Review Article

Applications of artificial intelligence in predicting the risk of child abuse: A literature review

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Abstract

Child abuse is a major problem in most of the developing and developed countries. Medical practitioners and law enforcement authorities have often tried to tackle the problem using several conventional approaches. Nevertheless, there are other modern methods to screen, detect, and predict child abuse using artificial intelligence (AI). Therefore, this article aimed to critically review the currently available AI tools including data mining, computer-aided drawing systems, self-drawing tools, and neural networks used in child abuse screening.

Keywords: Applications, Artificial intelligence, Child abuse, Machine learning

Impact

(1) This article explores the currently available artificial intelligence (AI) approaches to diagnosing and predicting the risk of child abuse.
(2) In addition, it describes the future opportunities for AI applications in the field of child abuse and limitations of AI applications.

Introduction

Abuse against children is considered a universal threat and potential factor for worry.[1] Every year throughout the world, every third child suffers from violence.[1] Around a billion cases are estimated between the age group of 2 to 17 years in a given specific year.[1] In 2021, a report by the Prevent Child Abuse Kentucky Organization showed that the most common form of child abuse is neglect (74%), followed by physical abuse (17%), sexual abuse (8%), and emotional abuse (1%).[2] Furthermore, a statistical report by the U.S. Bureau of Justice revealed that 93% of child sexual abusers are known to the victims (34% are family members and 59% are acquaintances).[3]

Even though there are increased cases (both registered and identified), there is evidently an upward drift in unregistered/unidentified cases of victims mainly due to the lack of complete information leading to interruption in the investigation.[4] Training the stakeholders can help improve the registration of violence in children.[4] The use of artificial intelligence (AI) in predicting the risk of violence against children, for instance, by text mining can be beneficial. A study conducted in Germany stated that skilled interdisciplinary practice and teaching are required for individuals functioning in the field of child protection.[4] Yet, training can be expensive and time consuming.[4] An alternative is to deliver a system that provides decision assistance for frontline workers to recognize the possibility of abuse/violence, along with increased accuracy and precision.[4] Its goal is to provide frontline workers with an instant and timely decision-informed process in cases of child abuse, according to the patterns observed in information about health that doctors usually gather through their routine protocol.[4]

After the literature review, it is concluded that there are considerable chances of assessment models and tools driven by AI to help assess the risk of abuse and violence to a greater extent.[1] Its effectiveness can be easily evaluated in developing countries, although its possible efficiency has not been lucid enough.[1] In 2016, the World Health

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Organization formulated the INSPIRE strategy, an approach where there are seven different strategies in an attempt to prevent violence against children; moreover, it is the only universal practical solution to date.[1,5] The main reason for establishing INSPIRE was to advance investigatory procedures to help identify scientific proof when someone is affected by physical violence or injury.[1,5] Trouble is experienced in the development of a child's emotions when he/she is subjected to violence/abuse at an early stage of life, and it can affect their behavior in addition to potentially harming them [see Table 1].[1,5]

Hospitals and healthcare systems can specialize in training child abuse pediatrics, but the underdeveloped regions have no facilities, which makes finding indications of abuse tough.[6] The child is detached from his/her caretaker if the identification is false positive, whereas with false negatives, there is a chance that the child is left in the wrong company.[6] There are many investigatory procedures where sensitivity is of utmost importance. However, we can tackle low specificity through secondary testing.[6] The determination of abusive acts by both specificity and sensitivity is essential.[6] Deep learning, a subfield of AI, shows promise for a variety of clinical tasks, including image analysis and the natural language processing (NLP) of electronic medical records (EMRs). For instance, deep learning has been comprehensively applied in areas such as radiology, drug interactions, and cancer detection.[6] Moreover, applying NLP can be useful to extract useful clinical features from EMRs.

The existing risk management practices in organizations that are responsible for safeguarding children and establishing robust systems for child safety are augmented by AI tools, which can aid healthcare workers and provide highly precise child protection services.[7] Therefore, this review article aimed to critically review a selection of currently available AI tools used in child abuse screening, including data mining, computer-aided drawing (CAD) systems, self-drawing tools, and the use of artificial neural networks (ANN).

