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A Review on Automated Bone Age Measurement Based on Dental OPG Images

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Abstract

Bone Age Measurement (BAM) is a process of assessing skeletal maturity levels to measure one’s factual age. It has been used for clinical and medical investigation and forensic science. This paper provided an overview of bone age measurement techniques and investigated their limitations to find the most suitable automated method for BAM. This assessment is usually achieved by two approaches: radiographic image analysis or traditional methods and machine learning technique. Traditional techniques have been applied to estimate chronological age by comparing the radiographic image of one’s wrist or dentition with an existing standardized chart, which includes a set of recognizable images for age at each stage of development. Traditional methods are known based on the analysis of specific areas of hand, face, skull, dental structures, etc. Still, this method has various disadvantages, such as extensive error range, low accuracy, observer change, and time-consuming. This issue leads to the emergence of an automated process, such as machine learning algorithms. This article explores the automated techniques used in the previous literature and highlights the challenges and issues. Finally, we propose a framework based on the gap in the literature reviewed.

Keywords: Bone Age Measurement, Radiographic Image, Traditional Age Measurement, Automatic Age Measurement, Machine Learning Technique, Automatic Age Measurement.

I. INTRODUCTION

Bone age measurement is a process of assessing skeletal maturity levels to measure one's factual age. It is a crucial issue that has raised interest and attention in forensic science and law enforcement [1]. The BAM method is a significant part of resolving many legal matters, specifically in civil proceedings. Also, in the event of an explosion or other unusual scenarios, age estimation may help identify the profiles of people who perished in those situations [2, 3]. Furthermore, bone age measurement is an essential tool for solving migration issues, where age needs to be determined due to the lack of appropriate documents. It can help decide when a child can start school and the earliest age that one can legally get married [4]. The BAM method is used in clinical practice in pediatrics, clinical trials, sports medicine, and forensic science orthodontics [5-9]. In general, the suitability of the non-invasive age measurement methods has made it a more preferred approach. Therefore, medical experts evaluate bone maturity by examining the skeletal system's wrist, hand, face, or dental X-ray. The prediction of one’s age based on facial features is assumed to be the most widespread method [10]. It is now used in many real applications such as security, human-computer interaction, multimedia communication, entertainment, and other applications. Numerous conditions may influence the reliability of the estimation of one’s facial age [11]. The different aging rates for people of various racial backgrounds have made facial age progression a subject-dependent process [12, 13]. Furthermore, other aspects, such as health background, lifestyle habits, external environment, and smoking history, may also affect people's age [14].

Additionally, facial age estimation may not be applied in explosions as the facial attributes may be severely affected [15, 16]. To evade facial age assessment issues, measurable researchers generally endeavor to gauge a person's age by assessing the advanced phases of the tooth and connecting the assessed phase to the maximum probable age [17]. Each body section is diverse. Hence, the teeth, too, have distinctive improvement stages. X-rays are the first and most common method of estimating dentistry's age used by forensic physicians [18, 19]. Total information that needs to evaluate dental growth is found in dental X-ray images [17]. Haavikko K. presents one process where drawings of teeth are used at various development stages and a table that correlates with each stage's age. Age ranges are given for both males and females due to inter-sex variation. This manual estimation of age, however, can be a repetitive, laborious, and subjective procedure. Therefore, to enhance age estimates' accuracy and reproducibility, there is a need for automated evaluation of one’s dental age [20, 21].

Traditional dental age estimating approaches require multiple steps, including pre-processing, segmentation, extraction of features, classification, or regression [22]. This method is different to identify, in case of classification, different age classes of individuals or assessing an individual's actual age in case of an inversion. In these strategies, every move's effectiveness is strongly contingent on the success of the last moves. In essence, the function's extraction's progress ultimately relies on the outcome of the subdivision procedure [23]. Likewise, the classification and regression process's progress depend on achieving the segmentation and feature extraction steps. Besides, segmentation and extraction of extraordinary performance depend on the problem [24]. Age segmentation assessment is based on a corresponding procedure that involves comparing a radiographer's image of the subject to an existing reference that includes a sample of known gender and age [25]. The estimating age process is mainly a measurement of biological maturation, which is changed into a period by comparing a picture with a specified reference [26]. Skeletal age can be measured using several different bones of the body [26]. The high cost, long-term monitoring, and radiation exposure risk suggest that this is not feasible or practical for maximum segments of the human body [27]. Researchers have looked at the frame's entire progress and examined the numerous approaches used in different parts of the body. Extensive methods are usually extracted based on the body part of 100 centers [28, 29]. The regions used to measure bone age from the body comprise the foot, shoulder, ankle, hip, elbow, cervix, ankle, face, and teeth [30]. The Greulich Pyle (GP) and Tanner Whitehouse (TW) approaches [31-33] are also a commonly used method depending on the X-ray image of the left hand, fingertips, and human wrist. [31-33]. The age estimation of a skeleton comes from the appearance of epiphysis and bone size. These can be undermined by a deficiency in nutritional status and systemic diseases. However, hand and wrist methods are somewhat susceptible to error due to changes in bone maturation under the influence of environmental insults [34].

Significantly, the teeth are not reconstructed; thus, estimating age is more closely related to the temporal age and is essential in estimating age [35]. Besides, teeth are useful for identifying and evaluating age because they are more durable in the skeletal system and can withstand high temperatures without physical damage. Another important feature about teeth is that they have distinct histological and morphological aspects that can often provide useful information about the deceased based on dental treatment and comparing morphological and other data [36, 37]. Further, this is a vital tool for solving migration issues, where age needs to be determined due to the lack of appropriate documentation. It can help decide when a child can start school and the earliest age that one can legally get married [38]. Adult forensic age estimation (18 years of age) is typically performed by studying the developing dentition and the hands and wrists' epiphysis area as the primary growth markers [6]. Until present, most bone age researchers are measured in +_ 1 years [1, 39, 40]. Figure 1 shows the tooth eruption of the primary and permanent teeth age.

