BONE AGE ASSESSMENT USING ENHANCED K-MEANS AND CNN

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***Abstract*: Bone age is an important pointer for the diagnosis and timing of different diseases and the main scope of an assessment of bone age is to determine growth and development and in addition to that used to diagnose and treat childhood diseases mainly with the use of X-ray images. The main reason for this BAA is to know how the bone grows when the child develops. Segmentation of the hand bone is mainly needed at this point to explain the properties of the hand bone in detail in medical records with x-ray images. The newly developed lightweight multi-scale U-Net convolution neural network is used with the use of x-ray images in a previous study for the betterment analysis of BAA. This approach is limited to segmentation maps in pixel forms and it has been addressed by developing a new model based on profound education that considers the field of interest within and outside the field and the dimensions of the borders during the training using K-mean clustering algorithms as a pre-segmentation constraint. The children lightweight hand bone design is based on U-Net architecture it has achieved promising segmentation results, especially for segmentation of small bones of the hand for BAA.**
Keywords - BAA, U-Net, K-mean clustering.

I. INTRODUCTION

The term "Mining" is generally the process of extracting some valuable material from the earth such as coal mining, diamond mining, etc. "Data Mining" refers to extracting useful information from a bulk of data or data warehouses in the context of computer science. One can see that the term is somewhat confusing itself. The result of the extraction process is coal or diamond mining. But the result of the extraction process is not data in the case of Data Mining!! Rather, the result of data mining is the patterns and knowledge gain at the end of the process of extraction. In that context, Knowledge Discovery or Knowledge Extraction is also known as data mining. The data gathered from Data Mining helps to predict hidden patterns, future trends and behaviors and enable businesses to make decisions. Functionally, data mining is the process of data analysis from different perspectives, dimensions, angles and categorization / summarization into meaningful information. Data Mining can be used for any data type, e.g. Data Warehouses, Transactional Databases, Relational Databases, Multimedia Databases, Space Databases, Databases of the Time Series, World Wide Web. Three primary stages of data mining are 1) Pre-processing of data–Data is cleaned, integrated, selected and transformed, 2)Data extraction–Exact information mining occurrence and 3)Data evaluation and presentation–Analysis and presentation of outcomes

Image processing in some sense dates back to the most basic human utilize of graphics. Process prices were quite high, that modified within the seventies once digital image process became accessible as cheaper computers and dedicated hardware. The digital imaging with numerous techniques has become the foremost fashionable variety of image process with the fast computers and signal processors out there within the 2000s and is typically utilized on account of it's not solely the foremost versatile technique however additionally the most affordable. Themes like median filtering were exciting recent study subjects within the period of time. All the way through the last four to 5 centuries, numerous strategies are created in image process. Digital imaging technique permits reversible, nearly noise-free alteration of an image within the variety of an integer matrix rather than classical room manipulations otherwise filtration of time-dependent voltages needed for analog pictures and video signals. Though several image process algorithms are tremendously robust, activities on digital pictures are usually applied by the typical client without fear for the elemental values behind these manipulations. The images ensuing from lackadaisical manipulation are usually considerably corrupted or otherwise broken with relevancy people who might be generated if digital process software's authority and flexibility were utilized properly. Image segmentation is the most fundamental and significant component of image processing, segmenting a picture into significant fields according to certain features such as gray level, spectrum, texture, color, etc. The objective of image segmentation is to divide a picture into a set of disjoint areas with uniform and homogeneous characteristics such as intensity, color, tone or texture, etc. Nontrivial image segmentation is one of the most challenging tasks in image processing. The' discontinuity' strategy is to segment the picture, as edged in the pictures, based on abrupt change in intensity. The second method is based on certain predefined criteria for partitioning pictures.

