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Original Research Article

Artificial Intelligence (AI): An Armamentarium of Forensic Odontologist to Discern Child Abuse

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Abstract: Three in every four children has confronted child abuse of one kind or another, and the past few decades have shown a tremendous rise in the tally of such incidents. The most common type of child abuse includes physical, mental, emotional, and psychological abuse. There has been a rapid breakthrough in artificial intelligence technology in recent years, and it has also spread its branches in the field of Forensic Odontology. Forensic Odontologists have significantly used AI technology to decipher bite marks and mandibular morphology and estimate age. Pediatric Forensic Odontology presents significant challenges and opportunities for applying AI. In this article, we discuss the application of AI, particularly concerning recognizing signs of child abuse in head and neck structures. Sixteen papers were selected, keeping their practical relevance in the steps of diagnosis of child abuse in mind. Dental forensic experts should consider an advanced diagnosis of child abuse as it could considerably allow the identification of child abuse cases and early intervention.

Keywords: Artificial Intelligence, Deep learning, Convolutional Neural Network, Child Abuse, Forensic Odontology.

INTRODUCTION

According to statistical data, nearly 75% of children aged 2–4 are physically abused. One in five women and one in thirteen men are sexually abused [1]. Technological development has the means to replicate the human brain in every sphere of life. Forensic Odontology in general and Child abuse in specific has applications of Artificial Intelligence. Artificial Intelligence models assist in problem-solving and decision-making in incidents of child abuse.

Definition

i. **Child Abuse:** Child Abuse is any act of physical and/or emotional ill-treatment, sexual abuse, neglect and negligence, and commercial or other exploitation [2].
ii. **Artificial Intelligence:** According to Russell and Norvig, artificial intelligence is the study of intelligent agents [3].

Types Of Child Abuse

i. **Physical:** The most frequently form of child abuse constitutes clinical features of bruises, scratches, burns, bites, and fractures.
ii. **Sexual:** Any sexual activity without understanding or consent of the child is referred to as sexual abuse.
iii. **Psychological:** Any verbal or non-verbal and passive or active act affecting child's self-worth or emotional well-being, cognitive, social, emotional and physical development is referred to as the psychological abuse.
iv. **Neglect:** Developmental delay, physical and psychological damage resulting from educational, emotional, nutritional, physical and medical neglect [4].

Steps of Diagnosis of Child Abuse

The steps of diagnosis of child abuse are summarized below (Flowchart 1) [5]:

1. **Demographic Details:** Socio-economic status is one of predisposing factors involved in prevalence of child abuse. This can be easily analyzed through demographic details of patient. In addition, certain

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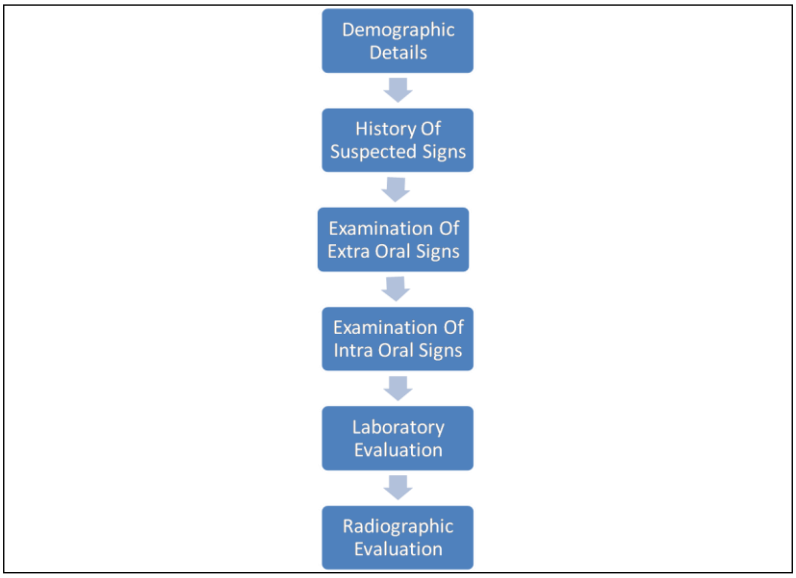
lesions are location specific and are to be ruled out to reach the diagnosis. Example - Mongolian spots.