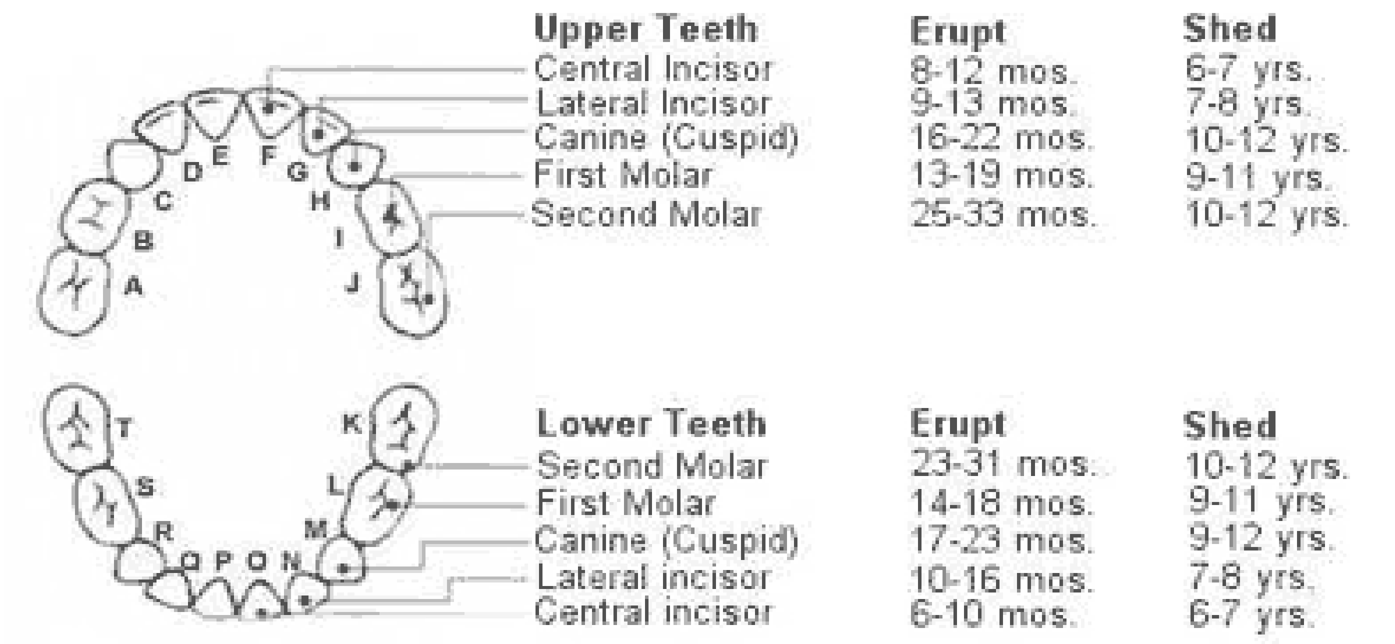

Fig 1. The universal numbering system for the primary teeth (from Brand, 1998).

II. MOTIVATION

In the modern environment, there are numerous experiments linked directly or indirectly to bone age calculation. It helps approximate age by automated systems when we need to identify an individual's age instead of their gender.

A. Forensic Point of View

In forensic science, bone age measurement is a skill that can assist in Forensic Age Estimation (FAE). FAE's goal is to obtain the chronological age (CA) with maximum accurate results of the unspecified subject for criminal or immigration examination purposes [41]. Despite the terminologies for diagnosis, the term "estimation" is more comprehensibly explained, and it also represents the significant limitations of the method mentioned above. Since the Second Mueller eruption throughout the Roman Empire as an indicator of young people's military service recruitment, the FAE has not been a new source in forensic medicine or forensics [42]. In a forensic study, they allow an approximate estimate of age variation during a person's development [43]. The most common forensic method for assessing age, based on the arm and wrist's skeletal maturity, is the method introduced by Taner et al. [44]. However, hand and wrist methods are somewhat susceptible to error due to bone maturation changes under the influence of environmental insults [45]. Dental growth assessment is less affected by nutritional deficiencies and pathology [46]. Dental growth is genetically controlled and is less influenced by environmental factors and is, therefore, less variable [41, 47]. Dentition development is, therefore, more accurate for estimating skeletal puberty than for adolescents. Although the degree of dental growth is one of the most effective approaches for determining an immature individual's chronological age, differences between local populations must be considered. The best estimates will come from specific local criteria for the people [42].

B. Security Inspection Point of View

The bone age study can help clinicians estimate a child's skeletal system puberty. The United Nations Children's Fund (UNICEF) 2018-2019 annual report stated that 93% of children migrating to Italy, Greece, and Bulgaria were boys aged 15 and 17. If they did not have birth certificates, they are considered minors. In many developing countries in Sub-Saharan Africa and South Asia, 64 % to 65% of deliveries are not registered. These children without any legal documents are deprived of their privileges [48]. With no proof of their age, these children are in danger of being recruited as juvenile armies in conflict regions or forced to marry early or be deported to other countries as illegal immigrants. When they are brought to the criminal courts or looking for international protection, they should prove their chronological age [48, 49]. Therefore, Silvia Logar claimed in 2020 that child confinement was a significant segment of the general health response to the COVID-19 emergency. To date, there are 161 juveniles in the Italian penitentiary system, most of them in pre-trial detention, as well as 50 children [50].

In contrast, the COVID-19 epidemic in some countries shows no signs of slowness. At present, the risk of death has increased all over the world. This situation has made this issue more hazardous for immigrant children who do not have written identities because they cannot obtain their legal rights.

C. UNICEF Report

Unregistered children or immigrants are subjected to many types of fanaticism and damage. In Guinea, for example, several unregistered refugee children were indiscriminately detained by law enforcers as they failed to verify their age. Many exile teenagers in Europe have faced a similar situation. They were registered as adult asylum seekers because of uncertainty regarding their age [51]. Therefore, they were dispossessed of any rights that would have benefited children of their age. In the UK, this means that they are more entitled to an asylum interview and do not have an advantage of attorney to support them in the interview, and they are even arrested during decisions [49, 52-54]. Being an adult gives refugees special opportunities and financial benefits, making them consider not disclosing their age. Affirmative resolutions through public actions have been made to record the date of birth of aged refugees. Afghanistan and Bangladesh were the first governments to adopt the registration system as India and Pakistan sought to expand birth registration in Asia [55, 56]. UNICEF and other international non-governmental organizations have often discovered that many children globally are still deprived of document recording of the registration [57, 58].

