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ORIGINAL ARTICLE

Can We Predict Psychiatric Disorders at the Adolescence Period in Toddlers? A Machine Learning Approach

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Abstract

Objective: Recent studies show emotional and behavioral problems in toddler hood affecting later stages of development. However, the predictive factors for psychiatric disorders were not studied with machine learning methods. We aimed to examine the predictors of outcome with machine learning methods, which are novel computational methods including statistical estimation, information theories, and mathematical learning automatically discovering useful patterns in large amounts of data.

Method: The study group comprised 116 children (mean age: 27.4±4.4 months) who are evaluated between 2006-2007 years in a clinical setting. Emotional and behavioral problems were assessed by the Brief Infant-Toddler Social Emotional Assessment and Child Behavior Checklist/2-3.Child psychiatry residents made follow-up evaluations with telephone calls in 2018. We tested the performance of machine learning algorithms (Decision tree, Support Vector Machine, Random Forest, Naive Bayes, Logistic Regression) on our data, including the 254 items in the baseline forms to predict psychiatric disorders in adolescence period.

Results: 26.7% (n: 31) of the cases had diagnosed with a psychiatric disorder in adolescence period. In machine learning methods Random Forest outperforms other models, which had reached an accuracy of 85.2%, AUC: 0.79. Our model showed BITSEA item 20, 13, and CBCL total external problems scores filled by mother at the age of 12-36 months are the most potent factors for a psychiatric disorder in adolescence.

Conclusion: We found very early behavioral and emotional problems with sociodemographic data predicted outcome significantly accurately. In the future, the machine learning models may reveal several others are more important in terms of prognostic information and also planning treatment of toddlers.

Keywords: Child Psychiatry, Artificial Intelligence, Prediction, Supervised Learning, Classification

INTRODUCTION

The first three years of life are the most rapid and complicated stage of development. The development of psychiatric disorders in infancy leads to multi-dimensional processes affecting later stages of development. The period of early childhood is defined as infancy and toddlerhood and is stated to be the "critical period" in almost every psychiatric concept. It is thought that the vast majority of mental disorders are continued through to adulthood from childhood with various routines (1). The relationship of behavioral problems in infancy and the psychiatric problems that can develop from these problems at later stages has been researched in very few follow-up studies. The first studies to include the period of early childhood consisted of short-term follow-up, and it was shown that behavioral problems in infancy continued into early childhood (2-5). Long-term studies have shown that internalizing and externalizing problems in infancy could be related to behavioral problems in adolescence and various functional impairments (6, 7).

Machine learning methods such as classification

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trees, support vector machines, ensemble methods, deep learning are state-of-art computational methods discovering useful patterns in vast amounts of data. These methods include mathematical learning, information theories, and statistical estimation and have the advantage of accurate prediction, forecasting, and interpretation within non-experimental data sets (8). Recent studies in psychiatry are showed these methods been successfully used for predictive risk modeling for preventing child maltreatment (9), in diagnostics of Autism Spectrum Disorder (10), predictive analysis for comorbid substance use in Attention Deficit and Hyperactivity Disorder (11), and suicide prediction in Schizophrenia (12). In our previous study (13), we demonstrated machine learning methods could uncover predictive factors in clinical settings and successfully predict the outcome for autism spectrum disorders.

It can be assumed that identification, diagnosis and treatment of precursors of mental disorders at as early a stage as possible will have a positive effect on an individual's mental health in the long-term (14). Psychiatric evaluation in infancy and interventions to identify risky behavioral problems are of importance. Furthermore, social, emotional, and behavioral problems seen in adolescence could be symptoms of possible psychiatric disorders. This study aimed to investigate predictive factors of psychiatric disorders in adolescence, were psychiatrically evaluated at the age of 1-3 years.

METHODS

Participants and Study Design: The children included in the study (n:462) were those who had been evaluated by psychiatry residents in an outpatient clinic at the age of 1-4 years in 2006-2007 years for an assessment validity study (15). Child Behavior Check List (CBCL) had been filled by mothers and the Brief Infant-Toddler Social and Emotional Assessment (BITSEA) scale by mothers and fathers. Child psychiatry residents made follow-up evaluations with telephone calls in 2018. Of the 139 caregivers who could be contacted, 116 agreed to participate in the study.

