Identifying a Minimal Set of Behavioral Features for the Differential Diagnosis of ASD And ADHD Using the National Survey of Children's Health

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Abstract
Autism Spectrum Disorder (ASD) and Attention-Deficit Hyperactivity Disorder (ADHD) are two of the most commonly observed neurodevelopmental conditions in childhood. Providing a specific computational assessment to distinguish between the two can prove difficult. We trained machine learning models on the National Survey of Children's Health (NSCH) data to identify behavioral features that can be used for automated clinical decision support tasks. A model trained on the binary task of distinguishing ASD or ADHD vs. neither achieved sensitivity >92% and specificity >94% while a model trained on the 4-way classification task of ASD vs. ADHD vs. both vs. none demonstrated >65% sensitivity and >66% specificity. While the performance of the binary model was respectable, the relatively low performance in the differential classification of ASD and ADHD highlights the challenges that persist in achieving specificity within clinical decision support tools for developmental conditions.

Introduction
Autism Spectrum Disorder (ASD) is often characterized by the presence of restrictive or repetitive behaviors, asynchronous emotions, sensory irregularities, and challenges in social communication. By contrast, attention deficit hyperactivity disorder (ADHD) is defined by difficulties in attention and impulse control[1]. Although the two conditions differ in their diagnostic descriptions, it is frequently noted that a child with ADHD may exhibit symptoms of ASD and vice versa. Prior research studies have investigated the prevalence rates of the co-occurrence of ASD and ADHD in both children and adults, suggesting that 20-50% of individuals with ADHD also have ASD, and conversely, 30-80% of individuals with ASD have concurrent ADHD[2-4].

Despite numerous clinical observations noting overlapping diagnostic characteristics, distinguishing between conditions and the possibility of comorbidity remains challenging. In recent years, machine learning (ML) has demonstrated its utility in extracting relevant feature subsets specifically for ASD[5-9] and uncovering complex patterns from diverse healthcare datasets such as genotypic[10-12], phenotypic[13-20], and brain imaging data[21-23]. ML holds promise for transforming clinical decision processes by improving efficiency while maintaining quality. The results of such feature selection techniques have often been used as the basis for crowdsourcing-enabled diagnostic workflows[24-26].

Most, though not all, prior studies have focused on either a single binary diagnosis, enhancing the individual sensitivity of ASD[27-33] and ADHD[34-38] classifiers, or comparing the two conditions without considering co-occurring diagnoses. A few prior studies have examined the differential diagnoses between the two conditions[5,13,21,39,40]. These works demonstrate the potential of machine learning to optimize the features for comorbid diagnosis that could help build mobile risk assessment platforms. However, these findings focus on gold standard clinical assessments, developed primarily for ASD detection, limiting the availability of data related to ADHD.

Building upon this rich body of prior work, we aim to identify a subset of behavioral features from the publicly available National Survey of Children's Health (NSCH) data that could potentially be used for differential diagnosis of ASD and ADHD, including the possibility of comorbidity. Using population based data instead of gold standard clinical assessments not only provides more data samples but also enables the analysis of a diverse and representative sample of the population. While some prior works have used similar data, they either focused on ADHD classification alone[36,41] or provided statistical analysis using socio demographic features[10,42-44] rather than building ML models. The objective of our work, by contrast, is to identify the distinct subset of features that can effectively capture the complex patterns differentiating ASD and ADHD comorbidity between a diagnosis of only a single condition.

Methods

Data Description

We used publicly available data from the National Survey of Children's Health (NSCH)[45], a project overseen by the Health Resources and Services Administration (HRSA) Maternal and Child Health Bureau (MCHB). This survey targets children ages 0 to 17 years and offers comprehensive national and state-level insights into various facets of child health and emotional well-being. Responses to questions on social determinants such as health care access, neighborhood conditions, physical, dental and mental health and school performance of the child are completed by the parents or guardians of the children who live in the same household.

We used data from the years 2016 (n=50,212), 2017 (n=30,530), 2018 (n=29,433), 2019 (n=42,777), 2020 (n=50,892), 2021 (n=21,599) and 2022 (n=54,103). Records missing any target labels for diagnosis such as Tourette's syndrome, ASD, ADHD, anxiety, depression, speech disorder, learning disability and developmental delay were excluded to ensure the reliability of labels for ML model training. The filtered dataset resulted in 270,978 data points and 365 feature columns. Given the study's focus on identifying behavioral markers pertinent to ASD and ADHD diagnosis, columns not describing an observable behavior were discarded. We additionally used sociodemographic variables for preliminary data analysis and to ensure balanced representation across different groups.