Therefore, when a government or any agency must determine an unregistered child's age, it needs a proper and precise age identification tool. Law enforcement agencies can apply BAM in conjunction with medical institutions and forensic organizations. In forensic organizations, forensic odontology is a combination of dental science and art and the legal system, a dental science and law intersection used to help bring criminal justice to justice [59, 60]. Forensic dentistry involves the dental analysis of living and deceased people, including children and adolescents. These analyses depend on morphological examination methods such as radiological examination of skeletal and dental development. In life, for illegal immigrants, children, and accepted refugees, age assessments may be performed. For these reasons, age estimation is more relevant for children than adults [61]. Estimating age at death is the beginning point for reducing the probability of identical local, regional, and national missing persons' data. Besides, it is beneficial in cases of limited population casualties and in cases of mass casualties where the victims' age varies, and other identifying information is not available [62]. Figure 2 shows the single dental radiography, which shows the tired molar growth, and the specialist doctors can read approximate bone age from the picture.

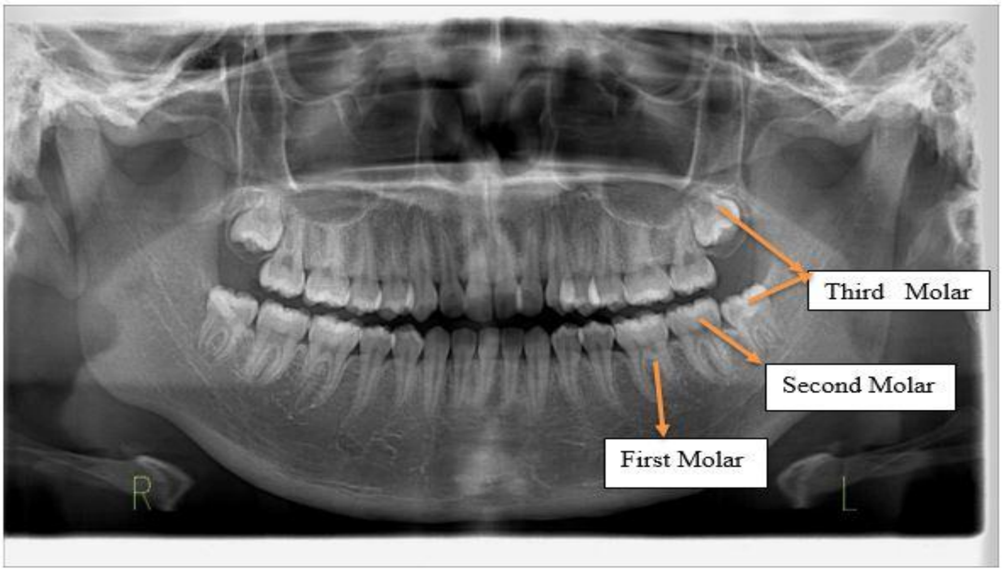

Fig 2. Sample of dental radiography

In most literature, determining the legal age is crucial to identify the living and the dead. In forensic medicine, it is also essential to distinguish the age of the unknown and suspicious age. Literature has considered height, weight, mental development, and tooth and bone growth for identifying age. According to histology, morphology, and radiological description, techniques applied in estimating age are categorized as morphological and radiological methods are commonly used to determine the age [41, 63, 64]. However, these procedures can be influenced by driving, living, eating routines, genetic features, and weather, as they vary in society [65-67]. In the skeletal system, teeth can withstand microbial pastime, high temperature, and mechanical forces, harsh environmental situations, making it more useful than bone for predicting age [49, 51].

As of now, between the European Union Countries (EU), there is no agreement on a specific method for estimating the living individual or minors' age. Although, several countries, such as the United Kingdom, use interviews to determine whether a person is a minor or not. Despite UNICEF and other international organizations' efforts to develop registration documents for the unregistered child worldwide, many children do not have registration documents that many are considered the age of the minor and the living individual. Hence, the need for a reliable and accurate method of assessing an unregistered child's age is necessary for the government or any organization to estimate the age of the individual [68]. Also, they need a reliable and accurate way to assess age [69]. Therefore, an automated BAM model has a vital role in a safe approach in a clinical setting with an easy-to-use approach in BAM [70].

This paper examines recent research on dental age and helps the reader to have an overview of the work in this field with the current methods used by machine learning and with the advantages and disadvantages of previous research purpose a new way for bone age measurement using dental radiography. Finally, this article proposes its method by reviewing previously presented research. This review paper continuance by the following parts: Part 2 discusses the literature available on the BAM model from an automated perspective and explains categorizing them. In part 3, a framework developed based on the gap identified in the literature has been proposed. In part 4, the limitations and challenges of the BAM method are discussed. Lastly, future research conclusions and directions are presented in Parts 5 and 6 of this paper.

III. LITERATURE REVIEW

Automatic measurement of human bone age is an automated method that eliminates the role of human intervention through machine learning algorithms and artificial intelligence. Machine learning is a data analytics method that allows algorithms to learn from experience to do what comes naturally to humans and animals. Machine learning algorithms use computational approaches to discover knowledge from data without depending on a model on a predetermined equation [1, 31, 71, 72]. - If the number of samples available for learning increases, the algorithms enhances their output adaptively. Deep learning is a specialized form of machine learning. There are two different types of machine learning methods. The first method is supervised learning, which teaches a model on identified input and output data to forecast potential outcomes and build predictive models using classification and regression strategies. The other technique is unsupervised learning, which seeks hidden patterns or inherent structures in input data with the clustering technique. This is the most prevalent unsupervised learning technique [73]. With the emergence of big data, machine learning for medical image identification, facial recognition, motion detection, object detection, detection of the tumor, drug discovery, and DNA sequencing has become an essential approach for solving image processing and computer vision. Predicting the age from X-ray image is a supervised classification technique that is a very complex task with numerous scientific researchers' methods from measurement using machine learning algorithms with continuous accuracy [74-76].

BAM researchers have indicated that the automation of age estimation has benefits. These involve the use of intelligent strategies. Some are used entirely for research, as a classification of dental images. It is calculable that by saving time for radiologists, computerized BAM methods can scale back age forecasts. The latest dental automated procedures using learning strategies for calculating bone age will be explained in-depth in the following part below.

