

Applying Graph Neural Networks on Smart watch based data of physiological parameters and machine learning prediction of methylphenidate intake in children with ADHD

Tzuf Bechor 208721217 tzufbechor@campus.technion.ac.il

Uriah Asulin 322691718 uriah372@campus.technion.ac.il

Yoav Kehat 209028869 yoavkehat@campus.technion.ac.il

Roei Avraham 206966020 roei.avraham@campus.technion.ac.il

ABSTRACT

Introduction: Methylphenidate, the first-line medication for Attention-deficit/hyperactivity disorder (ADHD) has a distinct effect on autonomic and movement regulation, which may be used as biomarkers.

Objective: This study aim to leverage graph neural networks to enrich the physiological data collected through smartwatches, in order to elaborate them by a machine learning algorithm to assess methylphenidate intake on children and adolescents with ADHD. Moreover, to examine if insights gained from trial data can be leveraged to better understand observational data in children diagnosed with ADHD.

Methods: Fifteen children with ADHD aged 6 to 16 years (mean age 11.10 ± 2.69) were recruited to perform an assessment of behavioral, neuropsychological and physiological changes related to methylphenidate administration. Throughout the evaluations, children were required to wear a smartwatch. These measurements were conducted by Iluria Ltd., a digital health software startup.

Six of them participated in a trial, and there is labeled(0 indicate off-med, and 1 indicates on-med) and the treatment effect by physician that participated in that trial. And the other Nine children wore the watch during school days in which the medication taken, and medication time documented.

Our approach involved two experiments-

1. training a GNN on the labeled trial data with leaving one of the trial participants out of train data and testing the model on it.

2. training a GNN on the labeled trial data, where the medication's effectiveness is known. The GNN will then be applied to the entire dataset.

Findings: Results show a significant improvement for first experiment – i.e applying GNN within trial data, but not at trying leveraging the trial-labeled data to get insights from observational data.

INTRODUCTION

Attention-deficit/hyperactivity disorder (ADHD) is a common neurodevelopmental condition that makes it difficult to concentrate on daily requests and routines. It is characterized by symptoms of inattention, motor hyperactivity, and impulsivity that are inconsistent with age or developmental level. People with ADHD tend to have difficulty with organization, thinking before acting, designing realistic plans and adapting to changing situations [1].

The worldwide prevalence of ADHD in children and adolescents is between 5% and 7% [2], with no particular geographic differences [1], approximately two-thirds of children with ADHD continue to exhibit clinical or subthreshold symptomatology into adulthood [3].

Recent research on the physiological measures associated with ADHD and with the possible effects of pharmacotherapy on physiological measures is currently innovative and, to our knowledge, the literature on the correlation between physiological activation and methylphenidate administration has not yet produced consistent and clear-cut results. It has been shown that in order to modulate physiological arousal according to the demands of the environment, the joint work of the two branches of the autonomic nervous system (ANS), sympathetic nervous system and parasympathetic nervous system, is required [4]. to the best of our knowledge, there are no studies in the literature that use smartwatches to measure physiological changes during medication administration, and no studies that leverage Graph neural networks on smartwatch based psychological data.

METHODS

This is an observational study aimed to evaluate the effectiveness of the use of GNN in evaluating physiological changes in children with a clinical diagnosis of ADHD after the start of methylphenidate intake, and the possible correlation with changes in symptomatology. In trial data, Medication compliance was assessed through a clinical diary for the patient's medication intake, on which the prescribed medication, dosage and corresponding times of intake are recorded.

Physiological measures

To assess physiological parameters such as heart rate variability, movement levels, sympathetic nervous system arousal and other relevant metrics during clinical evaluations, advanced smart wearable devices were used. These devices are equipped with different sensors, such as accelerometer (x, y, z), heart rate monitor, and gyroscope (x, y, z). The accelerometer data, when combined with gyroscopic inputs, enhances the accuracy of motion tracking algorithms. Gyroscopes track rotation movement and detect orientation changes, while accelerometers measure acceleration for activity recognition. Heart rate sensors use photoplethysmography to gauge heart rate and detect subtle changes in blood volume, enabling the continuous measurement of heart rate variability and resting heart rate.

The GNN in this study involves structuring time-series data into a graph-based format.

First, the data is loaded and organized by user and medication type, creating unique identifiers for each combination. Edges between nodes (data points) are created to represent sequential connections in the time-series data, forming "string-like" graphs. A specific set of features is extracted as node attributes and converted to tensors for GNN processing. The GNN model itself uses a three-layer architecture with Graph Attention Convolution (GAT) layers, leveraging dropout for regularization and RELU activation functions. After training, the model generates embeddings for both trial and daily observational data, converting the resulting

tensors into new feature columns in the original dataset. Additional data processing includes converting timestamps to hourly format and adjusting user labels based on medication usage patterns, making the dataset ready for downstream analysis.