2. **History of Suspected Sign:** This step involves recording of mechanism of injury, the medical history and the family history with open questions and in a non-judgmental manner. Any inconsistency in history about mechanism of injury or developmental age of child is suggestive of child abuse.
3. **Examination of Extra Oral Signs:** One must look for multiple fractures in various stages of healing, associated with coexisting injuries in extra oral region.
4. **Examination of Intra Oral Signs.** Oral injuries include injuries to the lips, tongue and oro-nasal bleeding.
5. **Laboratory Evaluation:** They are directed to rule out differential diagnosis of disorders like bleeding disorders. The parameters generally included are full blood count, liver and renal function tests, clotting studies, septic screen and urinalysis.
6. **Radiographic Evaluation:** This is used to look for complex skull fractures.



Flowchart 1: Showing steps of diagnosis of child abuse

MATERIALS AND METHODS

A computerized database search in PubMed and Google Scholar was conducted using the following search terms: (“Artificial intelligence”) and (“Child abuse” or “Forensic odontologist”). The articles that were published in the English language, from the year 2000 to November 2022 with an emphasis on the forensic odontologist’s perspective in child abuse were considered for compilation of the present review. Articles in languages other than English were excluded. Since the literature search was intended only for compilations of a narrative review there were no strict exclusion criteria.

Review of Applications of Artificial Intelligence in Identification of Child Abuse by Forensic Odontologist

A. Demographic details

I. Age Estimation:

Chronological age estimation with the help of teeth is considered to be one of the crucial elements of demographic details in diagnostic procedures of child abuse. Blanco *et al.,* used two fully automatic methods of estimation of the chronological age of a subject from the OPG images [6]. The first method used a sequential Convolutional Neural Network (CNN) path for prediction of the age. On the contrary, the second method uses a second CNN path for predicting sex and through sex-specific features an improved age prediction performance was observed.

The sample size comprised of 2289 OPG images of subjects from 4.5 to 89.2 years old to make comparison between the two methods. In addition, both bad radiological quality images and images showing dental conditioning characteristics were not discarded. The results showed that the second method outperformed the first one in every aspect, reducing the median Error (E) and the median Absolute Error (AE) by about four months in the entire database.

Further, a multi factor-based age estimation methods based on deep CNN using MRI data was proposed by Stern *et al.,* In this method, they extend the maximal age range from 19 years, as commonly used for age assessment based on hand bones, up to 25 years by combining with estimation using wisdom teeth and clavicles [7]. This method achieved a result of 1.14 ± 0.96 years of the mean absolute error in predicting chronological age.

II. Address:

AI-Driven International Address Database is a concept to decipher and cross-check the reported address of the patient in case of disparities found in correlating normal regional variants and abusive lesions.

B. Extra-Oral Examination

I. Bite Marks:

Generally, Forensic dentistry addresses the problem of identification based on unique characteristics of teeth or bite mark impressions (Figure 1). However, the bite mark identification process generally involves human interaction and has human bias. Therefore, a system with reduced human bias and high accuracy matching performance would be beneficial.

Figure 1: Showing Multiple, overlapping bite marks on the inside leg of a female child aged 5 years [8]

Mahasantipiya *et al.,* conducted an initial study to evaluate the effectiveness of applying the artificial neural network approach in bite mark identification. Set of specific features of the bite marks were selected and the results showed matching accuracy in their study [9].

C. Intra-Oral Examination

I. Mucosal Wounds:

Freehand wound imaging is commonly practiced in clinical settings with the advent of easily accessible digital cameras. However, a demand for a single user-friendly system for assessment of accurate wound healing, combining dimensional measurements and tissue classification remain unavailable for a longer time.

Later, Wannous *et al.,* computed a 3-D model for wound measurements using uncalibrated vision techniques [10]. They classified tissues based on color and texture region descriptors computed after unsupervised segmentation. This innovative device is used for therapeutic follow-up in hospitals and for telemedicine and research as it truly showcases repeatability and accuracy which are key element of correct wound assessment. The experimental classification tests demonstrate achievement of metric assessment through actual area and volume measurements and wound outline extraction.

Monitoring wound size is an integral component of assessing and treating chronic wounds. Conventional methods, such as rulers and transparency tracings, for measuring wound size often have low accuracy and reliability. Newer high-tech methods, while more reliable and accurate, are often expensive and difficult to use. Nemeth ME *et al.,* has overcome these issues by designing a wound measurement device (WMD) based on Wound Suite mobile software with the features like ease of use, low cost, non-contact, time-saving, hand-held, reliable, and battery operation [11]. The performance of the WMD was evaluated in two rounds of bench testing for accuracy and reliability, followed by a single round of clinical testing to assess ease of use. The WMD was easy to use for the clinician.

