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A Systematic Literature Review on Bone Age Assessment using Machine Learning and Deep Learning Models

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***Abstract*—Bone Age Assessment (BAA) is a general medical practice for investigating genetic, endocrinology and growth defects in kids and adults. Nowadays, automatic techniques for assessment of wrist and hand radiographs were introduced that reduce interrater-variability over manual techniques. Deep learning (DL) is a proliferating and useful method of machine learning (ML). Varied appliances, like medical image processing, speech detection, and so on have deployed DL, as it is offering accurate resultants. This survey makes a significant analysis on about 30 papers regarding BAA using ML and DL schemes. More particularly, varied performance measures that are contributed in diverse articles are analyzed. In addition, a comprehensive study is made regarding the chronological analysis and finally, the future challenges to be resolved are discussed.**

***Index Terms*— Bone Age Assessment; Deep learning; Machine learning; CNN; Performances.**

Nomenclature

Acronyms	Descriptions
ANN	Artificial Neural Networks
AAE	Average Absolute Error
BAA	Bone Age Assessment
BMD	Bone Mineral Density
CAD	Computer-Aided Diagnosis
DCN	Deep Convolution Networks
DNN	Deep Neural Network
DCNN	Deep Convolutional Neural Networks
DL	Deep Learning
e2e	End-To-End
Faster R-CNN	Faster Region- CNN
GP	Greulich And Pyle
GCLM	Glutamate Cysteine Ligase Modifier Subunit
HMM	Hidden Markov Models

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LBP	Local Binary Patterns
ML	Machine Learning
MTT	Mean Trabecular Thickness
MAPE	Mean Absolute Prediction Error
MAE	Mean Absolute Error
MAD	Mean Absolute Difference
microCT	Micro-Computed Tomographic
NSCT	Non-Subsampled Contourlet Transform
NN	Neural Network
PA-TFSA	Photoacoustic Time-Frequency Spectral Analysis
Re-CNN	Regression CNN
Re-NN	Regression Neural Network
R-CNN	Region-Based CNN
RNN	Recurrent Neural Network
ROI	Regions Of Interest
RB-FCL	Region-Based Feature Connected Layer
rHOA	Radiographic Hip Osteoarthritis
ResNet	Residual Network
SVMs	Support Vector Machines
SBA	Shorthand Bone Age
TW2	Tanner And Whitehouse
VGGNet	Visual Geometry Group Network

I. INTRODUCTION

BAA is essential for the genetic assessment and endocrinology of patients with endocrine defects and development disorders. In addition, the bone age of a kid from radiological skeletal scan of hand in evaluation with chronological age provides the evaluation of upcoming adult height of kid. BAA is done physically by optical assessment of the patient's hand radiographs depending upon a benchmark chart [14] [25]. The conservative BAA model is separated into GP and TW2, TW3. The GP technique is a holistic evaluation, which portrays the age of bones by comparing the reference chart and entire hand bones. The GP technique offered a simple method to attain considerable accuracy. On the other hand, the GP method is receptive to differentiations amongst observer experience and observers. In contrast, the TW3 technique split the hand image to specified ROI [24] [31]. The bone ages are computed from scores of ROI. Even though the TW3 offer more precise bone age evaluation than GP, it consumes more time and necessitates more comprehensive specialist knowledge [2].

Some traditional classification models were developed using ANN and SVMs. Certain image augmentation schemes were deployed for BAA namely, HE, TW2 technique, HMM and so on. However, the aforesaid approaches entail the shortage of accuracy and they need numerous multifaceted manual interferences [10] [4]. There are only some systems with improved user interfaces like BoneXpert [2].

In recent times, stimulated by the accomplishment of DCNN in classification of images, the medical field is exploring such techniques. DL oriented techniques allows to evade feature engineering by learning the hierarchy of classified features automatically from a training data set [12] [31]. DCNN was exploited successfully in estimating bone age. Such a technique suggests an e2e learning structure for estimating bone age by means of DCNN. Nonetheless, holistic image- oriented study can enclose inappropriate data in image for analysing bone age, and does not concern on the significant areas, which mostly find out bone age [2].