A. Machine Learning Automated BAM Based on Dental Radiography

Emre Avuçlu submitted a morphological measurement on dental X-ray images in 2020 to assess age and gender. Details of age and gender were typically identified by function along with dental X-ray images of the teeth. With 1315 dental images and 162 different dental classes, the photos went beyond the borders. Three pre-process procedures have been exposed to these images. Each pre-processed picture is registered in different folders (M1, M2, M3) folders. The image processing techniques are applied to the tooth images for the first time (area, circumference, the center of gravity, the ratio of resemblance, and measurement of radius) were then applied. This dental knowledge is also contained in separate XML (XML List 1, 2, 3) directories. The application was built in the language of C # programming. A picture of the tooth can then be uploaded into the program by the user. It is possible to predict this image by comparing it after the desired pre-processing with the comparison group (area, etcetera). The highest estimated age and gender estimates are 95% for (+_ 1 Year) accuracy [41]. Figure 3 shows the general methodology of this study.

A deep neural network algorithm estimating the age using dental X-ray images was used by Noor Moala (2020) as a foundational forensic science role. Various mathematical approaches to teeth and mandible consideration have been suggested. Features are derived using two deep neural networks, AlexNet and ResNet, in the recommended process. Several classifications, including decision tree, k-nearest neighbor, linear separation, and help vector machine, have been proposed to carry out classification work, including decision tree, k-nearest neighbor, linear differentiation, and support vector machine. A dataset with 1429 dental X-ray images was used. The proposed approach is tested using several acceptable output parameters. The findings indicate that the method suggested has an excellent output on the (+_1 year) [19].

Two fully automated methods are proposed to determine a person's biological age from the OPG image, introduced by Nicolas Vila-Blanco (2020). The first (DANet) consists of a sequential age prediction path for the Convolutional Neural Network (CNN). In contrast, the second (DASNet) applies a second CNN path to sex prediction and uses sex-specific characteristics to boost the efficiency of the estimation of age. The two methods were tested on a sample of 2289 OPG photographs of participants aged 4.5 to 89.2 years. Both poor images of radiological quality and images displaying dental conditioning properties were not discarded. The outcomes revealed that in every way, the DASNet outperforms the DANet, minimizing the median Error (E) and the median Absolute Error (AE) in the whole database by around four months. The AE values decline when testing the DASNet in the decreased datasetsthe actual age of the subjectsdrops until they attain a limit of about 8 months for subjects under the age of 15 years. The DASNet solution was also comparable to the advanced manual age estimation approaches, demonstrating considerably fewer issues over or under-estimation. As a result, it is concluded that the DASNet can be applied to accurately estimate the actual age of a person efficiently, specifically in young with dentitions for (+_ 1 year) growth [78].

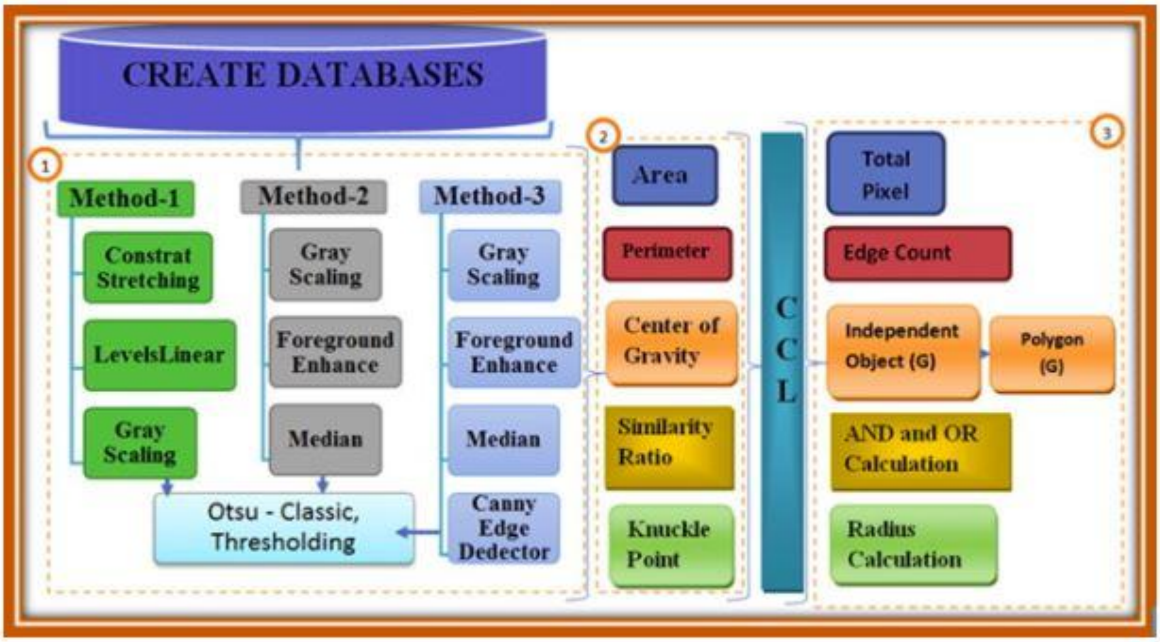

Fig 3. General methodology [77]

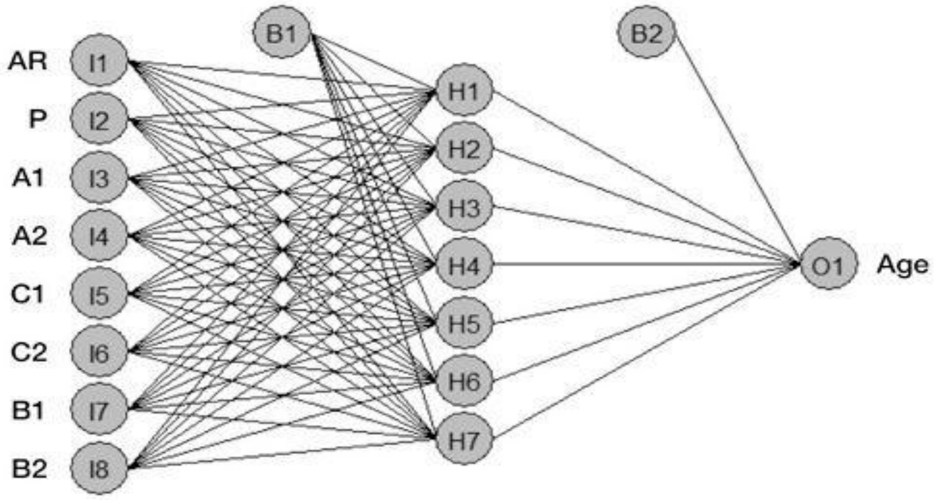

Fig 4. Structure of the developed feed-forward neural networks for age estimation [80]