Clinicians must use scrupulous documentation to determine severity of wound and monitor healing progress over time when treating chronic wounds. However, digital photography's current wound documentation practices are often cumbersome and labor-intensive. The most common problem associated is that transferring photos into Electronic Medical Records (EMRs) requires many steps consuming several days. Newer smartphone and tablet-based solutions, such as Epic Haiku, have reduced EMR upload time. However, issues still exist involving patient positioning, image-capture technique, and patient identification. The Snap Cap System for chronic wound photography is a remarkable development in this area. By leveraging the sensor capabilities of Google Glass, Snap Cap [12] enables hands-free digital image capture and the tagging and transfer of images to a patient's EMR. In a pilot study with wound care nurses at Stanford Hospital (n=16), examining feature preferences for hands-free digital image capture and documentation and comparing Snap Cap to state the art in digital wound care photography, the Epic Haiku application was made. The Wilcoxon Signed-ranks test evaluated differences in mean ranks between preference options. Preferred hands-free navigation features include barcode scanning for patient identification, $Z(15) = -3.873$, $p < 0.001$, $r = 0.71$, and double-blinking to take photographs, $Z(13) = -3.606$, $p < 0.001$, $r = 0.71$. In the comparison between Snap Cap and Epic Haiku, the Snap Cap System was preferred for sterile image-capture technique, $Z(16) = -3.873$, $p < 0.001$, $r = 0.68$. Responses were divided concerning image quality and overall ease of use. The study's results have contributed to the future implementation of new features aimed at enhancing mobile hands-free digital photography for chronic wound care.

Hettiarachchi NDJ *et al.*, proposed a portable wound area measurement method based on the segmentation of digital images [13]. It was to provide a practical, fast and non-invasive technique for medical staff to monitor the healing process of chronic wounds. Segmentation is based on active contour models, identifying the wound border irrespective of coloration and shape. The user can also modify the initial segmentation, providing higher control and accuracy. Area measurements are further normalized to remove the effects of camera distance and angle. The application has been implemented for Android version 2.2 with a prototype model running on Samsung Galaxy Tab. The results to evaluate the efficacy of the application have been encouraging, with an accuracy level of 90%. As the biomedical sciences are moving towards multidisciplinary fields and large-scale omics big data, artificial intelligence technologies and network informatics for generating and processing large biological data sets are promoting fundamental changes in biomedical scientific research. Ren K *et al.*, indicated that biomedicine, forensic medicine, and computer science would be cross-disciplined [14]. It can expound on the feasibility of combining multiple omics technologies and artificial intelligence algorithms in wound age estimation in forensics to explore the new direction of wound age estimation in forensic research. This new application of multiple data sets combined with artificial intelligence algorithms on wound age estimation in forensics is based on our newest achievements based on the transcriptomics data.

II. Frenal Tear:

The frenal tear is a common intraoral finding in cases of child abuse (Figure 2).

Figure 2: Showing Frenal Tear [15]

Fan S *et al.*, developed a model incorporating image cropping and compression on a deep learning framework aimed to detect small intestinal ulcers and erosion in wireless capsule endoscopy (WCE) images [16]. The Alex Net convolutional neural network (CNN) was trained to the database with tens of thousands of WCE images to differentiate lesions and normal tissue. The ulcer and erosion detection results reached a high accuracy of 95.16% and 95.34%, a sensitivity of 96.80% and 93.67%, and a specificity of 94.79% and 95.98%, correspondingly. The area under the receiver operating characteristic (ROC) curves over 0.98 in both networks. The promising results indicate that the proposed method is the potential to work in tandem with doctors to detect intestinal ulcers and erosion efficiently.

D. Laboratory Examination

I. Sexually Transmitted Diseases:

Human Papillomavirus (HPV) genotyping plays a key role in diagnosing the case of sexual child abuse.