The major contributions are as follows.

1. Carries out a review on BAA by analysing 30 research papers.
2. Presents a comprehensive review on various methodologies including ML and DL approaches adopted in each reviewed articles.
3. Makes evaluation on performance metrics in each of the reviewed articles.
4. Makes reviews on chronological analysis and elucidates about the future gaps in BAA.

Here, Section II illustrates the related works on BAA. The extensive review on implemented schemes is preferred in section III. The review on performance metrics is represented in Section IV. Furthermore, Section V organized the challenges and the conclusion is portrayed in Section VI.

II. Literature Review

A. Related works

In 2021, Sonal *et al.* [1] developed the novel TW3-oriented automated BAA approach for kids with the aid of Faster R-CNN and Optimal trained RNN. The adopted scheme covered 3 most important phases: Segmentation, feature learning, and classification. Furthermore, the segmentation was carried out by modified Otsu thresholding. In 2019, Toan *et al.* [2] have adopted a deep learning-oriented scheme for estimating bone age by incorporating the TW3 schemes and DCN depending upon derived ROI and Inception-v4 and Faster-RCNN classification. The investigational resultants had shown a high accuracy and minimal error of around 0.59 years.

In 2019, Baoyu *et al.* [3] proposed a new deep automatic scheme for estimating bone age via R-CNN. Here, Faster R-CNN scheme was transferred from object recognition to bone age regression for evaluating the age of bone. It extracted the features automatically and detected the major portions and further predicted the age of bone. In 2019, Jiajia *et al.* [4] proposed a bone age evaluation scheme for X-ray images. Specially, a regression model 'BoNet+' was initially established depending upon densely connected CNN. Subsequently, 3 model schemes were introduced for improving image quality. Experimental resultants have shown that the developed scheme estimated the bone ages of poor-quality image precisely.

In 2019, Yu *et al.* [5] proposed a multi-scale data fusion approach for assessing bone age with X-ray image depending upon NSCT and CNNs. Different from extant CNN-oriented BAA techniques, a set of features were pre-extracted for input image by carrying out NSCT for obtaining its multi-direction and multi-scale depictions. In 2019, Ren *et al.* [6] proposed a Re-CNN for assessing the paediatric bone age automatically from hand radiographs. Here, the attention module was initially adopted for processing every image and attention maps were generated as inputs. Then, training was done using CNN and the bone age was estimated more accurately. In 2019, Liu *et al.* [7] applied ranking learning for assessment of bone age using 2-phase network. The initial phase deployed CNN and subsequently, a conditional GAN was deployed for assessing bone age. Accordingly, ranking CNN was used as generator that included numerous dual classification outputs. In the end, the test outcome exposed that the typical accuracy was proficient. In 2019, Son *et al.* [8] proposed an absolute e2e BAA approach for automating the whole procedure of the TW3 technique. Here, CNN was exploited, where; specified modifications were done for enhancing the results. At end, analyses were done to validate the effectiveness of proposed technique for estimating the accuracy.

In 2021, He and Jiang [9] proposed an e2e BAA scheme depending upon squeeze-and-excitation deep residual network (SE-ResNet) and lossless image compression. Initially, the compression module was applied for compressing the raw image devoid of losing significant features. Then, the SE-ResNet-oriented scheme extracted features of compressed images. In 2021, Li *et al.* [10] developed DCNN approach depending upon enhanced classification model. This approach located informative parts automatically and extracted local features for recognizing hand bone images. After that, the derived local features were united with overall features of a total image for classifying bone ages. This technique achieved e2e bone age evaluation, thus enhancing the accuracy and speed of bone age evaluation. In 2020, Gerges *et al.* [11] have evaluated the reliability and accuracy GP models and examined if the diminution in time compromised their effectiveness. Here, SBA and GP schemes were used for determining bone age for females and males of 213 each. After 3 weeks, the 2 raters reiterated the analysis and timed with online stopwatch.

