The Role of Machine Learning in the Identification and Outcome Prediction of Post-traumatic Stress Disorder in Children

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Abstract

Abstract Post-traumatic stress disorder (PTSD) exerts detrimental effects on child development, with impacts extending into adulthood. However, traditional diagnostic approaches struggle to achieve rapid, objective, and accurate identification and diagnosis of childhood PTSD. As an emerging methodology for processing large-scale variables and data, machine learning has been progressively applied in research concerning early prediction, identification, and auxiliary diagnosis of childhood PTSD. Leveraging its advantages in performance and theoretical underpinnings, machine learning can be employed in the identification and prognosis of childhood PTSD. Compared to self-report-based diagnostics, machine learning-assisted identification and diagnosis of childhood PTSD offers distinctive advantages including high efficiency, objectivity and accuracy, and resource conservation. Nevertheless, machine learning also exhibits limitations regarding hardware costs, algorithm selection, and predictive accuracy. Future researchers must further enhance the accuracy of machine learning in diagnosing and identifying childhood PTSD, and pursue greater exploration and application through the integration of machine learning algorithms with traditional diagnostic methods.

Full Text

Preamble

Machine learning applications have become increasingly widespread in recent years. A search of PubMed, for instance, yielded 111,233 studies on machine learning as of April 21, 2021, with 185 focusing on PTSD, yet only 10 specifically examining child populations. Machine learning was first applied to mental health in domains with more established diagnostic technologies, such as depression, schizophrenia, and bipolar disorder (Koprowski & Foster, 2018). In

2012, James et al. optimized cognitive-behavioral interventions for adult PTSD using machine learning, marking its introduction to the PTSD field (Kelly et al., 2012). Glenn et al. (2017) subsequently pioneered the application of machine learning concepts to child PTSD, exploring factors associated with its development (Saxe et al., 2017). Research on machine learning in child PTSD has followed a logical progression: exploring risk factors, using these factors as features for PTSD identification and diagnosis, predicting outcomes based on longitudinal follow-up, and finally evaluating treatment efficacy (Li et al., 2020; Ge et al., 2020; Ucuz et al., 2020). Throughout this process, supervised machine learning has predominated, with decision trees, random forests, support vector machines, and regression being the most commonly employed models (Li et al., 2020; Saxe et al., 2017). More recently, researchers have begun exploring unsupervised machine learning and deep learning methods to optimize performance (Schultebraucks, Yadav, et al., 2020).

We conducted literature searches across major databases including PubMed, Embase, Scopus, Web of Science, Ovid, CNKI, and Wanfang, ultimately including five survey studies. The search strategy, results, and screening criteria are presented below (Table 1):

Table 1. Search Strategy, Results, and Screening Criteria

Search Terms: - Machine Learning: "Machine Learning" [Title/Abstract] OR "Artificial Intelligence" [Title/Abstract] OR "Deep Learning" [Title/Abstract] OR "Neural Network" [Title/Abstract] OR "Support vector machine" [Title/Abstract] OR "Prediction Network" [Title/Abstract] OR "Forecast Model" [Title/Abstract] OR "Data mining" [Title/Abstract] OR "Supervised Learning" [Title/Abstract] - PTSD: "post-traumatic stress" [Title/Abstract] OR "posttraumatic stress" [Title/Abstract] OR PTSD[Title/Abstract] OR PTSS[Title/Abstract] OR PTS[Title/Abstract] - Children: child[Title/Abstract] OR children[Title/Abstract] OR girl[Title/Abstract] OR boy[Title/Abstract] OR infant[Title/Abstract] OR baby[Title/Abstract] OR babies[Title/Abstract] OR toddler[Title/Abstract] OR preschool[Title/Abstract] OR "pre-school"[Title/Abstract] OR minor[Title/Abstract] OR teen[Title/Abstract] OR adolescent[Title/Abstract] OR youth[Title/Abstract]

Inclusion Criteria: 1) Participants: children under 18 years; 2) Study design: cross-sectional, cohort, or case-control studies in English or Chinese (Chinese search yielded zero results); 3) Content: application of machine learning to analyze PTSD or post-traumatic stress symptoms.

Exclusion Criteria: 1) Participants: adults over 18, elderly, or special populations; 2) Study design: policy analysis or descriptive studies; 3) Content: studies unrelated to PTSD, not using PTSD as an outcome variable, or not applying machine learning methods; 4) Publication type: narrative reviews, commentaries, letters to editors, case reports, book chapters, reports, conference proceedings, or unpublished manuscripts.

See Figure 2 [Figure 2: see original paper] for the retrieval process of studies applying machine learning to diagnose and identify child PTSD.

