NSSI thoughts, subjects tended to report positive affect, and more specifically tended to be more relaxed (f_5) and happier (f_1). These are the next most important features for the models, indicating that being relaxed or happier will, to certain degree, impede the subject to cause a self-injury.

The first model only relies in these emotions, while the second model, having the same structure of the first one for the first leaves, includes the emotion of distress (f_4) and the number of times having sex (f_{11}) as important features. When participants reported less happiness, they tended to engage in NSSI and report consequent feelings of distress. In this case, subjects tended to engage in multiple sexual intercourses, as a possible indicator of coping mechanism to deal with NSSI thoughts. The second model helped us to decrease the number of false positives, from 831 to 709, while maintaining almost the same false negatives from 5 to 6, as can be seen in Table 1 and Table 2.

Despite the accuracy in the training was far from perfect, it's important to note that the prediction (test step) obtained a better result, even if the model was trained with only 50% of the samples of the underrepresented class. It's also interesting to note that the sensitivity or true positive rate is equal or higher than 85% in both models. This means that the model is able to predict when the subject will cause a self-injury with an 85% of success, only using the information collected by the app. The fact that the specificity or true negative rate is lower (about 60% for the coarse tree and about 65% for the larger tree) it's not an important issue because in that case the model is predicting a self-injury that will probably not occur. As the app will be more responsive in these cases, we are also reducing the likelihood of self-harm.

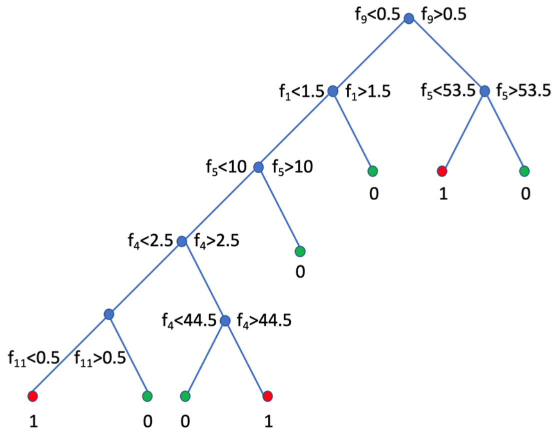

Figure 3: Larger classification tree. Now the algorithm selected five different features to model the data. See Table 1 for the decoding of the features.

Nonetheless, we suggest that a more detailed exploration of results should be carried out and that, further research should apply these models to bigger databases to obtain more accurate results, especially if aiming at integrating them with cutting-edge technology. Also new classification models should be addressed, such as neural networks or SVM.

However, although recent research has focused on the usefulness of apps for direct patient's support (Torous 2021), little attention has given to digital platforms for clinical support to automatise prompt interventions through the app itself. In our study, we provide evidence that EMA data can be a valuable data for real-time prediction of NSSI as well as knowing whether the patients are about to engage in disruptive coping mechanism to deal with NSSI, such as having several sexual intercourses, as reported. In this case, we propose that apps like Sinjur may help in reducing the risk of self-injurious thoughts and subsequent behaviours.

5 CONCLUSIONS

Giving the growing yet little research in the field of digital mental health, our findings shade a light on the great advantage of ML applications to predict real-time NSSI at the individual patient level. Nonetheless, this promising data needs to be built upon in future studies and needs major translation in the everyday clinical practice to demonstrate its real-world efficacy and later, to be translated to the enterprise world.

ACKNOWLEDGEMENTS

We thank the Agency for Management of University and Research Grants (AGAUR) of the Catalan Government for their support to Chiara Capra (Industrial Doctorate programme).

REFERENCES

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (2017). Classification and regression trees. Routledge.

Briones-Buixassa, L., Alí, I., Schmidt, C., Nicolaou, S., Pascual, J.C., Soler, J., & Vega, D. (2021). Predicting Non-Suicidal Self-Injury in Young Adults with and without Borderline Personality Disorder: A Multilevel Approach Combining Ecological Momentary Assessment and Self-Report Measures. *Psychiatric Quarterly*, 92(22).

Lewis, R. J. (2000). An introduction to classification and regression tree (CART) analysis. In Annual meeting of the society for academic emergency medicine in San Francisco, California (Vol. 14).

Snir, A., Rafaeli, E., Gadassi, R., Berenson, K., & Downey, G. (2015). Explicit and inferred motives for nonsuicidal selfinjurious acts and urges in borderline and avoidant personality disorders. *Personal Disord*, 6(3), 267–77.

Turner, B.J., Cobb, R.J., Gratz, K.L., Chapman, A.L. (2016). The role of interpersonal conflict and perceived social support in nonsuicidal self-injury in daily life. *J Abnorm Psychol*, 125(4), 588-98.

John Torous, Sandra Bucci, Imogen H. Bell, Lars V. Kessing, Maria Faurholt-Jepsen, … & Firth, J. (2021). The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. *World Psychiatry*, 20, 3.

Wolff, J.C., Fraizer, A., Esposito-Smythers, C., Burke, T., Sloan, E., & Spirito. A. (2013). Cognitive and Social Factors Associated with NSSI and Suicide Attempts in Psychiatrically Hospitalized Adolescents. *J Abnorm Child Psychol.*, 41(6): 1005–1013.

Wolff, J.C., Thompson, E., Thomas, S.A., Nesi, J., Bettis, A.H., & Ransford, B. (2019). Emotion dysregulation and nonsuicidal self-injury: a systematic review and meta-analysis. *Eur Psychiatry*, 59, 25-36.

Yuan, Y., Wu, L. & Zhang, X. (2021). Gini-Impurity Index Analysis. *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 3154-3169

Zetterqvist, M. (2015). The DSM-5 diagnosis of nonsuicidal self-injury disorder: a review of the empirical literature. *Child Adolesc Psychiatry Ment Health*, 9, 31.