Predicting ADHD Symptoms Using Smartphone Sensing Data

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Adult attention-deficit hyperactivity disorder (ADHD) is an impairing disorder that affects multiple domains of functioning and manifests itself in the daily lives of adults with the disorder in far-reaching ways. ADHD affects a substantial minority of college-age students. Current diagnostic methods rely on self-report, which may introduce recall and other biases, and collateral reports may suffer from their own sources of bias. In addition, tracking treatment related change across time can be difficult. Smartphones are ubiquitous for many populations and can function as human sensors that generate a wealth of behavioral data; for example, GPS, SMS/call, and app usage data. In a pilot study, we explore the feasibility of using smartphone sensing data collected passively from an android app to predict ADHD symptoms. Our results indicate that specific ADHD inattention, sluggish cognitive tempo and hyperactivity symptoms could be predicted fairly accurately using the smartphone data collected from college students in a pilot study, with F_1 score as high as 0.75.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; • **Computing methodologies → Machine learning approaches**.

Additional Key Words and Phrases: ADHD symptoms; Prediction; Sensor data analysis

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1 INTRODUCTION

ADHD affects a substantial minority of college students, leads to significant impairment in major functional domains and is associated with psychiatric comorbidity [3, 12]. In the DSM diagnostic system ADHD symptoms are categorized into two dimensions-inattention and hyperactivity-impulsivity—that define three sub types of ADHD [1]. In addition, symptoms of cognitive disengagement currently described as sluggish cognitive tempo (SCT) [4] form a distinct but related set of symptoms. Researchers have found that college students with ADHD have difficulty prioritizing and completing tasks and following plans through [13]. Recent studies have used smartphone data for mental health prediction–for example, depression [5, 8, 9, 11, 16, 18–20]. Smartphones are ubiquitous in nature and are embedded with rich set of sensors like GPS, WiFi, Activity, SMS, Call etc. Thus, they act as "human sensors" that can be used to construct behavioral data. Text messaging is the most common communication platform among college students and studies have associated social interaction with personality factors [6, 10, 14]. In this paper, we have used SMS data to predict ADHD symptoms in a small pilot sample. This approach is based on continuous behavioral data collected automatically from participants' phones. We have used machine learning to predict if a symptom is present or not.

Such objective data may be helpful for clinicians to make treatment decisions. This research may lead to new sources of data that can counter the known shortcomings of adult ADHD assessment based only on self-report [17]. To the best of our knowledge, this is the first study that uses smartphone data for ADHD symptom prediction.

2 APPROACH

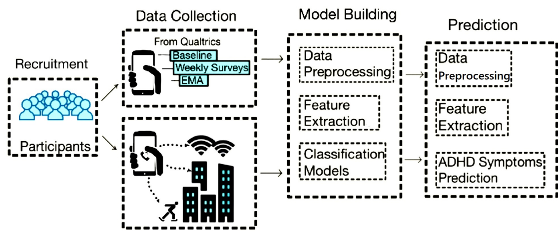

Fig. 1. Illustration of our high-level approach.

As illustrated in Figure 1, our approach contains two stages: data collection and learning model, and using the models for prediction. In the first stage, we recruit participants and passively collect smartphone sensing data through an app installed on their phones along with regular self-reports. All the collected data is stored at a secure server maintained by the Information Services at the University of Richmond. We calculate an array of features using smartphone data and then use them to train a family of machine learning models for ADHD symptom prediction (if a symptom is present or not). In the second stage, the models from the first stage will be used on unknown data to predict if an ADHD symptom is present or not.

3 DATA COLLECTION AND ANALYSIS

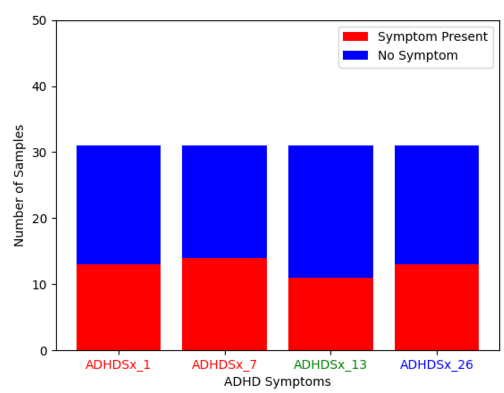

Fig. 2. Number of Samples for ADHD Symptoms with Significant F_1 Scores.