Bone Age Assessment (BAA) is employed to judge radio logically from their hand and neck x-ray appearances the biological and structural maturity of immature patients. In children with development and endocrine disorders, it forms a big facet of the diagnostic and management method. It's helpful within the designation of various growth disorders and may give patients with short stature with a forecast of ultimate height. Bone age calculation is additionally accustomed estimate chronological age below circumstances wherever there are not any precise birth records. In our portion of the world, missing birth data could be a giant issue. Sixty fifth of all births in South Asia don't seem to be recorded by the age of five years (Smithand Brownlees, 2011). Thus, age estimation needs being precise in circumstances wherever a child's age must be precise, like throughout immigration, lawsuits and competitive sports. Age is employed in these instances to produce the closest age estimate.

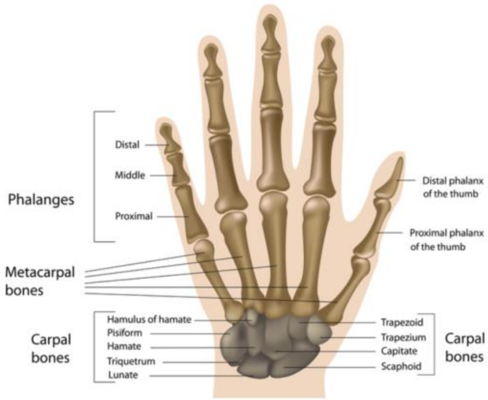

Figure 1.1 Bones of a human hand and wrist (Human Anatomy library, 2017)

As well, the bones of the skeleton change in size and shape during the development of the organism, and thus a distinction between the allocated bone of a child and chronological ages could show a issue of growth. Clinicians have used the evaluation of bone age to assess the maturity of the skeletal system of a child. Bone age evaluation techniques generally begin by taking from the wrist to the fingertips a single X-ray picture of the left side, see Figure 1.1. In a uniform bone development atlas, bones in the X-ray picture are likened to radiographs. Such atlases of bone age are based on big amounts of radiographs gathered from the same sex and age kids.

II. LITERATURE SURVEY

Medical image segmentation has two-dimensional (2D) or three-dimensional (3D) image automatic or semi-automatic detection. Image segmentation is that the manner a digital image is split into a numerous set of pixels. The segmentation's primary objective is to alter stuff and switch medical image illustration into a significant topic. Thanks to the high variability of the photographs, segmentation may be a tough task. Additionally, several variant modalities, together with CT, X-ray, MRI, microscopy, anti-electron emission pictorial representation, single photon emission computer imaging, build segmentation laborious. The challenge is to phase areas with missing edges, lack of different texture, region of interest (ROI), and background. Several segmentation strategies were steered with promising outcomes to report these issues.

Strumia, Maddalena, Frank R. Schmidt, Constantinos Anastasopoulos, Cristina Granziera, Gunnar Krueger, and Thomas Brox. "White matter MS-lesion segmentation using a geometric brain model" - 3D disseminated sclerosis is calculable on the premise of an adaptive geometric brain technique for lesion segmentation. They created the model of the topological properties of the lesion and also the brain tissue to limit the lesion segmentation to nervous tissue for the independence of the imaging atlas.

Subbanna, Nagesh K., Deepthi Rajasheka, Bastian Cheng, Götz Thomalla, Jens Fiehler, Tal Arbel, and Nils Daniel Forkert. "Stroke lesion segmentation in FLAIR MRI datasets using customized Markov random fields." - a completely unique technique is made and assessed for segmenting sub-acute ischaemic stroke lesions from information sets for magnetic resonance imaging (MRI) fluid-attenuated reversal recovery (FLAIR). A Bayesian technique supported Gabor textures extracted from the aptitude signal intensities is employed once the preprocessing of the info sets to get a primary estimate of the segmentation of the lesion. A tailored Markov random field model supported intensity and Gabor texture characteristics is employed to refine the segmentation of the stroke lesion victimization this original segmentation.

Ashwani Kumar Yadav, Ratnadeep Roy, Rajkumar, Vaishali, and Devendra Somwanshi, "Thresholding and morphological based segmentation techniques for medical images" - during this job, supported thresholding and morphological strategies, a recent algorithmic program for segmenting magnetic resonance imaging and CT image was advised. On Brain MRI and CT imaging, the advised algorithmic program was confirmed. The advised technique has been shown to be higher than this strategies. Supported performance parameters like completeness and correctness, this verification is performed.