Trajectories of Child PTSD

The outcomes of child PTSD refer to different developmental trajectories following diagnosis, encompassing two main approaches: quantitative trajectories (typically analyzed using latent growth mixture modeling) and qualitative trajectories (typically analyzed using latent transition analysis or latent class analysis). Trajectory classifications vary depending on the data and analytical methods employed. Betty et al. summarized three basic PTSS trajectories based on existing literature: chronic, recovery, and resilience (Lai et al., 2017). Galatzer-Levy et al.' s review proposed four trajectories following potential trauma exposure: resilience, recovery, chronic dysfunction, and delayed onset (Galatzer-Levy et al., 2018). Bonanno et al. argued that most individuals demonstrate psychological resilience after trauma, and that trauma exposure and psychological problems are not absolutely causally related (Bonanno, 2004). They categorized post-trauma responses into six types: resilience (35-65% of populations), persistent distress (5-15%), chronic dysfunction (5-30%), delayed symptom increase (10-15%), recovery (15-25%), and symptom improvement (5-10%) (Bonanno et al., 2011; Bonanno & Diminich, 2013). Only children who cannot recover spontaneously from PTSD require early intervention (Masten & Narayan, 2012). Therefore, studying child PTSD trajectories has strong theoretical and practical significance for screening high-risk populations and identifying children and adolescents needing psychological intervention (Cheng et al., 2019).

Child PTSD has numerous etiologies, features delayed onset, and exhibits multimodal and complex prognostic patterns, making long-term outcome tracking difficult. Consequently, research on child PTSD outcome trajectories remains limited (Takahashi et al., 2020). Traditional statistical classification methods such as Latent Class Analysis (LCA) and Latent Growth Mixture Modeling (LGMM) assign individuals to mutually exclusive groups based on their responses to categorical variables. For example, Jin Cheng et al. used LCA to explore PTSD trajectories in children following an earthquake, classifying survivors into four states: resilience (53.8%), low symptoms (32.6%), recovery (7.0%), and chronic dysfunction (6.6%) (Cheng et al., 2019). However, this four-year longitudinal study had limitations including recall bias and omission of important variables.

Machine learning offers two fundamental approaches for predicting child PTSD outcomes. The first is classification of discrete data, a supervised learning method where researchers predefine possible outcome categories in the training dataset. For instance, based on prior experience, one might assume children with certain features will exhibit specific PTSD outcomes such as recovery or deterioration, or use traditional classification methods like LGMM to first determine outcome categories. Machine learning then maps predictive features to these outcomes; once trained, the model can predict outcomes for new data. The second approach is clustering, where training data are automatically grouped into clusters based on features or latent concepts, after which researchers manually summarize commonalities across clusters. This unsupervised method can distinguish PTSD from other psychiatric disorders or evaluate relationships among PTSD symptoms (Ramos-Lima et al., 2020).

Luis et al.' s systematic review detailed studies applying supervised machine learning to classify PTSD outcomes, including primary algorithms and accuracy rates (Ramos-Lima et al., 2020). Other studies have attempted unsupervised algorithms such as graph analysis to explore PTSD trajectories. For example, Galatzer-Levy et al. first applied LGMM to identify two outcome trajectories —recovery and non-remission—then used support vector machines, random forest, and AdaBoost with five repetitions of 10-fold cross-validation, achieving an AUC of 0.82. Graph analysis further identified four categories of information related to PTSD outcomes: urinary cortisol, avoidance symptoms, NE/cortisol plasma ratio, and PTSD severity. The study also delineated two pathways for non-remitting PTSD symptoms: Pathway 1 involves individuals without reported childhood trauma who experience high sympathetic arousal and negative emotions in the emergency department, leading to avoidance symptoms and persistent PTSD; Pathway 2 involves individuals with reported childhood trauma where reduced urinary cortisol has a causal relationship with non-remitting PTSD (Galatzer-Levy et al., 2017). Compared to supervised machine learning, unsupervised methods yield more uncertain outcomes regarding disease trajectories. However, the current literature search found no studies exclusively applying classification or cluster analysis to child PTSD, possibly due to limited attention to machine learning for predicting child PTSD outcomes and the lower predictive accuracy of unsupervised methods. Applying machine learning to predict child PTSD trajectories can address challenges in traditional longitudinal prognosis research, such as high dropout rates, extended study durations, and delayed onset that may cause missed optimal treatment windows.