We recruited participants with and without prior ADHD diagnosis and who used an Android phone from the University of Richmond (UR) and Virginia Commonwealth University (VCU) for an Institutional Review Board approved

Table 1. ADHD Symptoms Prediction Results.

	F1	Precision	Recall	Specificity
ADHDSx_1	0.57	0.50	0.66	0.75
ADHDSx_7	0.75	0.75	0.75	0.86
ADHDSx_13	0.67	0.67	0.66	0.88
ADHDSx_26	0.67	0.75	0.60	0.83

pilot study between April 2022 to June 2022. Participants (n = 5) completed informed consent and provided two types of data- self-reports (baseline and weekly surveys for 10 weeks) and smartphone sensing data. From the screening, 2 out of 5 participants were diagnosed with ADHD. We assigned random userids to participants to anonymize their data.

3.1 Data Preprocessing and Feature Extraction

We preprocessed data collected in weekly survey intervals. We mapped the SMS data collected in these intervals with their corresponding ADHD symptom scores. The scores for each questions range between 1 (no symptom) to 4 (with symptom in increasing level of symptom severity between 2 and 4). In order to classify whether a symptom is present or not, we have mapped theses score values to labels 0 (no symptom) and 1 (with symptom). In order to handle missing data, we omitted a few weekly intervals. In this analysis, we have used a threshold value of 4 (decided empirically), i.e. we have only considered the survey intervals with at least 4 days of SMS data. Figure 2 illustrates the distribution of samples (number of self-report intervals) for symptoms with significant F_1 scores. ADHD inattention, sluggish cognitive tempo and ADHD hyperactivity symptoms [2] are indicated in red, green and blue print respectively. We present results from these four symptoms:

- ADHDSx_1 Fail to give close attention to details or make careless mistakes in my work or other activities.
- ADHDSx_7 Lose things necessary for tasks or activities.
- ADHDSx_13 Have difficulty engaging in leisure activities quietly (feel uncomfortable, or am loud or noisy).
- ADHDSx_26 Slow moving.

In this work, we extracted the following features using SMS data- # of incoming/outgoing messages, # of words and characters in incoming/outgoing messages, and # of unique contacts corresponding to incoming/outgoing messages. The app recorded only statistical information like # of incoming/outgoing SMS, word and character count etc. No content was recorded by the app as a part of this study.

3.2 Classification Methodology and Results

We used Support Vector Machine (SVM) with RBF kernel [7, 15] to classify if an ADHD symptom is present or not (using the labels described above). We have used Scikit-learn [15] module for our analysis. Table 1 presents the classification results. We observe that specific symptoms across various dimensions (inattention, hyperactivity and sluggish cognitive) are predicted fairly accurately. It also gives us an insight on how SMS data correlates well with an individual's day to day activities like spending time in leisure, movement and engagement in activities.

4 CONCLUSION AND FUTURE WORK

In this paper, we have explored the feasibility of using smartphone sensing data for ADHD symptoms prediction using machine learning. Our results indicate that specific symptoms from different categories can be predicted fairly accurately using SMS data collected on phones. However, we caution readers against generalizing our specific findings to other samples, given the small pilot size analyzed thus far. Our investigation provides a promising direction for future work. We will continue this work with a larger dataset (collected across both android and iOS platforms) in our upcoming research study. Furthermore, we want to include other types of sensing data like activity, location and app usage. We also plan to do a comparative analysis with different machine learning algorithms to compare the prediction results and observations.

REFERENCES

[1] A. P. Association et al. Diagnostic and statistical manual of mental disorders, text revision (dsm-iv-tr®). 2010.

[2] R. A. Barkley. *Barkley Adult ADHD Rating Scale-IV (BAARS-IV)*. Guilford Press, 2011.