Liu, Xiaoyun, and Fen Chen. "Automatic segmentation of 3-d brain mr images by using global tissue spatial structure information." - Offered 3-layer Gaussian mixture model algorithm and Expectation Maximization algorithmic program for tissue segmentation of three-dimensional MR brain picture victimisation structural abstraction information. It utilizes distinct GMMs to model information on intensity, information on abstraction structure, and vector perform intensity-space, severally. Here, the brain tissue segmentation task is enforced by increasing the 3L-GMM model's a posteriori chance.

Mahdi Hajiaghayi Elliott M. Groves, Hamid Jafarkhani and Arash Kheradvar,"A 3D Active Contour Method for Automated Segmentation of the Left Ventricle from Magnetic Resonance Images", - In thirty three topics with heterogeneous cardiovascular disease from the York University information, a completely unique 3D active contour technique was wont to establish the left ventricular cavity. A biconvex hull of the heart ventricle and interpolation were wont to establish and add papillary muscles to the chamber. The heart muscle was then divided consistent with anatomical knowledge employing a comparable 3D segmentation technique. To work out the effectiveness of the tactic, a multi-stage technique was taken.

Peyman, Sabouri, and Hamid Gholam Hosseini, "Lesion border detection using deep learning" CNN is recommended on clinical picture for border detection of skin lesion. This document reports on the identification of lesion border clinical picture to differentiate the first lesion from the normal skin context. Planned a convolutionary neural network for border detection.

Zhipeng Cui, Jie Yang, and Yu Qiao, "Brain MRI segmentation with patch-based CNN approach" A contemporary patch-based methodology is recommended to use convolutionary neural network (CNN) to mechanically phase brain imaging. 1st of all, each brain imaging obtained from a small a part of the government dataset is split into patches. Of these patches are then used for CNN coaching, that is employed for automatic brain imaging segmentation.

Li Yu, Yi Guo, Yuanyuan Wang, Jinhua Yu, and Ping Chen, "Segmentation of Fetal Left Ventricle in Echocardiographic Sequences Based on Dynamic Convolutional Neural Network" For the segmentation of foetal cardinal, a dynamic convolutionary neural networks (CNN) is usually recommended supported multiscale knowledge and fine standardisation. The CNN is pretrained by the number of coaching knowledge that has been marked. The primary frame of every echocardiographic sequence is manually delineate within the segmentation. So as to adapt to the individual craniate, the vibrant CNN is ok tuned by deep standardisation with the primary frame and shallow standardisation with the remaining frames severally. Additionally, the bicuspid valve (MV) base purpose trailing is employed to differentiate the link region between cardinal and left atrium of the heart (LA), an identical technique consisting of block matching and line matching. Compared to an active contour model (ACM), a dynamic appearance model (DAM), and a hard and fast multi-scale CNN method, the benefits of the instructed technique.

Ajala Funmilola A et. al.,"Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation" Their analysis focuses totally on clustering, especially on k-means and c-means clusters. These algorithms are combined into another technique referred to as "fuzzy k-cmeans clustering," that is longer intense.

III. ANALYSIS OF BAA SYSTEM

The Bone Age Assessment (BAA) could be a pediatric radiological examination to see any discrepancy between a child's skeletal age that's the age of their bones and age that's in years from the date of birth. Pediatricians these days have depended for > seventy five years on techniques to see skeletal maturation. Pediatricians got to be acutely aware that skeletal maturity assessments currently have broader applications, starting from alternative of elite sports and forensics to programs for world immigration. For example, several asylum seekers are required to expertise an age survey which will govern placement and resource access. Bone age is a sign of a personality's skeletal and biological development. This can be distinct from the written record era calculated victimization a personality's date of birth. Pediatricians and endocrinologists typically raise age to be compared with chronological age for the designation of sicknesses that end in youngsters of high or short stature. Serial measurements are accustomed appraise the effectuality of those diseases interventions.