The initial analysis of the data revealed that numerous behavioral features contained missing values, rendering simultaneous use challenging. This could be attributed to respondents either deeming certain questions inapplicable or choosing not to disclose information, resulting in skipped responses. Given the differing proportions of missing values across these features, we partitioned them into two distinct groups (Table 1) and assessed their significance in predictive tasks using machine learning algorithms. Three separate classification tasks were performed on each feature group: (1) distinguishing between any neurodivergent condition and none, (2) identifying the presence of either ASD or ADHD versus none, and (3) generating a multilabel probabilistic prediction for ASD and ADHD.

Table 1. Description of the two feature sets used for the ML classification tasks.

Feature group 1	Age, Sex, Difficulty concentrating, remembering or making decisions, Difficulty walking or climbing stairs, Shows interest and curiosity in learning new things, Works to finish tasks started, Stays calm and in control when challenged, Argues too much, Difficulty making or keeping friends
Feature group 2	Age, Sex, Shows interest and curiosity in learning new things, Difficulty making or keeping friends, Difficulty in coordination or moving around, Is affectionate and tender, Bounces back quickly when things do not go his or her way, Smiles and laughs a lot, Recognize beginning sound of a word, Recognize letters of alphabet, Gives good explanation of things he/she did, Can write his/her first name, Is easily distracted, Plays well with others, Shows concern when others are hurt or unhappy

For the target variables, we used the survey questions: "*Has a doctor or other health care provider EVER told you that the Selected Child (SC) has Autism or Autism Spectrum Disorder (ASD)?*" and "*Has a doctor or other health care provider EVER told you that SC has Attention Deficit Disorder or Attention-Deficit/Hyperactivity Disorder, that* *is, ADD or ADHD?*" If the answer to either question was yes, we encoded the output as "ASD only" or "ADHD only", respectively. If the answers to both the questions were yes or no, they were encoded as "Both ASD and ADHD" and "None", respectively. A similar strategy was used to categorize Learning disability, Depression, Anxiety, Behavioral problems, Developmental delay, Speech disorder, Tourette syndrome, and Intellectual disability.

Machine Learning classification

We built 3 ML models: (1) a binary classification model for distinguishing individuals with any neurodevelopmental condition from those without any condition, (2) a binary classification model to distinguish individuals with either ASD or ADHD from those without any condition, and (3) a multilabel classification model to distinguish ASD only, ADHD only, both conditions, and none. For all three models, the dataset was divided into training, validation, and test sets using an 8:1:1 split. Logistic regression (LR) and decision tree (DT) models were used to assess the performance of each classification task independently. We framed the differential diagnostics task as a multilabel classification problem between ASD only, ADHD only, both conditions, and neither condition.

Feature selection

We also combined all features to assess their collective performance. Because some features contained numerous missing values, we applied imputation using a kNN Imputer, leveraging the Euclidean distance matrix to estimate missing values based on the closest data samples. Subsequently, we performed all three classification tasks on this combined feature dataset, incorporating a feature selection technique to identify the optimal number of features. Employing the step forward wrapper method, we incrementally added one feature at a time to train the model. Specifically, we utilized the MLxtend sequential forward feature selector (SFS) implementation with a Random Forest (RF) classifier to identify the top 12 features yielding the highest classifier performance of Area under the receiver operating characteristic curve (ROC AUC) score. Utilizing the reduced feature subset identified, we retrained the model on the original dataset to compare its performance when using all features.

We built a separate model using the forward feature selection method on data from the 65-item Social Responsiveness Scale (SRS), a widely known assessment scale used in prior studies[5,39]. This parent-directed questionnaire assesses autistic traits over the preceding 6 months in children aged 4 to 18 years and is widely utilized in ASD phenotyping research[5,30,33,39]. By comparing the top-ranked features from the population-based NSCH data against those derived from the SRS data, we aimed to check for overlap in the salient behavioral features across different types of evaluations. The SRS data, however, was imbalanced, with the majority records for ASD (n=2779) and much fewer samples for ADHD (n=150). To address this, we randomly selected a subset of data points from the ASD records to create a balanced dataset, which was then divided by a 8:1:1 ratio to create the training, validation, and test sets. Given that this dataset did not include any comorbid diagnoses, we performed a binary classification task to distinguish between ASD and ADHD using a random forest classifier.