In 2019, Maryam Farhadi published a thesis that introduced a groundbreaking prediction system. Therefore, neural networks that relied on dental data and stated that could alter age assessment could change. The thesis aims to determine the potential to apply neural networks to quantify age by using a pulp-to-tooth coefficient to canines as a non-ruinous approach that is not expensive and accurate. The predictive efficacy of neural networks and the paradigm of linear regression were both compared to each other. The age group they used was between the ages of 14 and 60, and the overall volume of data was three hundred people. For statistical analysis, SPSS 21 statistical software (IBM Corp., Armonk, NY, USA) and R were utilized. The findings revealed that the neural network model usually performs age estimation with pulp-tooth ratio data more significant than the regression model. The extended neural network model had a predictive error with a mean root mean square error (RMSE) of 4.40 years and a mean absolute error (MAE) of 4.12 years for the appropriate secret dataset. The neural network errors were smaller than the regression model's estimation errors, with the test data set being RMSE of 10.26 years and MAE of 8.17 years. The neural network methodology, with an MAE of 4.12 years, showed reasonably good results. Therefore, neural networks' use offers a new ability in forensic science to achieve more reliable (+- 1 year) age estimates. [80]. 10. The design of the established feed-forward neural networks for age estimation utilized in the approaches of Maryam Farhadian is shown in Figure [79].

Using dental panoramic X-ray pictures, Sultan Alkaabi in 2019 intended to examine different Convolutional Neural Network (CNN) architectures for age estimation. The tests use end-to-end CNN to fix the inconvenience of forensic dentistry's automatic age calculation without any modifications. A custom dataset of more than 2000 X-ray images broken into seven different groups is used for training CNN architectures. The transfer learning principle is also used to train the common CNN architectures for age estimation, such as AlexNet, VGGNet, and ResNet. Age estimation efficiency is measured by evaluating its recall, accuracy, F1-score, accuracy, and average accuracy for all the tested architectures. The investigation yielded poor precision of less than 40 percent in the use of dental photographs for age estimate using CNN architectures because of rotating and tilt orientation, overlap teeth, missing teeth. They claimed that this is the first paper that seeks to predict age estimation from dental images using Capsule-Net with the best of knowledge. However, the proposed architecture indicates that Capsule Network has increased 36% over CNNs and transfer learning to reach a cumulative accuracy of 76%. (+_ 1 Year) [81].

Tao et al. (2019) have introduced the Multilayer Perceptron estimate, a dental age estimation technique that uses the Multilayer Perceptron calculation to approximate age. In the planning cycle, they use cross-validation to tackle the overfitting problem. The experiments are carried out on a dataset composed of 1636 samples (787 male and 849 female). The results obtained indicate the suggested approach's prominence over different conventional strategies, along with Demirjian's strategy and Willem's RMSE, MSE, and MAE strategy. They also experimentally confirmed that this latest feature set makes the dental age estimation more reliable (+_ 1 Year) [82].

An age evaluation approach tested on Malaysian adolescents between 1 and 17 years of age was suggested by Seyed M. M. Kahaki (2019). The technique is based on global fuzzy segmentation, local feature extraction using a feature transformation based on prediction, and a deep convolutional neural networks (DCNNs) model. A universal labeling process based on fuzzy segmentation was accomplished in the initial stage. The first to the third molar teeth were then segregated. Next, based on an intensity projection method, the invariant deformation characteristics were collected. This approach offered high-order elements that were invariant to modifications in rotation and partial deformation. Eventually, in the hierarchical layers, the designed DCNN model extracts a broad range of features: invariance of size, rotation, and deformation. Using a systematic and branded orthopantomography of 456 patients recorded by the Department of Dentistry and Study of University Sains Islam

Malaysia, the process using this technique was then evaluated. The study's findings indicated that the system would identify high-performance images, enabling automatic age estimation to be extremely accurate. (+_ 1 Year) [17].

Jaeyoung Kim (2019) used deep learning algorithms to estimate the age using dental panoramic images and stated that this assessment is a fundamental task in forensic science. Also, he mentioned previous studies conducted using statistical methods mainly to estimate the child's age with a focus on the teeth and mandible. Nonetheless, establishing an automated age estimation system for all age groups is challenging as changes in post-puberty dental conditions increase concerning dietary habits and dental management. In the proposed technique, a convolutional neural network (CNN) is utilized to measure age. The dataset used incorporates dental X-ray pictures of 9435 people (4963 male, 4472 female) sorted out in three-age gatherings. The result of deep learning algorithms based on CNN neural networks shows that the proposed approach functions evaluated based on a database of panoramic dental radiographs and worked well for (+_ 1 Year) accuracy [83].

Banar (2019) implemented a fully automatic staging method leveraging the full capacity of deep learning in every stage of the system, using convolutional neural networks (CNNs). In the dataset used to train the CNNs, 400 panoramic radiographs (OPGs) were available, with 20 OPGs per stage of development per gender, arranged with the agreement of three observers. In dealing with a restricted dataset, transfer learning principles, using pre-trained CNNs, and data augmentation were used to minimize the problems. A three-step protocol has been proposed in this work, and the findings have been confirmed using five-fold cross validation. Secondly, CNN was able to locate the geometrical center of the bottom left third molar, around which a square field of interest (ROI) was extracted. Second, a third molar had been segmented by another CNN inside the ROI. Thirdly, the final CNN used both the ROI and the segmentation to describe the third molar in its period of development. Finally, with a precision of 54 percent, a mean absolute error of 0.69 stages, and a linear weighted Cohen's kappa coefficient of 0.79, the developmental stages were graded. On average, it took 2.72s for the entire automatic workflow to compute, which is considerably quicker than conventional staging starting from the OPG. Given the small size of the dataset, this pilot study indicates that the completely automated solution suggested demonstrates encouraging outcomes relative to manual staging in (+_ 1 Year) [84].