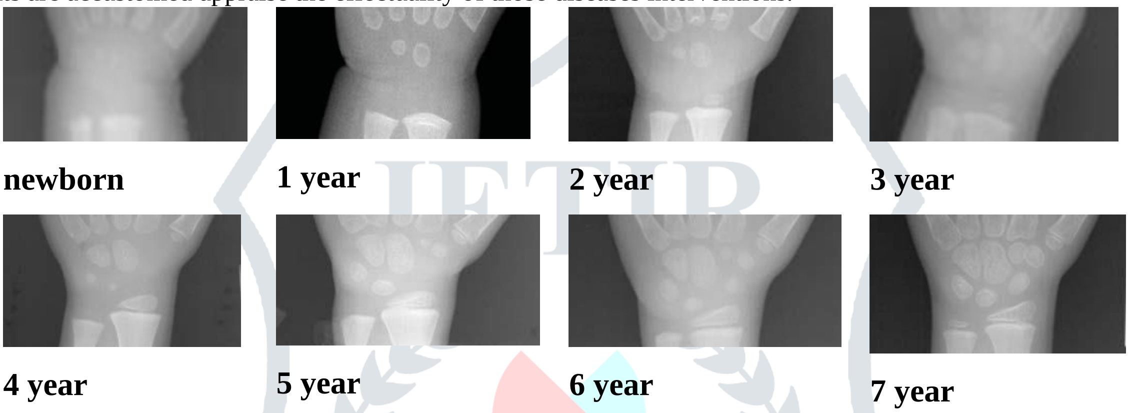

Figure 3.1 Growth patterns of carpal bones from newborn to 7-year-old

Methods For Bone Age Assessment

1. Basic Segmentation of Bone image using k-means clustering

K-means application is to segment the picture into K clusters and the method includes some measures to divide input picture data into the complete amount of clusters. The K-means algorithm could usually work with samples on an ongoing basis; furthermore, it can act as discrete data (Mignotte, 2008). The method k-means allows a collation between each line value to create the clusters and classify the samples where the line is based on range measurements. The algorithm calculates the centroid on each of the clusters following the initial distance calculation. The X-ray picture will be grouped into two and three regions with the K-means unsupervised clustering technique representing bone, soft tissue area and bone, soft tissue region and background with' K' value equal to two and three concurrently. Integration of this clustering method is performed through optimizing an objective function to reduce a squared error function which can be seen in equ.(3.1) in this situation.

$$\sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^j - c_j\right\|^2 \qquad (3.1)$$

2. CNN Method

CNN image classification captures, processes and classifies an input picture under certain categories (e.g., dog, cat, tiger and lion). Computer systems view an image input as a pixel array and it varies on the resolution of the picture. It would see $h \times w \times d$ (h= Height, w= Width, d= Dimension based on the image resolution). For example, a picture of $6 \times 6 \times 3$ RGB matrix array (3 relates to RGB values) and a gray picture matrix array of $4 \times 4 \times 1$ as shown in Figure 3.2. Theoretically, each input picture will pass through some kind of sequence of convolution layers with filters (Kernals), pooling, completely linked layers (FC) and use Softmax to classification an object with probabilistic values from 0 to 1. The figure 3.3 is a full CNN flow for processing an input picture and classifying items based on values.