Materials and Methods

Medical databases (MEDLINE, Google Scholar, and PubMed) were searched to select published articles using the following keywords: child abuse and machine learning, AI, and child abuse. The resulting studies were reviewed for AI applications in the screening and detection of child abuse. The following tools were selected for critical review: data mining, CAD systems, self-drawing tools, and the use of ANNs. Additionally, challenges in AI applications in the field of child abuse were explored, and recommendations for future use were provided.

Results

Child Abuse Screening Tools

It was observed that there are just a handful of child abuse screen tools available to help detect the potential risk of child abuse. A formal investigation is usually done after the occurrence of abuse, followed by a forensic examination.[8] In fact, industry practices today require a formal questionnaire to be used as a medium to ask about problems and evaluate the extent of abuse, and this sometimes leads to an emotional and psychological dilemma for the victim and their family.[9] Child abuse screening tools pose a more sensitive and definitive indication of understanding the situation compared to questionnaires. Even though there are checklists involved in the screening process that use indicators related to symptoms, different studies have reported a 170% increase in the cooperation of victims.[10]

With technological advancements in AI applications, a direct screening process for seeking direct questions from the abused is also available. Examples include spotting the signs and a screening technique by Thombs *et al*.[11] The overall sensitivity of the automated tool for addressing child abuse is noted to be close to 85% by the authors, whereas the specificity is close to 88%.[11]

Self-figure Drawings and Convolution Neural Networks

It is often difficult to get the abused victims to draw the figure of their offender. Technology has allowed the use of the Draw-A-Person test that develops the picture of the offender by cooperating with the victims.[12,13] It uses specific characteristics and directions associated with trauma and given by children to derive the image of the person responsible.[14] For example, some studies suggest that children who draw genitalia in their sketch notes might indicate sexual abuse, whereas the drawing of hair standing up, double ears, and an emphasized face line can indicate physical abuse. Similarly, drawing hollow eyes, and the omission of arms and hands can indicate emotional abuse [see Figures 1a to c].[15] The interpretation is based on simple commands received by autonomous tools, such as facial lines, hands and arms, private parts, and other body parts.[13] The tool is smart enough to comprehend that the presence of three or more of these features indicate child abuse.

However, Allen an Tussey reported that using only graphic indicators (e.g., genitalia and omission of body parts) or other predefined scoring systems can discriminate abused from nonabused children. The findings show that while some studies have found evidence to support particular indicators or scoring systems, these findings are rarely replicated. Studies that find significant results frequently have serious methodological flaws, and alternative explanations for findings (such as mental illness) are frequently offered. There was insufficient empirical evidence to support the use of any graphic indicator or scoring system for identifying sexual or physical abuse.[16]

Convolution neural networks (CNNs), a type of ANN, are commonly used for analyzing and classifying images.[13] To forecast child cases that are the most severe description of abuse in the United States, ANN technology was tested.[7]