Bayesian Convolutional Neural Networks were used for the dental age method based on dental X-ray images in 2019 by de Back et al. For age estimation, and the preferred technique uses a Bayesian convolutional neural network. Leading experiments on a dataset containing 12000 dental X-ray photographs have evaluated this method. The result shows that the proposed solution has a 0:91 concordance relation coefficient for (+ 1 year) precision [71].

Emre Avuçlu (2019) developed a multilayer perceptron neural network algorithm for predicting dental age by years. The database of 162 completely different groups of teeth made it manually. The image size was 150 x 150 pixels, and image processing techniques in dental imaging were utilized. These pre-processing methods are applied for dental imaging. The procedure image ripping was performed to extract the feature. Numerical data were obtained from the feature extraction of the dental images as multilayer perceptron neural network input. It was also mentioned that feature reductions could be made. Then classification for several dental groups, age estimation is accomplished with zero inaccuracy. This program is designed as a multidisciplinary study. This study showed 99% accuracy in dental age classified in (+_ 1 Year) [61]. Figure 5. showing the general methodology multilayer perceptron neural network algorithm.

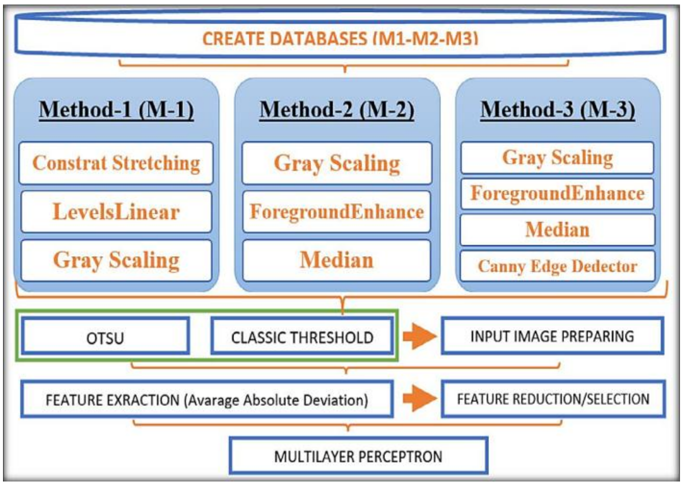

Fig 5. General Methodology [85]

In 2018 Hemalatha B., offered a fuzzy neural network with training-based learning optimization to estimate age in forensic medicine, and he mentioned clinical dentistry is incredibly essential. Multiple radiographic strategies in the southern population have been proposed for assessing dental age (DA), and a comparative evaluation has been identified, which is insufficient in the Indian population. Therefore, this study elaborates on the classification model for estimating DA in the Indian infant population using the Demirjian’s technique. The Orthopantomography (OPG) dataset was obtained from the Kovai Scan Centre, Coimbatore. OPG photographs are used to assess the dental age and compare around 100 healthy, South Indian children and teenagers between 4 and 18 years of age and the C.A. With this discovery, a fuzzy neural network with training-based learning optimization (FNN-TLBO) is suggested for DA classification. Initially, to minimize noise and smooth the image, the OPG input image is processed using anisotropic filtering (ADF). Thus, the whole teeth are segmented from the photographed teeth using the Active Contour Model (ACM) with hierarchical analytical procedure optimization (AHP). The morphological post is then processed for correct attachment order enhancement into the segmented object. Specific highlights are then eliminated, such as GLCM, Haralick, Haufsdroff distance, crown, root, tooth density, size, geometrical features such as roughness, concavity, convexity, area, and environment to improve accuracy. Finally, age is classified by FNN-TLBO. This FNN uses TLBO to solve the issue of system training. The outcomes show that FNN-TLBO is anticipated to perform better with 89% accuracy, 89.12% specificity, 64.152% accuracy, 92% recall rate, and 71.12% F measurement rate than existing algorithms. Such as Extended Learning Device Modified by Distributed Representative Classification Scheme (MELM-SRC), Radial Basis Function Network (RBFN), Neural, and Fuzzy Inference System (ANFIS) [86].

De Tobel J. (2017) developed machine learning algorithms available in MATLAB to evaluate the growth of bones of the hands and wrists and dental on radiography and magnetic resonance imaging. They stated that their techniques could be applied to estimate the age of children and minors. A modified Damirian staging technique consisting of ten stages of development was performed. Twenty panoramic radiographs at every step for each sex were retroactively elected for the FDI element 38. The two monitors were unanimously determined on the steps. If needed, a third viewer functioned as the referee to collect the third molar reference point. For machine learning algorithms for the automated step, the radiographic collection was used as training data. Initially, image optimization was the contrast setting for evaluating the third molar, and a standard rectangular box was positioned all around it is using Adobe Photoshop CC 2017. This narrow box shows the area for the next step. Next, the multi-machine learning algorithms accessible in MATLAB R2017a software were used to find the automatic phase. The classification presentation was then measured in a 5-fold reliability situation utilizing several credibility criteria (accuracy, degree-N detection speed, mean absolute difference, kappa linear coefficient). The mean accuracy was 51.0, the average unconditional disagreement was 0.6, and the kappa average was 0.82 in (+_ 1 Year). The automated empirical method's total performance presented for the lower third molar's developmental step in panoramic radiography was homogeneous to that apperceived by human observers. This is a step needed to achieve an automatic dental age estimation method, which is not available to date, it will be optimized in future research [87]. Figure 6 shows representative samples of lower left third molars in every stage of development.

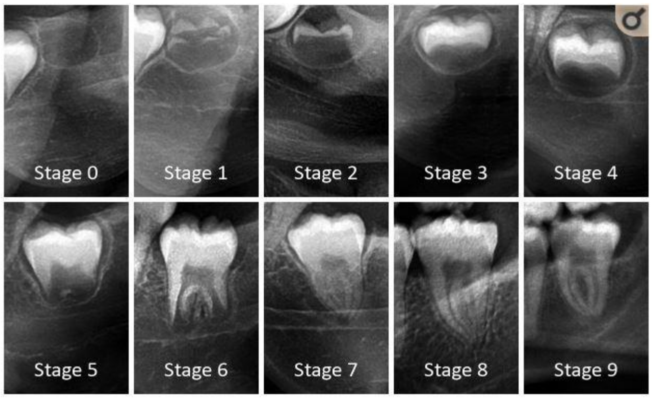

Fig 6. Representative examples of lower left third molars in each developmental stage.