Experiments

The effectiveness of the GNN-enhanced data representation evaluated through two tasks:

-Prediction Task: The performance of a prediction model (Random Forest) assessed using the AUC curve, comparing results with and without the GNN enhancement on the labeled trial data.

-Separation Task: A Linear Discriminant Analysis (LDA) conducted to evaluate the separation of different activity states, again comparing the results with and without the GNN's influence.

For the observational data, we conducted an analysis by generating weekly consolidated confidence graphs using the prediction model. These graphs could be assessed by comparison with established medication concentration profiles from the literature to determine if there are any correlations or patterns. (Appendix A)

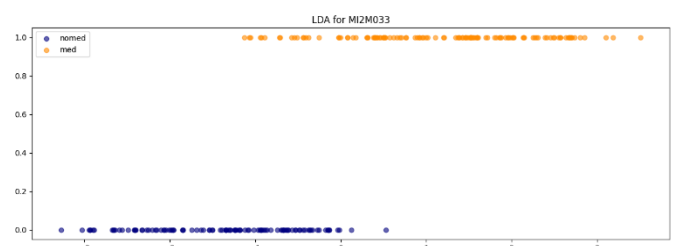
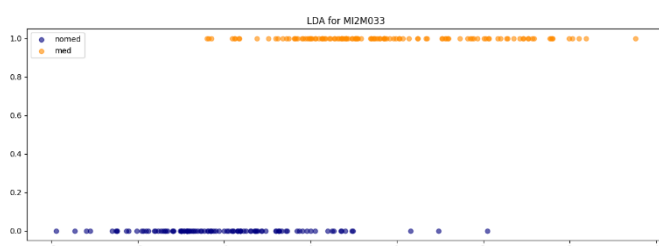
two experiments has been made-

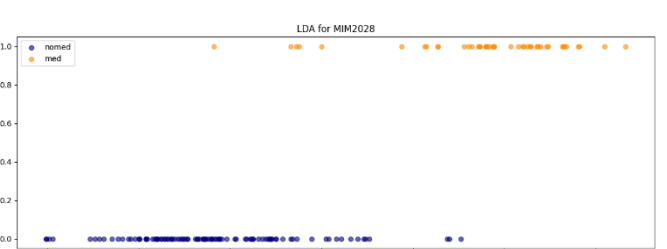
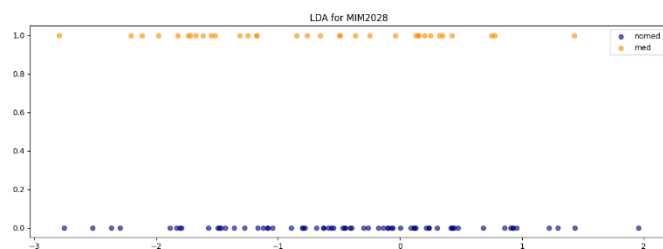
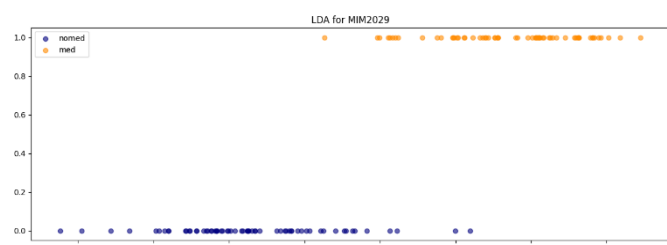
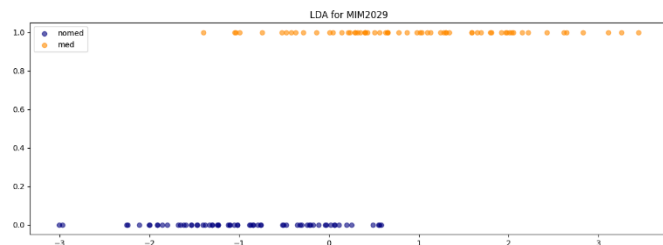
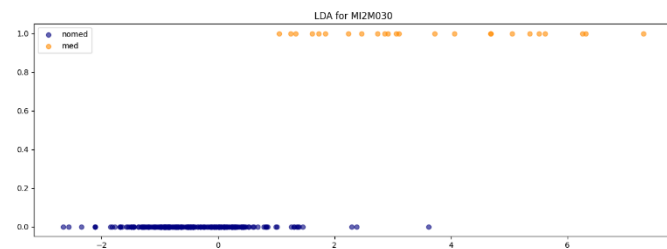
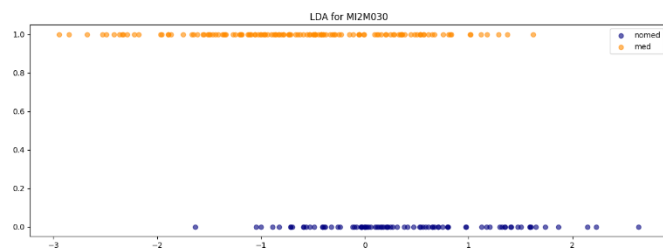
1. training a GNN on the labeled trial data with leaving one of the trial participants out of train data and testing the model on it.
2. training a GNN on the labeled trial data, where the medication's effectiveness is known. The GNN will then be applied to the entire dataset.