Results

Preliminary Data Analysis

We conducted a preliminary data analysis on our filtered dataset to understand the sex, race, and age distribution among children with ASD, ADHD, and both conditions. The demographic breakdown of the data is summarized in Table 2. We examined the distribution of samples across other diagnostic categories such as Tourette's syndrome, anxiety, depression and learning disability. These conditions are frequently known to co-occur with ASD, highlighting the importance of leveraging population-based questionnaire data in the study of neurodevelopmental disorders.

Table 2. Descriptive statistics of the subset of the NSCH dataset we examined.

Variable	**Overall**	**ASD only**	**ADHD only**	**ASD+ADHD**
Mean age (years)	9	9.5	12.3	11.9
Female	130745 (48.3%)	971 (22.5%)	7840 (34.3%)	773 (20.5%)
Male	140233 (51.7%)	3344 (77.5%)	15023 (65.7%)	2997 (79.5%)
White	208993 (77.1%)	3167 (73.4%)	18400 (80.5%)	2995 (79.4%)
Black or African American	18175 (6.7%)	370 (8.57%)	1759 (7.7%)	264 (7%)
American Indian or Alaska Native	2424 (0.9%)	43 (0.99%)	212 (0.93%)	33 (0.89%)
Asian	15140 (5.6%)	239 (5.53%)	382 (1.6%)	123 (3.3%)
Native Hawaiian and Other Pacific Islander	1455 (0.54%)	22 (0.51%)	73 (0.32%)	19 (0.5%)
Multiple races	22232 (8.2%)	430 (9.96%)	1894 (8.3%)	318 (8.43%)
Other	2559 (0.96%)	44 (1.04%)	143 (0.6%)	18 (0.477%)

Machine learning classification

Table 3 presents the evaluation metrics obtained on the test sets for each classification task using individual feature groups and the combined feature set. While the model demonstrates decent performance in correctly distinguishing individuals with any neurodevelopmental condition from individuals with no condition as well as those with ASD or ADHD versus neither, the performance diminishes for the 4-way classification task. Upon closer examination, we found that the probabilities associated with each prediction were often very similar, leading to confusion in the model's predictions (Figure 1). The 4-way model tends to erroneously confuse ASD for ADHD, and vice versa. Despite the adverse impact on model sensitivity, this misclassification underscores the model's capacity to discern patterns indicative of neurodivergence broadly defined.

Using forward feature selection on the combined feature set, the top 12 features identified were: age, sex, difficulty in making friends, difficulty in coordinating or moving around, affectionate and tender behavior, recognition of alphabets, easily distracted behavior, ability to play well with others, showing concern when others are hurt or happy, serious difficulty in concentrating or remembering things, tendency to work to finish tasks started, and arguing too much. Interestingly, these same features were consistently highlighted when training models using individual feature groups, further validating the model's performance on the combined feature set.

Table 3. Results for the 3 machine learning classification tasks on each feature group.

Features used to train the model	**Metric**	**Any neurodevelopmental condition vs None**	**ASD or ADHD vs None**	**Multilabel ASD+ADHD classification**
Feature group 1	Accuracy	72.78%	81.68%	68%
	Sensitivity	62.6%	74.11%	67.15%
	Specificity	83.62%	89.3%	66.12%
	ROC AUC score	0.73	0.817	ASD class: 0.83 ADHD class: 0.73
Feature group 2	Accuracy	73.3%	89.7%	73.4%
	Sensitivity	68.08%	87.2%	66.4%
	Specificity	78.7%	91.8%	63.5%
	ROC AUC score	0.734	0.895	ASD class: 0.82 ADHD class: 0.74
Combined features: feature1 + feature2 (after imputing missing values)	Accuracy	93.8%	93.5%	68%
	Sensitivity	93.6%	92.3%	67.15%
	Specificity	94.04%	94.7%	66.12%
	ROC AUC score	0.94	0.93	ASD class: 0.83 ADHD class: 0.73

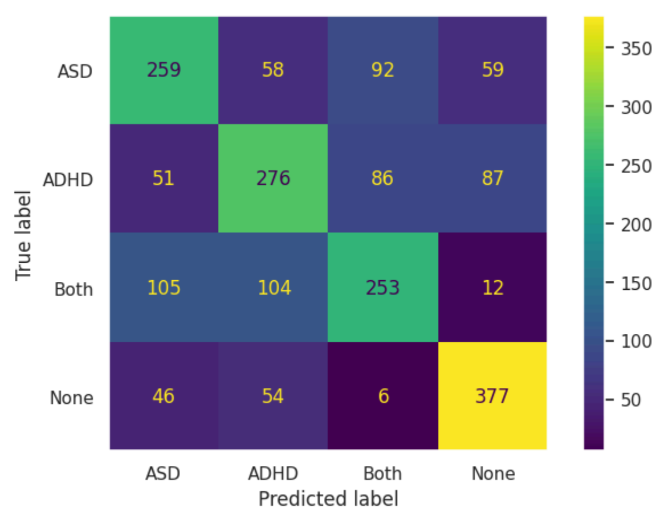

Figure 1. Confusion matrix for predictions specific to class ASD, ADHD, both and none.