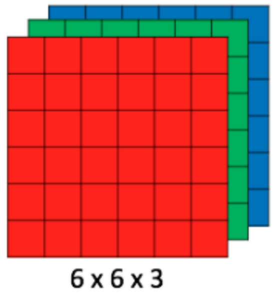

Figure 3.2. Array of RGB Matrix

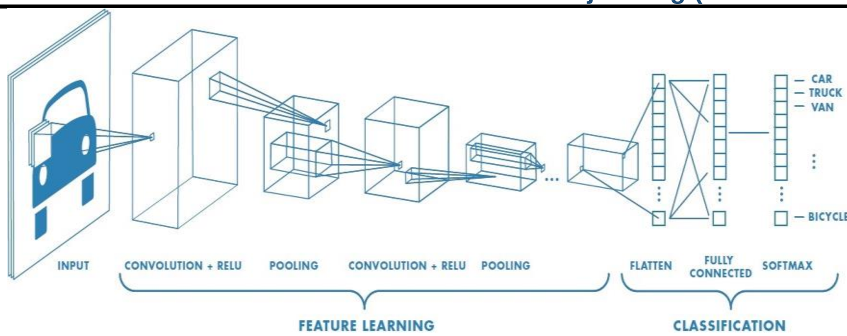

Figure 3.3. Neural network with many convolutional layers

3. Convolutional Neural Network Based Segmentation

Convolutional Neural Network is described as a graph that is directed. The nodes match the pixels of the image and the edges match the filters. CNN is a multilayer perceptron (MLP) specifically intended to acknowledge two-dimensional shapes with a large degree of translation, scaling, skewing, and other types of distortion invariance. By using weight sharing, the Convolutional Neural Network can be implemented in parallel form. The reduction in the quantity of free parameters is achieved by using weight sharing. This reduces the capacity of machine learning, which in turn increases the generalization capacity of the machine. Adjustments to the network's free parameters are produced using the teaching of back propagation stochastic mode. CNN learning has two fold advantages. It can learn complicated, high-dimensional, nonlinear mapping with the previous understanding of the pictures. Second, the syntactic weights and bias levels can be learned. The Convolutional Neural Network input is the raw EM input picture and the Convolutional Neural Network automatically detects the picture characteristics. CNN is taught through the online learning algorithm of stochastic gradient descent and tailored to fresh settings. The output of the Convolutional Neural Network gives two images. The affinity graph is built from the corners using the affinity feature. Partitioning a Connected Components Threshold Affinity Graph. Connected components (CC) are a very simple graph partitioning technique. More advanced algorithms, such as spectral clustering or graph cuts, may be more robust to misclassify one or several corners of the graph of affinity. The benefit of this algorithm for graph partitioning is its simplicity. Our course of action. A better outcome is the combination of the associated component algorithm with the affinity graph acquired from the Convolutional Neural Network

4. Lightweight U-Net Architecture

For greater segmentation precision, the amount of down-sampling and up-sampling activities in pyramid shape networks relies on the particular issue. Hence, various amount of U-Net architecture down-sampling and upsampling activities is compared to discover a particular lightweight network framework for hand bone segmentation. Figure 3.3 illustrates the initial U-Net (U-Net4) accepted for Input image size is 256* 256. It comprises of consecutive implementation of two 3x3 convolutions (unpadded convolutions), each accompanied by a linear rectified unit (ReLU) (Nair and Hinton, 2010) and a 2x2 max downsampling procedure with stride 2. Each phase in the extensive path consists of a feature map upsampling followed by a 2x2 convolution ("up-convolution") halving the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each accompanied by a ReLU.

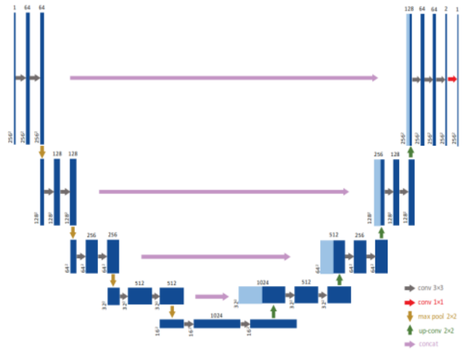

Figure 3.4. U-Net architecture down- sampling and up-sampling operations

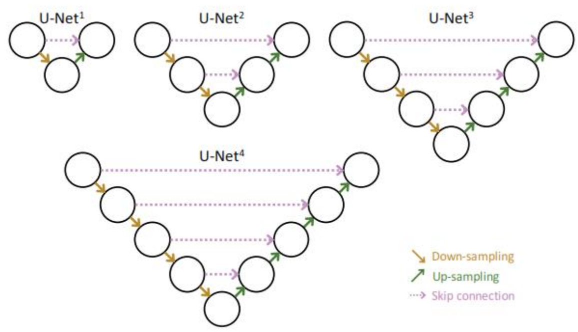

Figure 3.5. Different Number of down-sampling with 4 and up-sampling operations U-Net architectures