In 2021, Ahn *et al.* [12] evaluated the performances of a DNN scheme in evaluating bone age throughout puberty by means of elbow radiographs. The MAD in estimating bone age among the reviewers and model was 0.15 years on interior substantiation. Further, the MAD among the model and 5 specialists lied between 0.19 to 0.30 years. In 2017, Shreyas *et al.* [13] performed an evaluation of varied non-evolutionary and evolutionary segmentation schemes on digital hand radiographs for assessing bone ages. An evaluation was made among evolutionary segmentation schemes executed upon hand radiographs for recognizing bone shapes and borders. In 2017, SpampinatoS *et al.* [14] proposed and tested numerous deep learning schemes for automatically assessing bone ages. The resultants have shown an average difference among automatic and manual assessment of around 0.8 years. Moreover, this was the initial automatic bone age evaluation model analyzed on a public database, thus demonstrating a thorough baseline for upcoming study.

In 2020, Yaxin *et al.* [15] deployed deep learning technique for obtaining the X-ray skeleton image features, and the CNN was exploited for assessing the bone age automatically. Depending upon ResNet approach in the deep learning model, the AAE of bone age discovered by the bone age evaluation scheme was 0.455 superior to conventional schemes. In 2018, Hak *et al.* [16] validated the efficacy of tibia quantification by comparing microCT images in old masculine rats with histology analysis. MicroCT examination has shown considerable lower BMD and trabecular bone count in the old groups. In 2020, Thomas *et al.* [17] deployed the GP model on

MR images of wrist and hand for providing reference values for computing the bone age in hands. The descriptive examination and the conversion study have shown related resultants.
In 2020, Sven *et al.* [18] built an automatic scheme for paediatric bone age assessment, which mimicked and accelerated the workflows of radiologists. The entire scheme was dependent upon 2 NN schemes: (a) detector network and (b) regression networks that estimated the bone ages from the identified areas. In 2019, Xu *et al*. [19] deployed 2 phase approach for evaluating the age of bones. At first, the feature extraction utilized DNN for studying the X-ray image features, and GCLM features and LBP features were extracted. Subsequently, the classification technique based upon SVM was exploited for classifying the features. In 2021, Weiya *et al*. [20] evaluated the age of bones based upon DL model. Here, the ages of bones were computed depending upon the "Standards of Skeletal Development of Hand and Wrist for Chinese (CHN)" technique that observed only 14 hand bones via DCNN. The method was compared with the traditional method using whole hand evaluated using the same test dataset. The resultants have shown the increase of accuracy using the developed model.
In 2021, Ming *et al.* [21] have studied the possibility of deploying PA-TFSA to evaluate the bone structure and BMD. Finally, experiments and Simulations on bones with diverse MTT and BMDs were performed. In 2019, Štern *et al.* [22] developed automatic skeletal bone age evaluation depending upon DL. Other than analyzing every bone in hand, a skeletal maturity evaluation technique was proposed based upon CHN that observed only 14 hand bones by means of DCNN. Further, the effectiveness of the adopted scheme was proven from the outcomes. In 2020, Gao *et al.* [23] proposed an automated multi-factorial age evaluation technique depending upon MRI of hand, teeth, and clavicle for extending the utmost age range from 19 - 25 years when united with wisdom teeth and clavicle bones. The adopted technique utilized a DCNN, which was trained for achieving a minimal MAPE.
In 2021, Salim *et al.* [24] deployed U-Net based segmentation for acquiring the mask images that was distinguished with real image for obtaining the hand bone segment following the removal of background interventions. For the categorization phase, VGGNet was deployed based on attention mechanism In 2021, Hao *et al.* [25] introduced a unified DL approach for assessing bone age. Initially, image segmentation and annotation was done, and then background exclusion was done. Subsequently, Re-NN was designed for forecasting the bone age. Investigational assessment of hand radiograph demonstrated the reasonable performances of developed scheme in evaluation over extant DL schemes for assessment of bone ages. In 2020, Wibisono *et al.* [26] presented a new multi-modal data fusion-learning network, known as RT-FuseNet, for assessment of bone ages by deploying texts and radiographs. Particularly, a CNN was developed to guarantying the reliability of the image space data and for enhancing the fine differences of features amongst radiographs correspondingly.
In 2020, Booz *et al.* [27] proposed RB-FCL from crucial segmented area of hand x-ray. The DL schemes were treated as feature extraction for all regions of hand bone. Finally, the MAE resultants were found to be superior to extant schemes. In 2017, Lee *et al.* [28] investigated the efficiency and accuracy of new AI software for automatic BA evaluation in evaluation over GP technique. Here, the new AI software facilitated high precise automatic BA evaluation that improved efficiency with higher accuracy.
In 2019, Hirvasniemi *et al.* [29] proposed an innovative technique for assessing the capability of bone texture variables for predicting incident rHOA in 10 year epoch. Here, Elastic net was exploited for predicting the occurrence of rHOA after ten years. Finally, performance examination was done and the supremacy of the adopted approach was proven. In 2021, Li *et al*. [30] proposed a DL oriented CAD technique for carrying out bone age estimation. Firstly, localization depending upon an entire unsupervised learning technique was done and then, an image model was deployed for enhancing the consistency of prediction. At the end, minimal MAE was accomplished by developed scheme over extant ones.