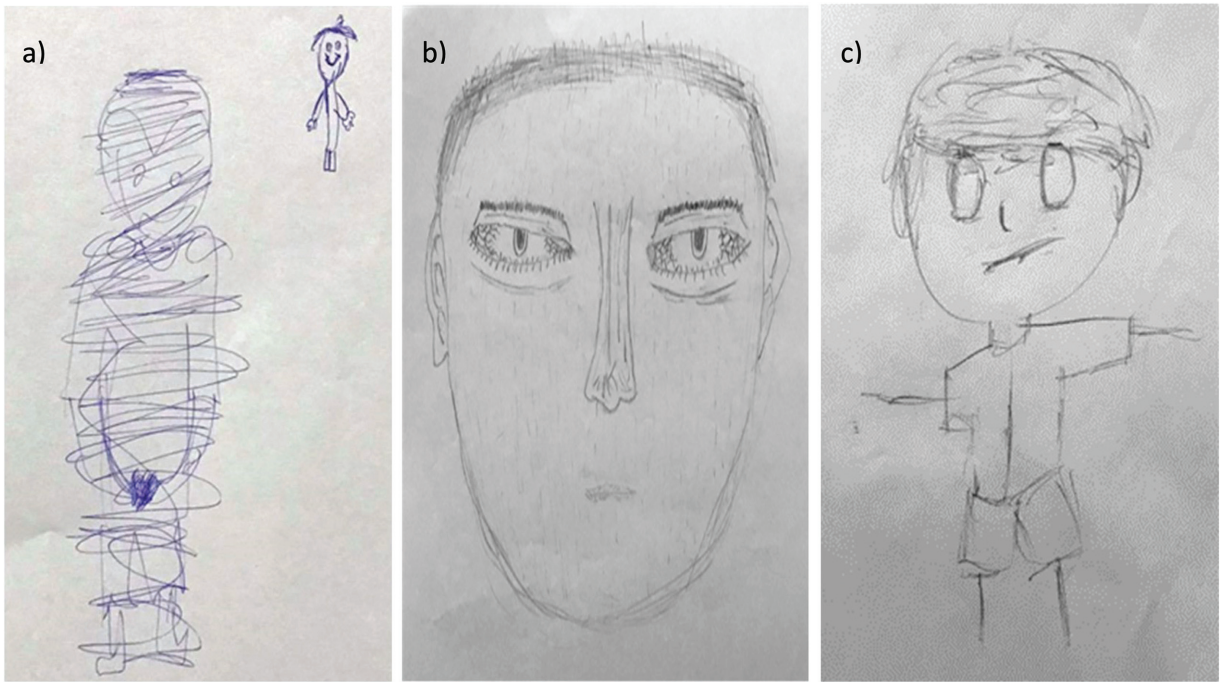


Figure 1: The artwork of three males who experienced various forms of abuse taken from the study by Jaroenkajornkij *et al*.[15] (a) A drawing of a 16-year-old participant, who disclosed having been sexually assaulted. The presence of genitalia and the emphasized face line were the key drawing cues. (b) A drawing of a 16-year-old participant, who disclosed having been physically abused. The emphasized hair standing up, double ears, or double face line were the important indicators. (c) A drawing of a 15-year-old participant, who claimed to have been subjected to emotional abuse. The drawing's hollow eyes, absence of arms and hands, and highlighted hair are all indications of emotional abuse.

This technique is an application of deep learning used to analyze and classify visual imagery in modern-day medicine.[13] ANNs are often inspired by connectivity patterns such as the function of neurons in the human brain, giving rise to CNN. Image classification is an application of CNN, that is tasked with feature extraction and identification of the target domain; this model bridges the gap between machines and human image extraction.[17] Therefore, it is used as a medium to direct human images and screen the culprit based on instructions from the victim. Studies have noted that ImageNet is a large-scale visual recognition platform that allows the evaluation of criminals based on this algorithm on CNN.[18] Furthermore, Krizhevsky *et al*.[18] in a popular study have proven the accuracy of CNN to be >85%. ANNs are capable of acquiring data from databases, estimating, and constructing models that can advance and update themselves with the help of random selections of case data files.[7]

ANNs are an innovative and new way of determining risks associated with children as they do not rely on principles, rules, or programming, but evolve from the primary behaviors of a model by evaluating its past and future data and regulating the weights between neuron layers.[7] In this regard, there are supervised/unsupervised ways to understand the conduct of neuron systems.[7]

Computer-aided Drawing Assessment Systems

This method employs digital technology to objectify image analysis, identifying patterns by rating colors and art using formal elements as a means of therapy for child abuse. For instance, Donald Mattson developed a method for the computerized evaluation of art-based tools in 2010 and the use of existing metrics with free image analysis software in 2009. These systems use distinguished and simple expression classes to help the victims in post-trauma recovery.[19]

The Computer Color-Related Art Therapy Evaluation System (C-CREATES), developed by Kim *et al*.[20] is another approach to use fundamental color-related aspects. It is an automatic computer program that determines the components of color within a given drawing; it was later created by researchers using the expert system model. The ability of the C-CREATES to identify color percentages, free space, color clusters, color areas, and lengths of pixilated lines that demarcate each color was successfully demonstrated through case examples.[19] Though challenging to detect with the human eye, color gradations and subtleties can be detected by computer systems. For instance, when separating the primary color from the color with the highest area within drawings, human raters performed worse than the computer system.[19]