To map each 64-component feature vector to the desired number of classes, a 1x1 convolution is used at the final layer. Various U-Net architectures contrasted with distinct down sampling and up sampling activities (Figure 3.4 and Figure 3.5) and U-Net (Zhou et al., 2018) for the same hand bone segmentation assignment and discovered that U-Net^2 could achieve ideal efficiency

5. Multi-Scale Network Architecture

A multi-scale convolutional neural network (msCNN) have developed based on the U-Net2 architecture to know the density maps from hand bones of distinct dimensions (Zeng et al., 2017). The first convolution layer is a traditional 9-99 kernel-size convolution layer to restore the image feature. Multi-Scale Blob (MSB) is used as an Inception-like model (Figure 3.18) composed of various filters with distinct kernel sizes (including 3, 5, 7, 77 and 99). In addition, to assess the segmentation efficiency with MSB, the MSBs taken in this network were substituted by single kernel dimensions (including 3regional, 5regional, 7regional and 9regional) and the segmentation outcomes were tested individually for 4 single kernel size networks. The energy function is calculated in combination with the dice coefficient loss function through a sigmoid activation function over the final feature map. The coefficient of dice is described as follows in equ.(3.1):

$$\frac{2 * S_1 * S_2}{S_1 + S_2} \qquad (3.1)$$

where S_1 is the segmentation result and S_2 is the groundtruth.

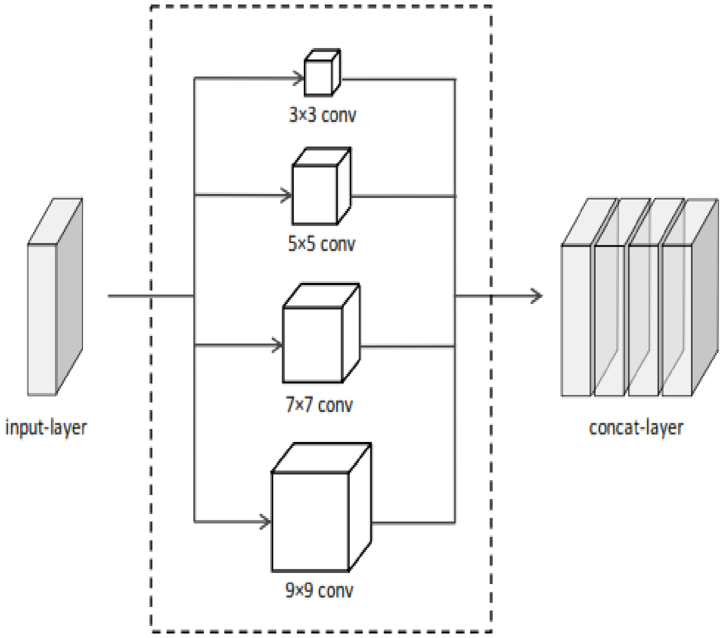

Figure 3.18. Multi-scale block with different kernel size

V. RESULTS AND DISCUSSION

Digital Hand Atlas Database System(Gertych et al., 2007), a government and detailed X-ray dataset for automated bone age benchmarking, conducted an evaluation of the segmentation precision of the proposed network outlined in the prior chapter. The dataset includes 1391 left-hand X-ray scans, separated by gender and ethnicity, of kids up to 18 years old. Each X-ray scan is given by two specialist radiologists with two bone age values. In order to assess the segmentation efficiency of tiny hand bones, pictures of kids over 7 years of age are excluded in this experiment as children's tiny hand bones begin to fuse together as they are 8 years of age. Eventually, here used 429 X-ray images of kids from birth to 7 years of age and randomly divided the dataset into training sets (252 pictures), validation sets (89 pictures), and test sets (88 pictures), instead of patient overlap.