At the first experiment, for four of the subjects, there was better separation at the LDA graphs after applying GNN, and the ROC curve indicated higher performance of the prediction model in three of those four subjects. For the remaining two of the subjects, the GNN failed to achieve decent performance at its training face, therefore evaluation wasn't applied on those.

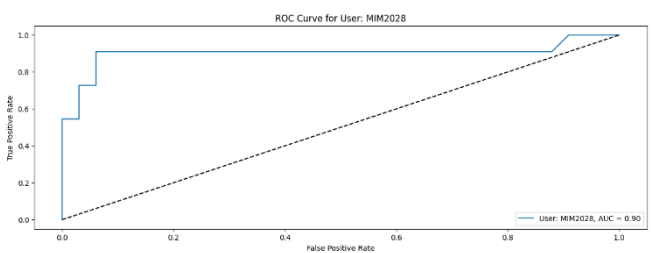
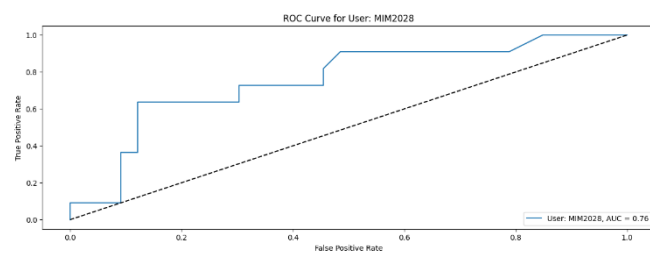
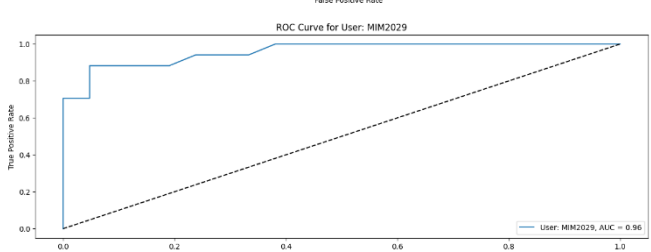
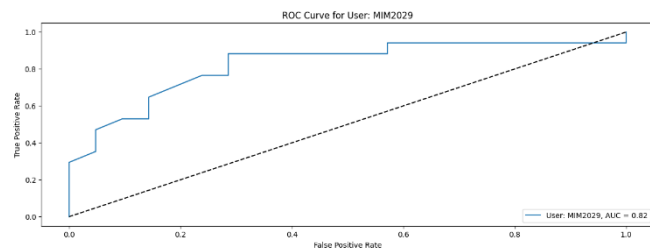
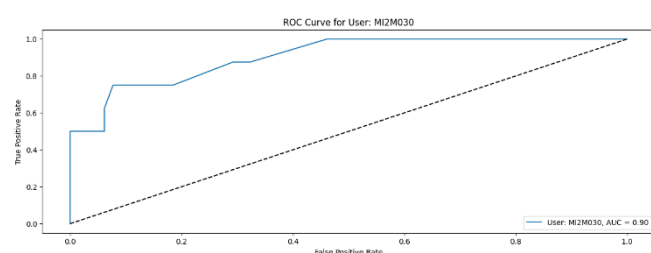
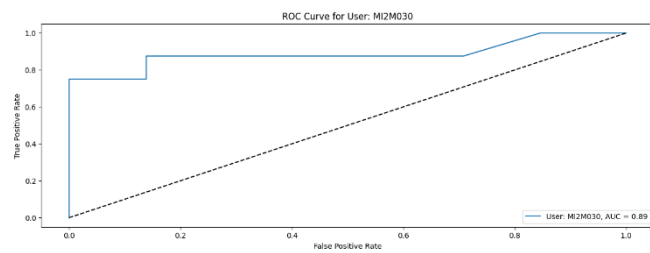
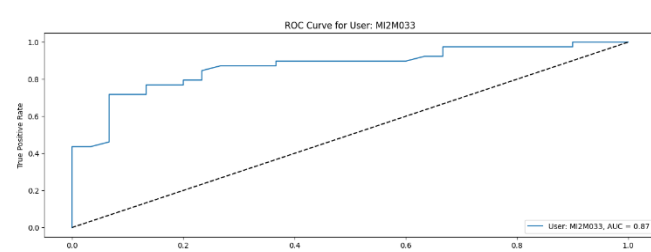
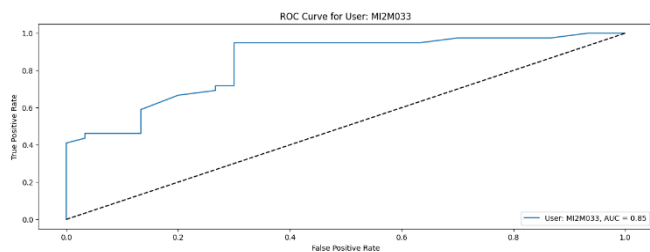
Before GNN:

After GNN:





Before GNN:



After GNN:

At the second experiment, there was not much an insightful change at the consolidated graph, results can be seen in the attached code.

Discussion

This study explored the application of Graph Neural Networks (GNNs) to physiological data collected via smartwatches, with the goal of predicting methylphenidate intake effects in children with ADHD. Key findings indicate that applying a GNN model within a trial dataset demonstrated improved prediction performance, as reflected in enhanced separation of activity states in four out of six participants. However, attempts to leverage insights from trial data to interpret observational data yielded limited success, highlighting the challenges in generalizing GNN-derived patterns across different data contexts.

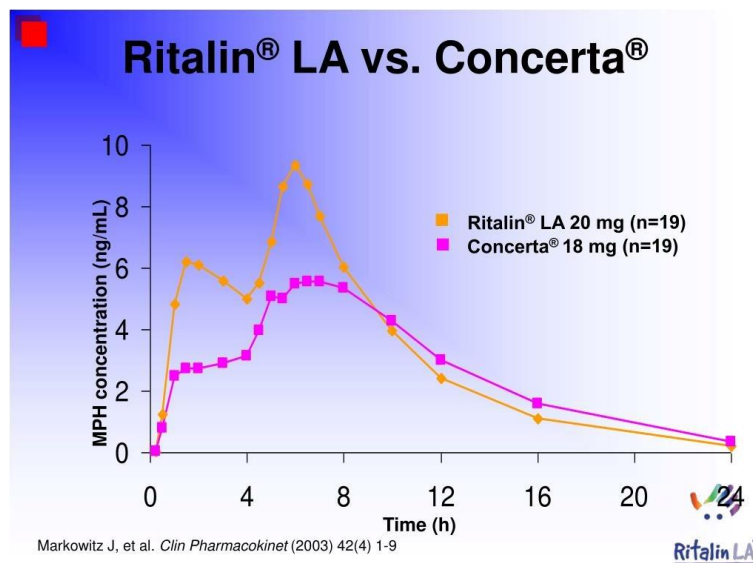
The study suggests promising potential for using GNNs to enhance physiological data interpretation in ADHD-related research. Nevertheless, the limited success in the observational dataset points to potential improvements. Future work could focus on increasing sample size and exploring additional data pre-processing techniques to better align the observational data with trial data characteristics. Furthermore, incorporating more contextual information, such as environmental and behavioral variables, could enhance the model's interpretive power. Finally, evaluating alternative GNN architectures and expanding the analysis to include different machine learning models could provide a more comprehensive understanding of the GNN's applicability and improve generalizability across varied datasets.

REFERENCES

1. Faraone SV, Bellgrove MA, Brikell I, et al (2024) Attention-deficit/hyperactivity disorder. Nat Rev Dis Primers 10: 11. doi: 10.1038/s41572-024-00495-0.
2. Thomas R, Sanders S, Doust J et al (2015) Prevalence of attention-deficit/hyperactivity disorder: a systematic review and meta-analysis. Pediatrics 135: e994-1001. doi: 10.1542/peds.2014-3482.
3. Wootton RE, Riglin L, Blakey R et al (2022) Decline in attention-deficit hyperactivity disorder traits over the life course in the general population: trajectories across five population birth cohorts spanning ages 3 to 45 years. Int J Epidemiol 51: 919-930. doi: 10.1093/ije/dyac049.
4. Quadt L, Critchley H, Nagai Y (2022) Cognition, emotion, and the central autonomic network. Auton Neurosci 238:102948. doi: 10.1016/j.autneu.2022.102948.

Appendix

A



Git - <https://github.com/roeiAv/Applying-Graph-Neural-Networks-on-Smart-watch-based-data-of-physiological-parameters/tree/66f908640e2abcfa9367ee53c8eabaa9c2f53f69>