The Brief Infant-Toddler Social and Emotional Assessment (BITSEA): This scale was developed for the scanning of psychosocial development problems and the severity of psychiatric symptoms in children aged 1-3 years (16). The scale consists of a total of 42 items, 31 evaluating psychiatric problems (PP) and 11, psychosocial development (PD). Each item is scored from 3 options (0: not true/occasionally; 1: partly true/ sometimes; 2: extremely true/often). Higher PP points indicate a higher level of psychiatric problems, and higher PD points indicate a better level of psychosocial development. Validity and reliability studies of the BITSEA were made by Karabekiroğlu et al.(15).

Child Behavior Checklist for Ages 2-3 (CBCL/2-3): This scale, which is in widespread use throughout the world, scores the behavioral and emotional problems of the child as an internalizing problem score, an externalizing problem score and the total score. It has sub-scales of anxiety/depression, somatic complaints, social internalizing, sleep problems, aggression, and attention problems (17). The CBCL/2-3 was translated and confirmed for Turkish populations by Erol et al.(18).

Telephone interview: Telephone interview done by child psychiatry residents with primary caregivers in the 2018 year. The primary caregivers responded to the follow-up questionnaire items related to the history of traumatic events, prior medical diseases, family conflict, school attendance, hospital/school reports, confirmed a psychiatric diagnosis by psychiatry specialist, and actual treatment.

Data Analysis: All the data were evaluated using SPSS 21.0 statistics software. The T-test was applied to the BITSEA and CBCL/2-3 sub-scale points evaluated with a normal distribution. ROC analysis was applied to determine the relationship between the scale points and receiving a psychiatric diagnosis. The area under the curve (AUC) values for the ROC analysis were accepted as 0.90-1.00: very good; 0.80-0.89:good; 0.70-0.79: moderate; 0.51-0.69: poor; 0 – 0.59 insignificant.

Machine learning methods: We used Rapid Miner Studio Educational (19) software for modeling. The data had been pre-processed in two steps. First step, data had been cleaned by using imputation for missing values. If more than %30 of data missing column-wise delete had used. For CBCL and BITSEA points, the last-observation-carried-forward method had used and, other missing values imputed by using the k-nearest neighborhood method: second step, the principal component analysis used for dimension reduction. Scale points converted into discrete classification in order to apply classification algorithms. Variables that had more than 60% correlation, did not use for outcome overfitting.

Performance of machine learning algorithms tested on our data using 288 items as prediction class. Ten-fold cross-validation used for train and test sets, where the data split is repeated ten times with 90% training to a 10% test set by changing the test set each time. At the end of the test process success and error rates calculated by the average of each repetition.

After performance testing with cross-validation, machine learning classifiers used for prediction models. All subsets and means acquired by this process calculated for Receiver Operation Characteristic (ROC) curves and Area Under Curve (AUC) had been calculated. In order to avert overfitting problems, algorithms changed with their primary settings and minor tuning for constant default values. After performance testing, the machine learning algorithm with the highest AUC had been chosen for results (Table 1).

Table 1. Results of the cross-validation method for each machine learning classifiers' metrics

Classifier	AUC	Accuracy (%)	Sensitivity (%)	Specificity (%)
Random Forest	0.79	85.2	60.1	96.0
Support Vector Machine	0.77	82.4	53.3	96.0
Desicion Tree	0.74	75.2	26.2	91.3
Naive Bayes	0.71	72.3	40.0	84.0
Logistic Regression	0.61	71.3	26.0	91.0

Ethics committee approval and budget: Approval for the study was granted by the Clinical Research Ethics Committee of Ondokuz University, no: 1397-1542, dated 04.04.2018). The authors reported no potential conflict of interest, and no fundings to declare.

RESULTS

The study included a total of 116 children, comprising 65 (56%) males and 51 (44%) females, who were aged mean 27.4±7.7 months (range, 13-42 months)at the time of the first evaluation. The mothers were aged mean 28.7 ± 5.4 years, and the fathers, mean 31.5 ± 5.5 years. At ten years after the first evaluation, 40.5% of the children had presented at a psychiatric unit, of which 9.5% were in the previous six months. Of the total sample, 35 (30.2%) children had a confirmed psychiatric diagnosis, and 13.8% were currently receiving psychopharmacological treatment. The sociodemographic characteristics of the sample are shown in Table 2.