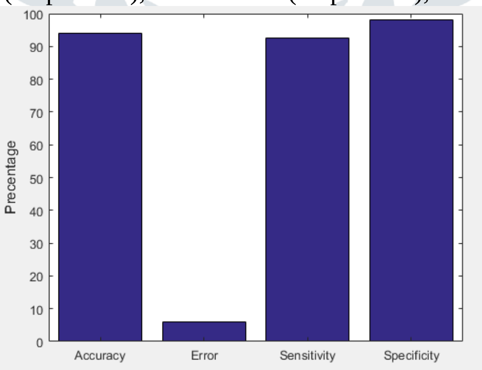

Figure 4.1. The Results of small bones of the hand of CNN with U-Net based network architectures

As indicated in Figure 4.1, on bone pictures, the suggested technique achieves a greater accuracy, sensitivity, specificity and low error art. CNN's findings with U-Net are precision of 95%, sensitivity of 92%, specificity of 98% and mistake of 8%. Improving segmentation efficiency with CNN with U-Net has been assessed to replace Multi-Scale Blob (MSBs) with distinct single kernel dimensions, showing that CNN with U-Net achieves better efficiency than single kernel size networks.

VI. CONCLUSION

Eventually, a lightweight U-Net architecture with k-means is implemented in this work as a multi-scale Convolutional network for pediatric hand bone segmentation in X-ray image, as well as exciting segmentation findings have been accomplished, particularly for the segmentation of small hand bones. As of final statement, k-means methods currently continue the gold standards for evaluating BAA. The k-mans used as the proposed pre-segmentation method to mitigate the triggers of inaccuracy by taking care to recognize X-ray quality. In addition, suggesting an appropriate positioning of the hand is essential as poor decision making can change the appearance of small born bones. It is therefore advantageous to use k-means with U-Net methods in years and months to use these strategies and test scores instead of BAA. Furthermore, consideration is given to possible variations in maturation between distinct populations.

There are several subsidiaries in the future direction of this studies. Intellectually stimulated in this part is modified U-Net to maintain the suggested model's amount of parameters similar to that of the U-Net model. Furthermore, it wants to perform experiments in the future to evaluate more comprehensively the best set of hyper constraints for the model. In addition, you would also like to assess the efficiency of the model on medical images from many other outcome measures. In addition, there is an interest in dealing with the suggested model by implementing several pre-processing and post-processing systems particular to the domain and implementation with swarm intelligence techniques.

VII. REFERENCES

1. Maddalena Strumia, Frank R. Schmidt, Constantinos Anastasopoulos, Cristina Granziera, Gunnar Krueger, and Thomas Brox “White Matter MS-Lesion Segmentation Using a Geometric Brain Model” in IEEE Transactions on Medical Imaging, Vol: 35, Issue: 7, pp 1636 – 1646, 2016.

2. Subbanna, Nagesh K., Deepthi Rajasheka, Bastian Cheng, Götz Thomalla, Jens Fiehler, Tal Arbel, and Nils Daniel Forkert. "Stroke lesion segmentation in FLAIR MRI datasets using customized Markov random fields." Frontiers in neurology 10 (2019): 541.

3. Ashwani Kumar Yadav, Ratnadeep Roy, Rajkumar, Vaishali, and Devendra Somwanshi, “Thresholding and morphological based segmentation techniques for medical images”, in International Conference on Recent Advances and Innovations in Engineering (ICRAIE), pp 1 – 5, 2016.

4. Liu, Xiaoyun, and Fen Chen. "Automatic segmentation of 3-d brain mr images by using global tissue spatial structure information." IEEE Transactions on Applied Superconductivity 24, no. 5 (2014): 1-5.