Applications of Machine Learning in Child PTSD Diagnosis and Identification

Table 2. Applications of Machine Learning in Child PTSD Diagnosis and Identification

Study	Sample Size	Age	Outcome Measure	Features	ML Methods	Validation	Performance
Machine learning methods to predict child posttraumatic stress: proof-of-concept study (Saxe et al., 2017)	105	-	UCLA PTSD Index	Child development, demographics, parental symptoms, stress, genetics, neuroendocrine and psychophysiological responses	SVM; RF; Lasso regression	5-fold CV	AUC=0.75

Study	Sample Size	Age	Outcome Measure	Features	ML Methods	Validation	Performance
Identifying predictors of probable post-traumatic stress disorder in children and adolescents with earthquake exposure: A longitudinal study using a machine learning approach (Ge et al., 2020)	-	-	Revised Children’ s Impact of Events Scale	Injury severity, demographics, earthquake experience, sleep, mood, somatic symptoms, daily functioning	-	5-fold CV	AUC=0.66~0.80

Study	Sample Size	Age	Outcome Measure	Features	ML Methods	Validation	Performance
Hippocampal subfield alterations in pediatric patients with post-traumatic stress disorder (Li et al., 2020)		11-16	PTSD diagnosis	Resting-state fMRI: hippocampal subfields—CA1, CA2, CA3, CA4, dentate gyrus, subiculum, fimbria	-	5-fold CV	AUC=0.65

Study	Sample Size	Age	Outcome Measure	Features	ML Methods	Validation	Performance
Estimation of the Development of Depression and PTSD in Children Exposed to Sexual Abuse and Development of Decision Support Systems by Using Artificial Intelligence (Ucuz et al., 2020)	-	-	DSM-5 criteria	Age, demographics, abuse type, abuse frequency, reporter	-	3-fold CV	99.2%

Study	Sample Size	Age	Outcome Measure	Features	ML Methods	Validation	Performance
Prediction of the development of depression and post-traumatic stress disorder in sexually abused children using a random forest classifier (Gokten & Uyulan, 2021)	-	-	DSM-5 criteria	Gender, age, demographics, smoking/alcohol habits, abuse experience/severity	Random forest	10-fold CV	AUC=0.76

Note: RF = random forest; SVM = support vector machines; CART = Classification and Regression Trees from XGBoost; ANNs = Artificial neural networks

Challenges and Limitations

Prediction results may vary across different models. Although child PTSD diagnosis can be predicted using numerous features, PTSD outcomes encompass diverse symptom structures and severity levels. For limited modeling approaches with broad definitions, consistency across runs cannot be guaranteed (Galatzer-Levy & Bryant, 2013). Second, current machine learning research on child PTSD predominantly employs supervised learning, with classifier selection relying on manual choice and personal understanding of models. Without specific evaluation criteria, researchers can only iteratively test various models to select the one with highest predictive probability, while uncomputed models remain unevaluated.

Prediction accuracy requires improvement. Previous studies report machine learning prediction accuracies of 65-80% (Ge et al., 2020; Gokten & Uyulan, 2021; Li et al., 2020; Saxe et al., 2017), which is relatively low compared to more mature applications of machine learning in other fields. Sample size, training methods, and model selection all influence accuracy. To advance practical application of machine learning in child PTSD diagnosis and identification, it is essential to experiment with different sample sizes, training frequencies, and model types to improve predictive accuracy and enhance efficiency.

Research on treatment methods remains insufficient. The purpose of early diagnosis and identification is to implement interventions that reduce long-term developmental impacts. Beyond treatment limitations themselves, selecting appropriate interventions for different PTSD severity levels is crucial for recovery and relapse prevention. However, research using machine learning to predict treatment efficacy is extremely scarce in child PTSD. Early intervention determines long-term health outcomes, and applying machine learning to evaluate and select interventions represents a critical next step following diagnosis and identification, potentially becoming an important factor influencing child PTSD development.

The machine learning algorithms applied to child PTSD diagnosis and identification are relatively homogeneous. Machine learning algorithms can perform regression, classification, and clustering, with different algorithms having varying applicability conditions and results. Theoretically, trying more algorithms helps select optimal models and improve accuracy. However, in child PTSD diagnosis and identification, supervised algorithms are common, while unsupervised algorithms (e.g., neural networks) and deep learning algorithms (e.g., convolutional networks) are rare. Supervised learning enables classification analysis of known outcomes, assessing both PTSD risk and diagnosis in high-risk children, whereas unsupervised learning enables cluster analysis of unknown outcomes, analyzing long-term trajectories and trends (Rajkomar et al., 2019). The most commonly used algorithms in child PTSD are supervised methods: decision trees (CART), random forest and other ensemble algorithms, kernel-based support vector machines, and regularized regression extensions (lasso, ridge). Random forest and support vector machines can both perform classification and regression, but SVM has better generalization capability, higher memory requirements, and longer training times, making it suitable for small samples. Random forest requires no feature selection, computes quickly, performs well on many datasets, has strong generalizability, and handles high-dimensional data effectively, though it shows poor classification performance on small samples. Thus, although some studies employ multiple algorithms, they are limited to supervised learning methods, appearing somewhat homogeneous compared to the broader machine learning algorithm spectrum.

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Note: Figure translations are in progress. See original paper for figures.