[3] R. A. Barkley, K. R. Murphy, and M. Fischer. *ADHD in adults: What the science says*. Guilford press, 2010.

[4] S. P. Becker, E. G. Willcutt, D. R. Leopold, J. W. Fredrick, Z. R. Smith, L. A. Jacobson, G. L. Burns, S. D. Mayes, D. A. Waschbusch, T. E. Froehlich, et al. Report of a work group on sluggish cognitive tempo: Key research directions and a consensus change in terminology to cognitive disengagement syndrome, 2022.

[5] L. Canzian and M. Musolesi. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pages 1293–1304, 2015.

[6] P. S. Chandra, H. Sowmya, S. Mehrotra, and M. Duggal. 'sms'for mental health–feasibility and acceptability of using text messages for mental health promotion among young women from urban low income settings in india. *Asian journal of psychiatry*, 11:59–64, 2014.

[7] C.-C. Chang and C.-J. Lin. *LIBSVM: a library for support vector machines*, 2001. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.

[8] A. A. Farhan, C. Yue, R. Morillo, S. Ware, J. Lu, J. Bi, J. Kamath, A. Russell, A. Bamis, and B. Wang. Behavior vs. introspection: refining prediction of clinical depression via smartphone sensing data. In *2016 IEEE wireless health (WH)*, pages 1–8. IEEE, 2016.

[9] A. Gruenerbl, V. Osmani, G. Bahle, J. C. Carrasco, S. Oehler, O. Mayora, C. Haring, and P. Lukowicz. Using smart phone mobility traces for the diagnosis of depressive and manic episodes in bipolar patients. In *Proceedings of the 5th augmented human international conference*, pages 1–8, 2014.

[10] D. Harley, S. Winn, S. Pemberton, and P. Wilcox. Using texting to support students' transition to university. *Innovations in Education and Teaching International*, 44(3):229–241, 2007.

[11] N. C. Jacobson and Y. J. Chung. Passive sensing of prediction of moment-to-moment depressed mood among undergraduates with clinical levels of depression sample using smartphones. *Sensors*, 20(12):3572, 2020.

[12] L. E. Knouse, L. Traeger, C. O'Cleirigh, and S. A. Safren. Adult adhd symptoms and five factor model traits in a clinical sample: a structural equation modeling approach. *The Journal of nervous and mental disease*, 201(10), 2013.

[13] S. J. Kwon, Y. Kim, and Y. Kwak. Difficulties faced by university students with self-reported symptoms of attention-deficit hyperactivity disorder: a qualitative study. *Child and adolescent psychiatry and mental health*, 12(1):1–8, 2018.

[14] S. Lee, C. L. Tam, and Q. T. Chie. Mobile phone usage preferences: The contributing factors of personality, social anxiety and loneliness. *Social Indicators Research*, 118(3):1205–1228, 2014.

[15] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.

[16] S. Saeb, M. Zhang, C. J. Karr, S. M. Schueller, M. E. Corden, K. P. Kording, D. C. Mohr, et al. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. *Journal of medical Internet research*, 17(7):e4273, 2015.

[17] M. H. Sibley, J. T. Mitchell, and S. P. Becker. Method of adult diagnosis influences estimated persistence of childhood adhd: a systematic review of longitudinal studies. *The Lancet Psychiatry*, 3(12):1157–1165, 2016.

[18] R. Wang, F. Chen, Z. Chen, T. Li, G. Harari, S. Tignor, X. Zhou, D. Ben-Zeev, and A. T. Campbell. Studentlife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*, pages 3–14, 2014.

[19] S. Ware, C. Yue, R. Morillo, J. Lu, C. Shang, J. Bi, J. Kamath, A. Russell, A. Bamis, and B. Wang. Predicting depressive symptoms using smartphone data. *Smart Health*, 15:100093, 2020.

[20] C. Yue, S. Ware, R. Morillo, J. Lu, C. Shang, J. Bi, J. Kamath, A. Russell, A. Bamis, and B. Wang. Fusing location data for depression prediction. *IEEE Transactions on Big Data*, 7(2):355–370, 2018.