There has been an increased push in recent years in studies that use drawing assessments to predict the risk of child abuse, the nature of abuse, and for identifying the offenders.[13] It was primarily because personal interpretation bias and reliance on samples affect the victim, leading to post-traumatic stress disorder. Manual identification of sexual abuse is also not advisable because

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of the lack of sensitivity toward children who experience serious mental damage as a result.[13]

Therefore, the need for AI-driven automatic systems has arisen in recent years, creating demand for appropriate indicators that can automatically identify various types of child abuse cases, including sexual abuse.[13] The algorithms included in these machines are designed to function as screening instruments for patients and predict the potential risk of abuse in children. Several studies have advocated the use of AI to design models by including a framework that uses a seamless algorithm to carefully and sensitively extract offender information from victims and then feeding the data into the model. Primitive information is fed into the system by utilizing data mining from clinical studies that have addressed similar problems in the past.[21] According to Gillingham,[21] a considerable amount of information is available for AI applications to aid victims of child abuse and their families. Such information can be useful in devising a model that conducts assessment and identifies existing patterns from its data to identify child abuse, including the depth of atrocity involved.[21]

Data Mining

The predictive risk modeling (PRM) technique can be used to search through large datasets for identifying anomalies, patterns, and correlations to predict child abuse. As this technique uses reference psychological patterns from its libraries, it could also efficiently help to predict child maltreatment from medical practitioners.[4,21] An early start program is a seemingly possible automated PRM that makes use of primitive studies fed into it to predict child abuse.[4] Furthermore, Vaithianathan *et al*.[22] also made use of administrative information from 57,986 records to develop a model that made predictions for child psychology, abuse, and maltreatment.

Key Challenges in Artificial Intelligence Applications

Several issues affect the models that are created to assess the risk of child abuse. These include bias in data, clinical documentation issues, lack of centralized evidence, lack of a gold standard assessment, and the evaluation of risk prediction.[23] These are common challenges faced by most countries and regions across the world. The bias in data is a common challenge where a secluded section of society is neglected. Under critical clinical reports, unstructured information is not harnessed by the system. When addressing gold standards, there is no foundation or basis that can be used as a benchmark for judging rational or irrational behavior by the system. Lastly, risk prediction includes inherent uncertainties in making proper risk-free predictions. Under biases in data, different issues affect the likelihood of child abuse, as there is a difference between aroused suspicion and child abuse reporting. There is also a difference in neglecting child abuse that AI finds difficult to comprehend.[23] The system is generally designed in such a way that the data included in it concentrates on racial bias, contributing to child abuse solely on this issue.[23]

Racial minorities, such as African-American and Latino families, are frequently included in the data, resulting in an overestimation due to feature imbalance in the "race" variable, which may lead to biased predictions by the trained model.[23]

Clinical documentation is an important process in which electronic healthcare reports are included in the data which would be analyzed to have a better understanding to carry forward with an interpretation, helping us to define or design our model.[23] There are many types of reports (structured or unstructured) with templates that address different clinical factors, which are often difficult for the AI system to read. Although there may be crucial information included in these documents that indicate suspicious child abuse activity, though often neglected, AI-driven tools can be used to harness such information to come up with a better interpretation.[23] The problem in this situation is that unstructured/narrated handwritten notes are not comprehended by the system.[23] Processing is difficult in cases where there is little or no standardization that allows convenient segregation of data.[23]

Risk factors are important in child abuse, and there is little centralized evidence available that shows the uncertainty and level of risk associated with abuse.[23,24] These risk factors often address the degree of child abuse and must be included in the data synchronized by machine-learning algorithms. However, these data are not often released by nongovernmental organizations (NGOs) and child protective services, making its availability difficult. A lack of standardized data that forms the basis or foundation makes it difficult for machine-learning algorithms to detect. A thorough basis will make it convenient for the system to reduce deviations.[24]