Tanchotsrinon W *et al.*, proposed Chaos Centroid and Chaos Frequency, the new feature extraction techniques, for predicting HPV genotypes associated with cancer [17]. The diversified 12 HPV genotypes, i.e. types 6, 11, 16, 18, 31, 33, 35, 45, 52, 53, 58, and 66, were studied. The proposed techniques deploy partitioned Chaos Game Representation (GCR) to represent HPV genomes. Chaos Centroid captures the structure of sequences in terms of the centroid of each sub-region with Euclidean distances among the centroids and the center of GCR as the relations of all sub-regions. Chaos Frequency extracts the statistical distribution of mono-, di-, or higher-order nucleotides along HPV genomes and forms a matrix of frequency of dots in each sub-region. For performance evaluation, four different types of classifiers were deployed, i.e., Multi-layer Perceptron, Radial Basis Function, K-Nearest Neighbor, and Fuzzy K-Nearest Neighbor Techniques, and our best results from each classifier were compared with the NCBI genotyping tool. The experimental results obtained by four different classifiers are in the same trend. Chaos Centroid gave considerably higher performance than Chaos Frequency when the input length was one, but it was moderately lower than Chaos Frequency when the input length was two. Both proposed techniques yielded almost and exactly the best performance when the input length is more than three. However, there is no significance between alignment-free techniques and the comparative alignment method. The alignment-free and scale-independent method can successfully transform HPV genomes with 7,000 - 10,000 base pairs into features of 1 - 11 dimensions. This signifies that our Chaos Centroid and Chaos Frequency can be served as effective feature extraction techniques for predicting the HPV genotypes.

Standard microplate-based enzyme-linked immunosorbent assays (ELISA) are widely utilized for various nanomedicine, molecular sensing, and disease screening applications.[18] This multi-well plate batched analysis dramatically reduces diagnosis costs per patient compared to non-batched or nonstandard tests. However, their use in resource-limited and field settings is inhibited by the necessity for relatively large and expensive readout instruments.

To overcome this problem, Berg B *et al.*, created a hand-held and cost-effective cell phone-based colorimetric microplate reader, which used a 3D-printed optomechanical attachment to hold and illuminate a 96-well plate using a light-emitting-diode (LED) array. This LED light was transmitted through each well and then collected via 96 individuals optical fibers. Captured images of this fiber bundle were transmitted to servers through a custom-designed app for processing using a machine learning algorithm, yielding diagnostic results, which were delivered to the user within 1 min per 96-well plate and are visualized using the same app. They successfully tested this mobile platform in a clinical microbiology laboratory using FDA-approved mumps IgG, measles IgG, and herpes simplex virus IgG (HSV-1 and HSV-2) ELISA tests using a total of 567 and 571 patient samples for training and blind testing, respectively, and achieved an accuracy of 99.6%, 98.6%, 99.4%, and 99.4% for mumps, measles, HSV-1, and HSV-2 tests, respectively. This cost-effective and hand-held platform could assist healthcare professionals in performing high-throughput disease screening or tracking vaccination campaigns at the point of care, even in resource-poor and field settings. Also, its intrinsic wireless connectivity can serve epidemiological studies, generating spatiotemporal maps of disease prevalence and immunity.

II. Hematological Diseases:

Quick and accurate diagnoses are crucial for successfully treating diseases and ruling out differential diagnosis of child abuse. Using machine learning algorithms and based on laboratory blood test results, two models have been built to predict a haematologic disease.

Gunčar G, Kukar M, *et al.*, suggested a predictive model using available blood test parameters [19]. However, the second model used only a reduced set that is usually measured upon patient admittance. Both models produced good results, obtaining prediction accuracies of 0.88 and 0.86 respectively. The models simultaneously indicated that a reduced set of parameters are representation of a relevant "fingerprint" of a disease. This knowledge indicates the model's utility for use by general practitioners and indicates that blood test results offer more information than physicians generally recognize. A clinical test showed that the accuracy of these predictive models was of levels of any hematology specialists. These results have opened up unprecedented possibilities for medical diagnosis.

E. Radiographic Examination

I. Dental Fractures:

Micro fractures (cracks) are the third most common cause of tooth loss and are very common clinical finding in child abuse. However, they are usually not detected early and continue to progress until the tooth is lost. Cone-beam computed tomography (CBCT) has been used to detect cracks but has had minimal success.

Vicory J. *et al.,* proposed an algorithm to detect cracked teeth. This model pairs advanced image analysis and machine learning with high resolution (hr) CBCT scans [20]. First, microfractures were simulated in twenty two extracted human teeth and further hr-CBCT and micro CT scans of the fractured and fourteen control teeth were obtained. Wavelet pyramid construction was used to generate a phase image of the Fourier transformed scan, fed to a U-Net deep learning architecture that localizes the crack's orientation and extent, yielding slice-wise probability maps that indicate the presence of micro fractures.