III. Extensive Review on Implemented Schemes

A. Review on various schemes

The performance metrics measured in diverse contributions concerning the BAA is portrayed in this section. The review on adopted techniques in each work is discussed, and the illustration is exposed in Fig. 1. Here, ML as well as DL based approaches were exploited in majority of the works and we have made an analysis on both ML and DL schemes individually. Initially, DL based faster RCNN based scheme was used in [1] [2] [3] [26] and CNN based method was adopted in [4] [5] [6] [14] [28]. In addition, Ranking CNN was adopted in [7] and RT-FuseNet was used in [25]. Furthermore, DNN based methods were used in [8] [12] [18] [19] and DCNN based technique was exploited in [10] [21] [22] [23]. Moreover, ResNet based scheme was adopted in [9] [15] [24]. In addition, MLP based model was deployed in [30]. Accordingly, ML based schemes like FCM was adopted in

[13] and Elastic net model was adopted in [29]. Moreover, other models like GP were deployed in [11] [17] [27], Marching Cubes Method and WT model were adopted in [16] and [20] correspondingly.

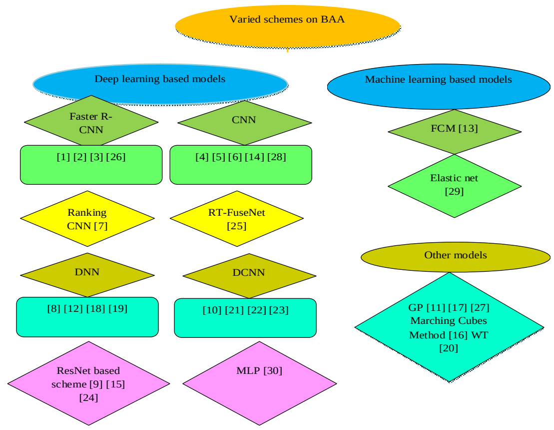

Fig. 1. Pictorial representation of various techniques adopted for BAAComprehensive review on varied Performance metrics

IV. Analysis on Performance Measures

The performance metrics measured in diverse contributions concerning BAA is depicted in Table I. From Table I, it is noticed that the analysis on MAE have been done in majority of works (around 19 works) and 16 works have made analysis on accuracy. 7 papers have made a performance study under RMSE and 3 papers analysed MAD, which have offered about 23.33% and 10% of the reviewed works. Similarly, sensitivity, time, loss, MSE and MAPE have contributed about 6.67% (2 papers), 6.67% (2 papers), 13.33% (4 paper), 13.33% (4 paper) and 3.33% (1 paper). Further, correlation and precision have been adopted in 6.67% (2 papers each).