On a separate model trained using the SRS dataset, we observed an accuracy of 87.5% and an ROC AUC score of 0.916 when using all features. The following top-14 features were identified: showing rigid/inflexible patterns of behavior under stress, displaying strange or bizarre behavior, experiencing difficulty making friends, struggling with changes in routine, becoming upset with lots of things going on, trouble keeping up the flow of normal conversation, difficulty relating to peers, wandering aimlessly from one activity to another, repetitive or odd behaviors and walking in between two people who are talking. Notably, only one top-ranked feature, difficulty making friends, overlapped between the NSCH data and SRS data. This is because while SRS is a clinical scoresheet, NSCH is a population-level survey for studying the emotional wellbeing of a child, and thus the features in both the datasets are different.

Discussion

Overview

This study emphasizes the importance of establishing behavioral markers that can distinguish between neurodevelopmental conditions with overlapping features. Using the NSCH data, the multilabel classifier demonstrates moderate accuracy in distinguishing between ASD and ADHD, albeit occasionally misclassifying data points. Nevertheless, it exhibits higher accuracy in distinguishing both groups from typical development. It is important to note that even though misclassifications may occur, the likelihood of the individuals falling into one of the two categories, if either category is classified, is very high. This indicates that ML has the ability to identify some neurodivergent patterns in the data that could help the clinicians with screening procedures.

The frequent co-occurrence of ADHD and ASD underscores the necessity of comprehensive assessment methods capable of considering both conditions. Using machine learning to uncover the overlapping patterns and distinguishing behavioral features could help in developing pre-screening tools for early identification and risk assessment of both disorders.

Limitations

There are several limitations of this study that must be noted. First, the NSCH dataset is not specifically tailored to differentiate between diagnostic groups but rather to survey various aspects of children's physical, mental, and emotional well-being, with a focus on social and healthcare access factors. This contrasts with dedicated diagnostic tools such as the Autism Diagnostic Observation Schedule (ADOS)[46] or the Autism Diagnostic Interview-Revised (ADI-R)[47], designed to gauge ASD spectrum severity, and the Conners Abbreviated Symptom Questionnaire[48], aimed at comprehensive ADHD assessment.

The NSCH dataset contains numerous missing values, and while the model achieved reasonable performance following imputation, discrepancies between the actual data and imputed values may negatively impact the model's performance. It is also important to acknowledge potential recall bias inherent in behavioral data obtained from parental questionnaires.

Finally, the most notable limitation of this work is that comorbidity is not always diagnosed. A lack of a formal diagnosis does not necessarily mean that the child does not have the condition. Because underdiagnosis of both ASD and ADHD is a well-known phenomenon[49-52], it is likely that several children in the dataset who were reported to only have one diagnosis should have had both, and some reportedly neurotypical children should have actually had a diagnosis.

Future Work

We plan to build upon this work by using the identified features to target behavioral and motor skills in comorbid diagnostic tasks through a human-in-the-loop machine learning pipeline[53]. This will involve utilizing multimodal data streams combined with annotations of behavior from health or crowd workers to train models for ASD and

ADHD classification. Building upon previous research that has utilized different modalities to enhance ASD trait detection[54-57], we will attempt, in particular, to improve performance metrics for ADHD classification using computational approaches. Additionally, we plan to broaden this work to include other disorders such as Tourette's syndrome, anxiety, and depression using validated questionnaires.

Conclusions

We aim to assist clinicians in identifying behavioral features for early screening, streamlining assessments, and reducing time-consuming evaluation processes for ASD and ADHD diagnosis. Achieving specificity in distinguishing the diagnosis of only ASD or ADHD from having both conditions poses a significant challenge. Solving this task is necessary given the high prevalence of comorbid ASD and ADHD, and this work provides an initial pass using parent-reported behaviors.

Acknowledgements

PW acknowledges funding from the National Institutes of Health (NIH) via the NIH Director's New Innovator Award (award DP2-EB035858). We used the generative artificial intelligence tool ChatGPT by OpenAI only to edit the grammar of the manuscript.

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