Table 2. Sociodemographic and clinical characteristics at first assessment and telephone interview of the study group

Study parameter	Mean ± SD (n:116)	
Age at first assesment(months)	27.4 ± 7.7	
Gender	56.0 % Male	
Birth weight (gr)	3316.1±687.2	
Developmental Cornerstones (months)	Walking	11.9±8.1
	First word	13.2± 11.1
	Two words	24.9±13.3
Mother age at birth (years)	28.7±5.4	
Father age at birth (years)	31.5±5.5	
Mother education (years)	11.0±2.7	
Father education (years)	12.5±2.1	
CBCL points at the first evaluation	Anxiety-depression	5.1±2.6
	Social-internalizing problems	3.2± 3.2
	Sleep problems	4.3±3.1
	Somatic problems	3.2± 2.6
	Aggressive behaviors	13.4±7.0
	Attention problems	3.5±1.8
	Total internalizing problems	8.3±4.9
	Total externalizing problems	17.0±8.0
BITSEA points at the first evaluation	Maternal problem total points	17.8 ±7.9
	Maternal competence total points	15.4 ±4.1
	Paternal problem total points	17.5 ±7.4
	Paternal competence total points	14.7 ±4.0
Reported psychiatric diagnoses at adolescent period	ADHD (n:15)	12.9%
	Anxiety Disorder (n:8)	6.8%
	ASD (n:4)	3.4%
	Learning Disorder (n:2)	1.7%
	Mental Retardation (n:2)	1.7%
Under psychiatric treatment at adolescent period	%13.8 (n:16)	

Abbreviations: ADHD: Attention Deficit and Hyperactivity Disorder, ASD: Autism Spectrum Disorder

We chose an automatically optimized random forest method for the highest AUC (0.79) and accuracy (85.2%). Random forests are a machine learning method that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) of each tree (20). Weights for the random forest method had shown to the interpretation of clinical significance the model in Figure 1.

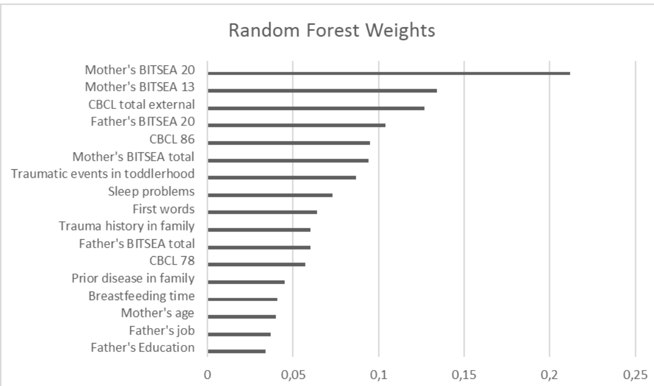

Figure 1. Weights of each data for Random Forest classifier (AUC: 0.79, Accuracy: 85.2)

DISCUSSION

We aimed to analyze several sociodemographic, clinical factors, scale items about predicting psychiatric disorders in adolescence. We compared 288 items of predictive factors in116 children with a psychiatric disorder (n: 31) at the adolescence period. We used the random forest, support vector machine, decision tree, logistic regression and Naive Bayes methods for predicting the outcome, then we choose random forest method, as it has the highest accuracy and AUC belong this method. Random forests are a combination of tree predictors; each tree in the random forest creates a class prediction, and the class with the most accuracy becomes the model's prediction. A large number of relatively uncorrelated trees operating as a one master model, that outperform any of the individual models. Our best model showed as random forest (table 1), different items acted in different weights in this model.

BITSEA item 20, 13 and CBCL total external problems scores filled by mother at the age of 12-36 months are the most potent factors for a psychiatric disorder in adolescence. BITSEA item 20 (can keep his attention on something for a long time) and item 13 (when you say his/her name, turns and looks at you). Aggression and other externalizing symptoms reach their peak between ages two and three, but a small minority of children continue to show high levels of disruptive behavior problems across childhood (21). As in attention and self-regulatory problems in toddlerhood has bidirectional relationship behavioral problems (22) and difficulty with emotional self-regulation may predict later social and behavioral problems (23). These results are preliminary, but this method may help clinicians to identify subgroups of patients. Also, this approach may provide different treatment strategies to achieve optimal outcomes.