TABLE I. Review On Different Performance Metrics For BAA Schemes

Citations	MAE	Accuracy	RMSE	MAD	Sensitivity	Time	Loss	MAPE	Correlation	MSE	Precision	Others
[1]	✓											✓
[2]	✓	✓										
[3]	✓	✓										
[4]	✓											✓
[5]	✓		✓									
[6]	✓											
[7]	✓	✓										
[8]	✓	✓	✓			✓						
[9]	✓											
[10]	✓	✓					✓					
[11]									✓			✓
[12]		✓	✓	✓								
[13]		✓				✓				✓		✓
[14]	✓									✓		
[15]	✓	✓										
[16]												✓
[17]	✓		✓									
[18]	✓	✓										
[19]		✓					✓					
[20]							✓					
[21]		✓										✓
[22]				✓	✓							✓
[23]	✓						✓					✓
[24]	✓	✓	✓									
[25]	✓	✓										
[26]	✓		✓					✓				
[27]				✓					✓			✓
[28]		✓	✓								✓	
[29]		✓			✓					✓	✓	✓
[30]	✓	✓								✓		

A. Analysis on Chronological review

The analysis regarding chronological review is depicted in Fig. 2. From Fig. 2, it is noticed that 8 papers (i.e. 26.67%) has been deployed between the years 2021-2020 and 16 works (i.e. 53.33%) has been deployed between the years 2019-2017. In addition, around 16.66% of the exploited works were published between 2016-2015 and 3.33% of the exploited works were published between 2014-2013.

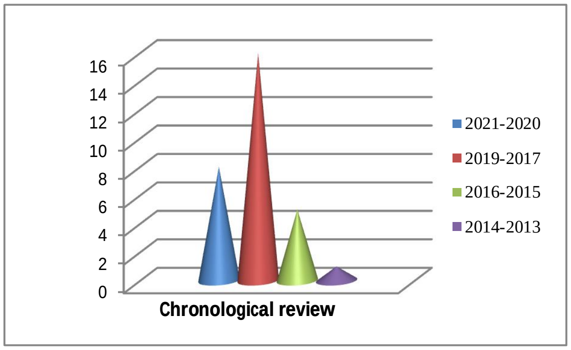

Fig. 2. Bar graph representation showing the chronological analysis

V. RESEARCH GAPS

BAA was dynamically explored currently, since it aids in identifying the existence of discrepancies in the bone age of child as well as adults. Image segmentation holds a major role in BAA, and it becomes essential for segmenting the images for precise analysis. Image segmentation divides the digitalized images into non-overlapping areas, and every segment differs from features of intensity, texture, and color [5] [8] [1].

Accordingly, segmentation of images in a manual way was exploited in BAA evaluation, and the effectiveness of resultants differed from single radiologist to another. This might generate uncertainties during analysis, and this paved the way for the advancement of automatic segmentation schemes [25] [15]. Certain manual techniques consist of TW2, G&P, etc and these schemes were booming in image segmentation and the features from segmentation are given to classifier for estimating ages. In spite of this, the easiness of use offered by these schemes was not effectual in offering acceptable performance for longer term research and usage. Owing to these drawbacks, the analysts concerned on the usage of DL schemes for assessing BAA. DL is a capable scheme since it offers effectual categorization; however, there is limit of input for assessing age [1].

VI. CONCLUSION

This work has presented a wide-ranging review on BAA models. Diverse works were reviewed and their performances were portrayed. Moreover, this survey analyzes varied DL and ML approaches related to BAA systems. In conclusion,

- This work has reviewed around 30 research papers and explained the noteworthy analysis on varied ML and DL based BAA schemes.
- The review has analysed different techniques and varied performance measures exploited in each works.
- Further, the chronological review of all considered works were analysed and the future gaps was also represented in brief.

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