Establishing a gold standard diagnostic test for child abuse remains a significant challenge faced by healthcare systems.[25] In most countries, many NGOs and child protective services do not release important information regarding child abuse, advocating sensitivity and confidentiality regarding child information.[25] This does not provide a basis for reliable data; if clinical data, including healthcare reports, are potentially linked with data mining, this will allow a gold standard to be established. This will also reduce racial disparities in the data, increasing consistency in reporting information. If data linkages are done in an ethical manner, a gold-standard AI-driven tool will be created and then used as a foundation for investigating child abuse.[25]

There are often errors in the predictions of systems that run on models devised on machine-learning algorithms.[26] These models often have a rigorous evaluation criterion that often develops international standards that allow for guidelines that make a convenient assessment of data.[26] Multiple criteria

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are added in the algorithms that include definitions and measurement thresholds in the model. Risk models in child abuse require fairness and metrics that do not discriminate based on groups such as ethnic groups.[26] A comparison group that accounts for fairness can be created. Machine learning is potentially used in error analysis and detection by developing independent evaluation algorithms added as a layer over the data-mining process. Feedback received from such models enables potential error-proof systems.[26]

In a competitive environment such as the healthcare industry, sensitive information poses challenges that cannot be directly put for evaluation in the system.[26] Certain data included in the study require clinical trials or observational studies, or even an experimental design.[27] The trends in AI allow for models to include these assessments, allowing a crossvalidation process. The need of the hour is a positive-based risk model that assesses information on child abuse, that works on high stakes, neglects any racial disparities, and includes transparency in the system for essential decision-making processes.[27] Transparency is essential in such sensitive situations; a clear understanding of machine learning–based risk models will allow the handling of these situations in a more responsible manner.[27]

Discussion

Child abuse is a universal threat that affects the entire world and must be tackled in innovative ways.[1] Over time, doctors and medical practitioners have tried to address the issue in several ways possible, but the complexity involved in the process is not helping to mitigate the situation in any way.[1,4] AI tools are modern methods in which data from primitive sources can be used to harness information and essentially estimate the re-occurrence of violence.[4,7]

Screening tools including data mining, computer-aided drawing (CAD) systems, self-drawing tools, and the use of ANNs are positive approaches in modern-day technology in which algorithms can be used to make predictions based on medical practitioners' unstructured notes and children's behavior to detect potential risk of child abuse.[6,11–14] Even though several positives are involved in the process, some challenges still need to be addressed. The data can be biased due to design-related issues in identifying unstructured notes of medical practitioners as well as a lack of a gold-standard basis with which the data can be compared.[23–26] In addition, applying these tools requires the inclusion of clinical information from victims in the system, and it is not often conveniently achieved, and might not be easily comprehended and mined by systems, making diagnosing difficult and reducing the likelihood of identifying abuse.[23–26] These challenges are often identified as hindrances that limit the capabilities of individuals in delivering success. Nevertheless, the possibilities of AI are endless and must be explored more in the context of child abuse to evaluate care and support for the victims.

Conclusion

The identification and assessment of child abuse is a delicate and complicated affair, requiring serious attention from medical practitioners, healthcare workers, governmental authorities, and other important law-enforcing authorities in their dominions of governance. The integration of AI-driven models and tools opens new doors and endless possibilities for assessing the risk of child abuse, including several fundamentals associated with it, such as imaging, screening, prediction, and post-traumatic treatment. It also creates useful pathways for technical challenges that need to be administered, such as decisive algorithms and key areas of expertise that will oversee its success. However, it is noteworthy that transparency is key. It is imperative to have transparency in the process for critical information to be shared in the data-mining process of AI so that the system can make accurate predictions in the future.

Declaration of patient consent

The authors certify that they have obtained all appropriate patient consent forms. In the form, the patient(s) guardian(s) has/have given his/her/their consent for his/her/their images and other clinical information to be reported in the journal. The patients understand that their names and initials will not be published and due efforts will be made to conceal their identity, but anonymity cannot be guaranteed.

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Conflicts of interest

There are no conflicts of interest.

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