We found that traumatic events reported by parents in toddlerhood, such as interpersonal violence and maltreatment, affected the outcome. Developmental timing of trauma exposure may be important for emotion regulation and behavioral problems in adulthood (24). Timing of trauma exposure may be critical for emotion regulation, which is known to develop rapidly during early childhood (25) and through the influence of observational learning, modeling, and social referencing (26). Distortion in this process in toddlerhood, like an early traumatic event, may cause behavioral and emotional problems in adolescence.

Sleep problems in toddlerhood also related to a psychiatric diagnosis. Early sleep problems may predict psychiatric disorders, and there may be an overlap between sleep problems and behavioral and emotional problems (27).Persistent sleep problems in childhood may be an early risk indicator of psychiatric disorders in adulthood (28).The biological mechanisms underlying these associations have yet to be fully elucidated; however, there is growing experimental evidence that the relationship between psychiatric disorders and sleep includes bi-directional causation (29). We found sleep problems have effects on the crucial determinant of long-term outcome.

Current research requires further classification of toddler's behavioral and emotional problems for the understanding prognosis of clinical disorders. Researchers will need more clinical data about toddlers to identify this problem. Likewise, the prognosis is dependent so many factors, that we need steady and efficient measures to help manage treatment options. Our research provides preliminary support to the machine learning methods as a state-of-art method that can assist clinical decision in predicting outcome in toddlers. In the future, more machine learning research is required to provide advanced levels of prediction performance.

Limitations: There are limitations of the machine learning methods. The main detriment of these methods is overfitting problems. There may many factors affecting the outcome of behavioral problems in toddlerhood;

overfitting occurs when using small data sets. To avoid this problem, we used random forest method and also cross-fold validation methods, that unlikely to represent overestimation and overfitting. However, this problem limits the generalizability of results. We used telephone interviews to obtain data about our patients, and psychiatric disorders reported by parents based on confirmed psychiatry specialist and hospital reports, that may be caused overlook of other disorders never diagnosed before. Also, we reached 139 of 462 patients family and 116 (%25.1 of total) had accepted to participate in the study. Most patient families cannot be reached by their home telephone contact numbers, which had been recorded 11 years ago. This may affect our results by selection bias, but authors hypothesized, most patient families changed their home numbers to cell phones, which is more prevalent at this time. However, our model predicted successfully 139 patients' psychiatric problems after 11 years and in future these models used for selection of patients which needs early interventions.

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REFERENCES

[1] Minde K. The relevance of infant psychiatry to the understanding of adult psychopathology. Can J Psychiatry 1987;32:513-7.

[2] Briggs-Gowan MJ, Carter AS, Bosson-Heenan J, Guyer AE, Horwitz SM. Are infant-toddler social-emotional and behavioral problems transient? J Am Acad Child Adolesc Psychiatry 2006;45:849-58.

[3] Mesman J, Bongers IL, Koot HM. Preschool developmental pathways to preadolescent internalizing and externalizing problems. J Child Psychol Psychiatry 2001;42:679-89.

[4] Shaw DS, Winslow EB, Owens EB, Vondra JI, Cohn JF, Bell RQ. The development of early externalizing problems among children from low-income families: A transformational perspective. J Abnorm Child Psychol 1998;26:95-107.

[5] Smith CL, Calkins SD, Keane SP, Anastopoulos AD, Shelton TL. Predicting stability and change in toddler behavior problems: Contributions of maternal behavior and child gender. Dev Psychol 2004;40:29.

[6] Sitnick SL, Brennan LM, Forbes E, Shaw DS. Developmental pathways to sexual risk behavior in high-risk adolescent boys. Pediatrics 2014;133:1038.

[7] Malti T, Averdijk M. Severe youth violence: Developmental perspectives introduction to the special section. Child Development 2017;88:5-15.

[8] Jordan MI, Mitchell TM. Machine learning: Trends, perspectives, and prospects. Science 2015;349:255-60.

[9] Gillingham P. Predictive risk modelling to prevent child maltreatment and other adverse outcomes for service users: Inside the 'black box'of machine learning. Brit J Soc Work 2015;46:1044-58.