Then examination of the ratio of high-probability voxels to total tooth volume to determine the likelihood of cracks per tooth was done. In micro-CT and hr-CBCT scans, fractured teeth have higher numbers of such voxels than control teeth. It is expected that expansion machine learning framework to 3D volumes and allow early detection of micro fractures which will lead to more appropriate treatment and longer tooth retention.

Rainey C *et al.,* investigated the performance of artificial intelligence (AI) systems currently in development for their ability to detect fractures on plain radiographic images and utilized the Preferred Reporting Items for Systematic Reviews and Meta-Analysis statement (PRISMA) [21]. Following the inclusion and exclusion criteria, sixteen studies were included in their final review. Except for one study, all studies report that AI models demonstrated an ability to perform fracture identification tasks on plain skeletal radiographs. Metrics used to report performance are variable throughout all reviewed studies and include area under the receiver operating characteristic curve (AUC), sensitivity and specificity, positive predictive value, negative predictive value, precision, recall, F1 score, and accuracy. Reported performances for studies indicated AUC values range from AUC 0.78 (weakest) to the best performing system reporting AUC 0.99. This study found a significant variation in the AI model architectures, training, testing methodology, and the metrics used to report the performance of the networks. Standardization of the reporting metrics and methods would permit comparison of proposed models and training methods which may accelerate the testing of AI systems in the clinical setting.

II. Jaw Fractures:

Amadea *et al.,* proposed an original maxillofacial fracture detection system (MFDS), based on convolutional neural networks and transfer learning, to detect traumatic fractures in patients [22]. Pre-trained convolutional neural network (CNN) are re-trained and fine-tuned on non-medical images using computed tomography (CT) scans to produce a model for the classification of future CT scans as either "fracture" or "no fracture." 148 CTs of patients with 120 patients labeled with "fracture" and 28 patients labeled with "no fracture" was used to train the model. 30 patients with 5 patients with "no fracture" and 25 patients with "fracture" were included in validation dataset for statistical analysis. An additional set of 30 CT scans, comprising 25 "fracture" and 5 "no Fracture" images, were used as the test dataset for final testing. If two consecutive slices were classified with a fracture probability higher than 0.99A then patient was categorized as fractured. The model accuracy in classifying the maxillofacial fractures is 80%. MFDS model can provide valuable assistive support, reducing human error, preventing patient harm by minimizing diagnostic delays, and reducing the incongruous burden of hospitalization. But, these models cannot replace the radiologist's work.

Nishiyama M *et al.,* aimed to verify the classification performance of deep learning (DL) models for diagnosing mandibular condyle fractures on panoramic radiographs using data sets from two hospitals [23]. Furthermore, comparison of their internal and external validities were done. Panoramic radiographs of 100 condyles with and without fractures were collected. This was followed by construction and evaluation of the DL models using fivefold cross-validation method. Accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) were evaluated for the internal and external validities of classification performance. External validity showed low performance and high performance was obtained for internal validity for the data sets from the two hospitals with AUC values of >0.85. The DL model exhibited high performance, slightly superior to or equal to that of the internal validity using combined data sets from both hospitals. Diagnosis of mandibular condyle fractures using panoramic radiographs can be done with the constructed DL model.

Available Softwares

Currently, AI software helpful in child abuse diagnosis and management includes [24]:

i. Image Hash Matching
ii. CSAM Image Classifier
iii. Video Hash Matching
iv. Safer List for Detection

Present Challenges:

The majority of studies are currently in experimental stages of development. Accurate measure of success in real-life scenarios is not possible to measure due to lack of real-life scenario and experimental nature. The included studies in the literature have significant limitation to uncover the real translational value of AI in child abuse.

CONCLUSION

Artificial Intelligence and its applications are widely used in Forensic Odontology, and the results are promising. These models have the advantage of overcoming human errors and being non-invasive. Decision-making is a very crucial aspect of child abuse diagnosis and AI provides assistance through excellent results along with the elimination of human errors. It is an supplemental aid in medico-legal cases. Future studies are recommended on the use of AI modalities in actual real-life incidences to use them as promising tools.

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