5. Mahdi Hajiaghayi Elliott M. Groves, Hamid Jafarkhani and Arash Kheradvar,”A 3D Active Contour Method for Automated Segmentation of the Left Ventricle from Magnetic Resonance Images”, in IEEE Transactions on Biomedical Engineering, Vol: 64, Issue: 1, pp. 134 – 144, 2017.

6. Peyman, Sabouri, and Hamid Gholam Hosseini, ”Lesion border detection using deep learning” in 2016 IEEE Congress on Evolutionary Computation (CEC), pp. 1416 -1421, 2016.

7. Li Yu, Yi Guo, Yuanyuan Wang, Jinhua Yu, and Ping Chen,”Segmentation of Fetal Left Ventricle in Echocardiographic Sequences Based on Dynamic Convolutional Neural Network”, in IEEE Transactions on Biomedical Engineering, Vol: 64, Issue: 8, pp. 1886 – 1895, 2017.

8. Li, Bing Nan, et al. "Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation." Computers in biology and medicine 41.1 (2011): 1-1

9. Ajala Funmilola A et. al.,“Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation”. Journal of Information Engineering and Applications, ISSN 2224-5782 (print) ISSN 2225-0506 (online) Vol 2, No.6, 2012.

10. M. Mignotte, ‘‘Segmentation by Fusion of Histogram-Based K-Means Clusters in Different Color Spaces," in Proc. IEEE Trans. Image Processing, Conf., Vol. 17, pp. 780-787, May 2008.

11. A. Gertych, A. Zhang, J. Sayre, S. Pospiech-Kurkowska, and H.K. Huang, "Bone age assessment of children using a digital hand atlas," Computerized Medical Imaging and Graphics, vol. 31, no.4-5, pp. 322-331, 2007.

12. A. Norouzi, A. Rahman, M. Shafry, and T. Saba, “Visualization and segmentation,” Int. J. Acad. Res., Vol. 4, no. 2, pp. 2028, 2012.

13. Aganj, Iman, Mukesh G. Harisinghani, Ralph Weissleder, and Bruce Fischl. "Unsupervised medical image segmentation based on the local center of mass." Scientific reports 8, no. 1 (2018): 13012.

14. Ali, Mumtaz, Mohsin Khan, and Nguyen Thanh Tung. "Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices." Expert Systems with Applications 91 (2018): 434-441.

15. Ambrosini, Pierre, Daniel Ruijters, Wiro J. Niessen, Adriaan Moelker, and Theo van Walsum. "Fully automatic and real-time catheter segmentation in x-ray fluoroscopy." In International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 577-585. Springer, Cham, 2017.

16. Bullock, Joseph, Carolina Cuesta-Lázaro, and Arnau Quera-Bofarull. "XNet: a convolutional neural network (CNN) implementation for medical x-ray image segmentation suitable for small datasets." In Medical Imaging 2019: Biomedical Applications in Molecular, Structural, and Functional Imaging, vol. 10953, p. 109531Z. International Society for Optics and Photonics, 2019.

17. Chen, Cheng, Weiguo Xie, Jochen Franke, P. A. Grutzner, L-P. Nolte, and Guoyan Zheng. "Automatic X-ray landmark detection and shape segmentation via data-driven joint estimation of image displacements." Medical image analysis 18, no. 3 (2014): 487-499.

18. Huafeng Liu, Ting Wang, Lei Xu, and Pengcheng Shi," Spatiotemporal Strategies for joint Segmentation and Motion Tracking from Cardiac Image Sequences", in IEEE Journal of Translational Engineering in Health and Medicine, Vol: 5, 2017.

19. Kuok, Chan-Pang, Min-Jun Fu, Chii-Jen Lin, Ming-Huwi Horng, and Yung-Nien Sun. "Vertebrae Segmentation from X-ray Images Using Convolutional Neural Network." In Proceedings of the 2018 International Conference on Information Hiding and Image Processing, pp. 57-61. ACM, 2018.

20. Mohammadi, Hossein Mahvash, and Jacques A. de Guise. "Enhanced X-ray image segmentation method using prior shape." IET Computer Vision 11, no. 2 (2016): 145-152.