Third molars are depicted within their bounding box

A semi-supervised fuzzy clustering algorithm with spatial limitations for dental segmentation from X-ray images was introduced by Le Hoang Son in 2017. The thorough contributions consist of i) formulating the spatial features of a dental X-ray image in a dental feature record; ii) modeling the dental segmentation issue in the form of semi-supervised fuzzy clustering with spatial constraints; iii) resolving the model by the Lagrange multiplier method; iv) determining the further data for clustering procedure by combining optimal findings of Fuzzy C-Means with spatial limitations; v) proposing a novel Semi-Supervised Fuzzy Clustering algorithm with Spatial Constraints (SSFC-SC) that merges the procedures meant for dental segmentation. The latest algorithm is certified on an actual dataset obtained from Hanoi Medical University, Vietnam, involving 56 dental images. The experimental findings show that the recommended work has superior accuracy than the initial semi-supervised fuzzy clustering and several related approaches. The most suitable values of parameters that should be chosen for the algorithm was also proposed [84].

Table 1: Summary of Literature Review on Automat

Author	Year	Country	Total Dataset Amount	Age	Sex	Type of Dental X-ray	Methods	Learning Architecture	Accuracy Results & Limitations
[86]	2020	**Turkey**	1315	N-A	N/A	OPGs	Machine Learning	C # Programming Language	The result was 95% accurate in +_1 year.
[19]	2020	**Kuwait**	1429	0-70	N/A	OPGs	Deep Neural Networks	AlexNet & Resnet	Their results showed that the proposed method has a promising performance. They have the limitations of a larger data set.

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Author	**Year**	**Country**	**Total Dataset Amount**	**Age**	**Sex**	**Type of Dental X-ray**	**Methods**	**Learning Architecture**	**Accuracy Results & Limitations**
[78]	2020	**Spain**	2289	4.5-89.2	N/A	OPGs	Convolutional Neural Network	DASNet	They validated the predicted age-related age in young people. Large sample size was required as the subject of the restriction.
[80]	2019	**Iran**	300	14-60	N/A	CBCT	Neural Network	Multilayer Perceptron	The result showed a more accurate estimate of age in forensic research.
[81]	2019	**Malaysia**	2575	20-90	N/A	OPGs	Convolutional Neural Network	AlexNet, VGGNet & ResNet	Their result of proposed architecture has been improved to achieve dental images for an estimated 36% age. Their limitation was the lack of large data sets.
[88]	2019	**China**	1636	11-19	787M/849F	OPGs	Neural Network	Multilayer Perceptron	Their results were more accurate than estimating traditional dental age.
[17]	2019	**Malaysia**	456	1-17	207M/249F	OPGs	Deep Convolutional Neural Network	DCNN Model	Their results show that this method can classify images with high performance, making automatic age estimation possible with high accuracy. Some limitations include the population of data in elderly patients to extend the general approach and suggest that CNN filters are in the early stages of future research.
[89]	2019	**Korea**	9435	2-98	4963M / 4472F	OPGs	Machine Learning	Convolutional Neural Networks	The result was validated, and this model promises to develop an automated factual age measurement.
[84]	2019	**Belgium**	420	7-24	N/A	OPGs	Machine Learning	Convolutional Neural Networks	This method had promising results compared to manual staging. Therefore, the limitations of the number of datasets were considered as a limitation.
[71]	2019	**Germany**	12, 000	5-25	N/A	OPTs	Deep Convolutional Neural Networks	Bayesian CNN Inceptionv3 Architecture	The result was a demonstration of the concept of using Bayesian CNNs as an automated age estimation model.
[90]	2019	**Turkey**	1315	4-63	N/A	OPGs	Neural Network	ANN Multilayer Perceptron	Their result had a high performance of 99.9% with an accuracy of +_1 year.

Author	Year	Country	Total Dataset Amount	Age	Sex	Type of Dental X-ray	Methods	Learning Architecture	Accuracy Results & Limitations
[80]	2018	**India**	100	4-18	N/A	OPGs	Machine Learning	Fuzzy Neural Network	The accuracy was satisfactory, and the data sample limit was contradictory.
[91]	2017	**China**	20	N-A	N/A	OPGs	Machine Learning	Algorithms Available in MATLAB	The result showed 51% accuracy with a promising development. The deficiency of the dataset was expressed as the study limits.
[92]	2017	**Vietnam**	56	N-A	N/A	OPGs	Machine Learning	Fuzzy Clustering with Spatial Constraints (SSFC-SC)	The proposed work was more accurate. The lack of a large data set was the main constraint.

All the current methods listed as automated dental procedures for BAM are listed in Table 1 below. The sources and differentiation of each method and research results indicate that all studies are focused on age by measuring up to the +_ 1 year only with different size methods. This study lists a wide range of literature reviews to find an actual gap.

IV. PROPOSE FRAMEWORK BASED ON THE GAP FROM REVIEWED LITERATURE

A general review of radiographic and computational approaches for BAM in this literature review was provided. We conclude this proposed model as the future work for this review is expected to improve BAM accuracy for clinical and research applications and computational approaches. Despite an increase in the usage of automated methods for BAM, they are still in the early development stages. There is still no robust computational approach for BAM with an accuracy of 6 months or below among the existing age estimation techniques. Teeth images and insufficient data or weak parts of dental imaging are the significant problems for automated BAM. Implementation of a combination of the hybrid circumstance and standard skeletal atlas as references can minimize the measurement problem due to limitations in the automated BAM technique using dental radiography. Figure 7 shows the proposed model of this implementation of hybrid machinery, which we hope to overcome the lack of accuracy by months in the health environment [93-95].