[10] Wall D, Kosmicki J, Deluca T, Harstad E, Fusaro V. Use of machine learning to shorten observation-based screening and diagnosis of autism. Transl Psychiatry 2012;2:100.

[11] Mueller A, Candrian G, Kropotov JD, Ponomarev VA, Baschera G-M, editors. Classification of ADHD patients on the basis of independent ERP components using a machine learning system. Nonlinear Biomed Phys; 2010: BioMed Central.

[12] Hettige NC, Nguyen TB, Yuan C, Rajakulendran T, Baddour J, Bhagwat N, et al. Classification of suicide attempters in schizophrenia using sociocultural and clinical features: A machine learning approach. Gen Hosp Psychiatry 2017;47:20-8.

[13] Usta MB, Karabekiroglu K, Sahin B, Aydin M, Bozkurt A, Karaosman T, et al. Use of machine learning methods in prediction of short-term outcome in autism spectrum disorders. Psychiatry and Clinical Psychopharmacology 2019:29:320-5.

[14] Karabekiroglu K, Uslu R, Kapci-Seyitoglu EG, Özbaran B, Öztop DB, Özel-Özcan Ö, et al. A nationwide study of socialemotional problems in young children in Turkey. Infant Behav Dev 2013;36:162-70.

[15] Karabekiroglu K, Rodopman-Arman A, Ay P, Ozkesen M, Akbas S, Tasdemir GN, et al. The reliability and validity of the Turkish version of the brief infant–toddler social emotional assessment (BITSEA). Infant Behav Dev 2009;32:291-7.

[16] Briggs-Gowan MJ, Carter AS, Irwin JR, Wachtel K, Cicchetti DV. Brief Infant-Toddler Social and Emotional Assessment (BITSEA) manual, version 2.0. 2002.

[17] Achenbach TM, Ruffle TM. The Child Behavior Checklist and related forms for assessing behavioral/emotional problems and competencies. Pediatrics 2000;21:265-71.

[18] Erol N, Simsek Z, Oner O, Munir K. Behavioral and emotional problems among Turkish children at ages 2 to 3 years.J Am Acad Child Adolesc Psychiatry 2005;44:80-7.

[19] Hofmann M, Klinkenberg R. Rapid Miner: Data mining use cases and business analytics applications: CRC Press; 2013.

[20] [20] Breiman L. Random forests. Machine Learning 2001;45:5-32.

[21] Shaw DS, Gilliom M, Ingoldsby EM, Nagin DS. Trajectories leading to school-age conduct problems. Dev Psychol 2003;39:189.

[22] Trentacosta CJ, Shaw DS. Emotional self-regulation, peer rejection, and antisocial behavior: Developmental associations from early childhood to early adolescence. J Appl Dev Psychol 2009;30(3):356-65.

[23] Gilliom M, Shaw DS, Beck JE, Schonberg MA, Lukon JL. Anger regulation in disadvantaged preschool boys: Strategies, antecedents, and the development of self-control. Dev Psychol 2002;38:222.

[24] Dunn EC, Nishimi K, Gomez SH, Powers A, Bradley B. Developmental timing of trauma exposure and emotion

dysregulation in adulthood: Are there sensitive periods when trauma is most harmful? J Affect Disord 2018;227:869-77.

[25] Calkins SD. Origins and outcomes of individual differences in emotion regulation. Monogr Soc Res Child Dev 1994;59:53-72.

[26] Morris AS, Silk JS, Steinberg L, Myers SS, Robinson LR. The role of the family context in the development of emotion regulation. Soc Dev2007;16:361-88.

[27] Gregory AM, O'CONNOR TG. Sleep problems in childhood: a longitudinal study of developmental change and association with behavioral problems. J Am Acad Child Adolesc Psychiatry 2002;41:964-71.

[28] Gregory AM, Caspi A, Eley TC, Moffitt TE, O'Connor TG, Poulton R. Prospective longitudinal associations between persistent sleep problems in childhood and anxiety and depression disorders in adulthood. J Abnorm Child Psychol 2005;33:157-163.

[29] Krystal AD. Psychiatric disorders and sleep. Neurol Clin 2012;30:1389-1413