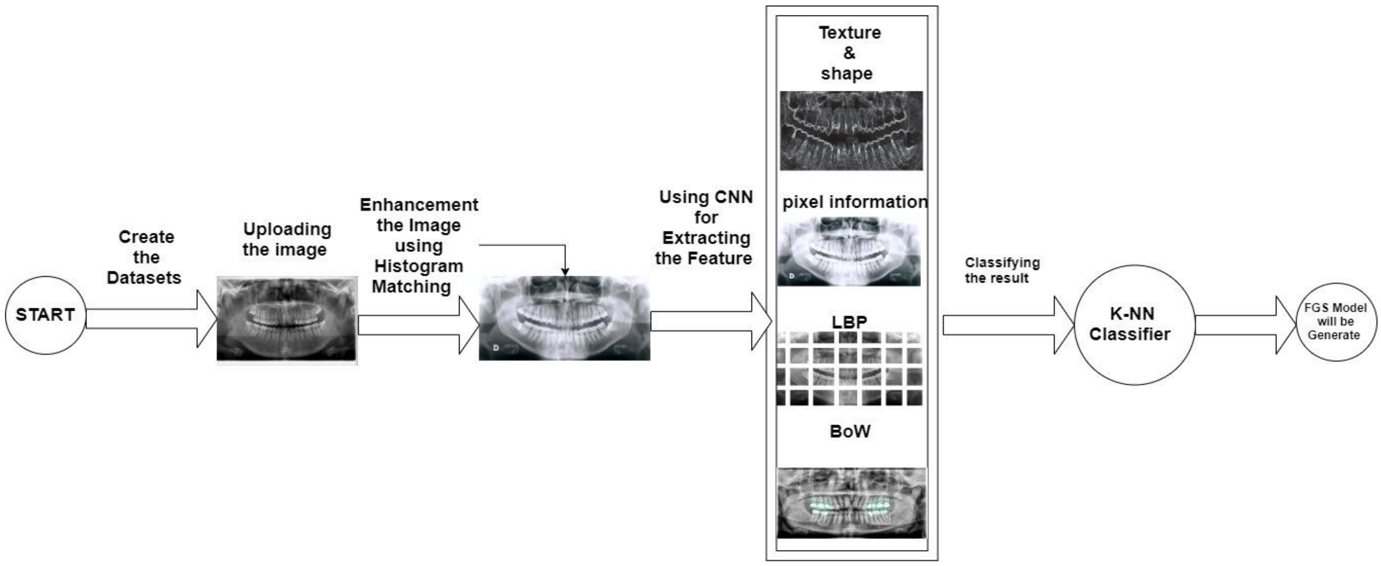

Fig 7. Proposed Model

V. DISCUSSION

Research has shown that most researchers have used machine learning algorithms like NN, SVM, KNN, Decision Tree in bone age measurement [31, 96-98]. Machine learning algorithms cannot process data in raw form, as they are subject to errors that lead to inaccurate class recognition. Therefore, carefully engineered attribute extractors need to convert raw data into attribute vectors for proper classification. However, extracting characteristics that can accurately represent behavior in different environmental conditions is a challenging task that has left a wide range of research open to researchers in this field [99, 100]. Also, choosing a classifier that can differentiate behaviors in terms of diversity within and outside the classroom is one of the challenges in recognizing behavior [101].

In some cases, existing recognition algorithms require a lot of data training, unaware that this enormous amount of data in some instances reinforces the problem of over-fitting. The difficulties raised led to in-depth learning of a new area of research leading to behavioral recognition. - Deep learning uses computational models with multiple layers of processing based on representational learning with different layers of abstraction. Metaphorical learning involves a set of methods that allow the machine to process data raw and automatically turn it into a convenient display for classification. This technique is a new field of technology that puts machine learning in bone age measurement in front of researchers. The results have led to a relative improvement over traditional methods of machine learning. Previous studies are presented in Table 1 and we compared and evaluated 14 automated approaches in dental age measurement with requirements for BAM. The literature clearly shows that a significant move towards automated methods is unavoidable. Automated age measurement techniques are cost-efficient. It also accelerates the human identification process as the computer systems for measuring bone age are described in 14 classifications. The usual process in the 14 systems is image processing, features extractions, image classification, decision making, and results. As stated in previous research, various methods of predicting age in adolescents have been measured for +_ 1 years [32, 53, 93, 102]. However, there are limitations such as inaccuracy [103, 104], Inadequate methods [103], and the failure of some system to perform dental age measurement as well as zero accuracies in measuring the age of the juvenile as minor's age [105, 106]. Criminal proceedings in which children provide superior protection to victims and are also responsible for illegal activity. In all cases, courts of law and public institutions require forensic practitioners to have a specialized Forensic Age Estimation (FAE) report, which requires the exact age of the victim (the minor) [107-110]. There is no robust computational approach for BAM in the healthcare setting, with accuracy within the range of +/- 6 months for dental age estimation techniques, due to limitations in image analysis and image processing techniques between previous research [111]. Therefore, no automated classification resolution for dental illustrations or lost personal information for any reason has been provided for forensic medicine. Consequently, this study was applied to direct the subjects above [41, 112, 113].

VI. CONCLUSION

In this paper, recent works in the field of Bone age measurement was discussed. One of the potential benefits of a hybrid system is that it allows for an assured decision about bone age measurement and a better and accurate calculation of age, which cannot be specified earlier. Two of these bones include the maxilla and lower jaw. Most maxillary and mandibular growths are usually performed at the age of 18 to 20 years old; the only skeletal components visible in these facial bones' macroscopic are teeth through post-mortem decomposition. As a result, the tooth and jawbone are selected to develop the hybrid method because it is a helpful bone for age assessment amongst other parts of the body. Estimating age based on tooth growth is a robust method. It is essential to define a predictive model for measuring bone age. Modeling an accurate method for measuring age in the medical field can help accelerate personal identification and thus reduce cost. Although the number of BAM models has increased, most of them remain in the testing phase because they have not obtained clear-cut results, especially predicting the minor's age. Furthermore, there are no robust computerized methods for BAM within the healthcare setting, with a precision to the range of +_ 6 months accuracy for dental age estimation techniques due to limitations in image analysis and image processing techniques.

VII. FUTURE WORK

Although the papers appraised in this review clearly show significant efforts to automate BAM, there are still some challenges with the existing machine learning system. There are still gaps in the improvement of BAM techniques. In the past, several studies were done on dental age estimation using a standardized or ready-made atlas for various age gaps, normally one year. In the future, with the combination multiples methods of deep learning techniques and radiographic techniques, the accuracy obtainable further improved to aid forensic and legal issues concerning age arbitration.

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