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A Novel Framework for Cloud Based Bone Age Assessment Integration System: Review and Analysis

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ABSTRACT
Bone age assessment (BAA) is a task performed on radiographs in hospitals to estimate the age of a skeletal, to predict the final adult height, to diagnose of growth disorders through monitoring skeletal development. The next generation of bone age system should be portable, mobile and more accurate with better usability. Hence, to meet these requirements, a new framework is proposed that builds cloud enabled bone age assessment system. This framework shows device to device communication models, network cloud layer structures and image processing algorithms which meets the requirement such as mobility, portability and high accuracy. The paper also explores answers to many questions that may arise, regarding the image diagnostic quality produced/ rendered or whether it can be used as per radiology standards and other critical requirements.

Keywords: Bone age assessment test, cloud computing, interoperable API, medical image processing, requirement analysis**.**

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I. INTRODUCTION

Large number of measurements underlying bone age assessment needs careful calibrations, especially in computing the coefficients of variation. Since, there are many methods of calibration for bone age assessment such as Tanner-Whitehouse (TW), Greulich and Pyle (GP), Point Distribution Model (PDM) [**1**,**2**], Experts have the fixed standard deviation in each case and software concerning these calibrations must confirm to such specifications. The specifications ensure the assessment of following aspects of bone age.

- Finding the rate of change in dimensions of bones between the visits of the subjects and correlate the dimensions with maturation age of the subject. The rate of change must not suffer from inter-rater variability problems [**3**], and random error must remain below 0.58 standard deviation [**4**].
- Assessment of child's growth or delayed maturation with lowest possible error. [**5**] [**6**] [**7**]
- Prediction of adult height [**8**].

It is apparent now that the automation of bone age assessment process is necessary because of inter-rater agreement, disagreement, unreliability and validity of manual results of bone age assessment [**9**]. The degree of stability of observations in this context can be increased by building distributed cloud based system for bone age assessment [**4**]. This system can serve the geographically distributed doctors to conduct standardized bone age test and data collected can be checked for inter as well as intra reliability and validity of the observations. This way, the validation can be done so as to verify the degree to which the results obtained by measurement procedures are replicable against the ground truth. Moving ahead logically, the result can only be valid if and only if the automatic methods of bone age assessment are accurate especially in context of image processing algorithm measurements and detecting bone related diseases. Therefore, this paper has been organized in such a manner that it illustrates building elements required for developing it. Most of the existing cloud based bone age assessment systems have high value preposition in terms of the ease of usage, the navigability and standardized algorithm for bone age measurement. The facilities are managed through the internet back bone and the cloud services are provided through different services to the medical consumers. Figure 1 illustrates the various layers of proposed system. Table [1] lists the main requirements or specifications necessary for developing the cloud based bone age assessment system.

Table 1.Requirement Analysis

S.No.	Features	Requirements
1	Sensors observation	X-ray images [**10**] [**11**] [**3**]
2	User types	Doctors/Patients
3	Consumption mode	Event base, contact, conditional
4	Persistency	Structured , Cloud based Storage
5	Format	Data Streaming , XML, DICOM
6	Standard	HL7 [**12**] [**13**],FHIR [**13**] [**14**] [**12**], DICOM
7	Data Integrity	Must be maintained , relaxed in case of unstructured formats
8	Fault tolerance	High level
9	Output rate, real time analysis	High, hard/firm, as the system will work for multiple hospital
10	QoS	High in medical field as there is no chance of error.
11	Reliability	High, no room for false alarm rate
12	Availability	24x7 Hospital Working Hours
13	Scalability • Consumer to producer • Producer to consumer	 • One to one, many to one, one too many, many to many. Producer to consumers • One to one, many to one, one to many, many to many. Producer to consumers
14	Privacy	High, must follow ethics of medical privacy
15	Security	High, HIPAA [**15**] Standard

As mentioned in the requirement analysis table, the output rates of such application and persistence storage of X-Ray images are going to be high. The analysis has been made to understand what needs to be done when there is a high growth in user population, transaction load as well as in the data volume and also to find, if there would be operational difficulties while running such systems (BAA). The analysis further shows that either there has to be a database that supports scalability through hardware upgrade, or read/write splitting operations.
Till date, U.S. Food and Drug administration organization (FDA) has legitimated the use of limited mobile devices for medical purposes. It has allowed viewing of the medical data generated from computer tomography (CT) [**19**] and magnetic resonance imaging (MRI) [**3**]. The decision in this regard was made on the basis of commendable performance of these heterogeneous portable devices. The quality of the image data produced by these portable devices follows the international guidelines in terms of luminance, image resolution and de-noising. The Section II discusses the various algorithms that may be used to ascertain the quality of "diagnostic" images produced using this technology.

II. TECHNOLOGY STACK FOR BAA SYSTEM

The medical images may require color balancing for attaining the required "diagnostic quality" in certain conditions. The acquired image values from electronic sensors (X-ray machine, scanning devices) must be transformed to the appropriate resolution, to make it possible for a radiologist to proceed with the study of the image data. For all the bone age assessment related measurements, accuracy is paramount. Therefore, the images may have to undergo color correction, white color balancing, de-noising, chromatic adaptation etc. Moreover, the medical image data is normally heavy in terms of bytes it holds. Hence, along with color correction, there is a need for fine tuning according to delay, jitter, bandwidth, encoding conditions of network at that time, especially, in case the data is being remotely steamed from a medical mobile device.

2.1. Mobile Technology Layer

This layer (Figure 1) needs to consist of logical group of portable medical equipment such as smart phones [**20**] that are used as medical devices for feeding patient information [**21**]. These portable x-ray or scanning machines should have rechargeable lithium polymer batteries. From current literature survey, it has been found that such machines may weigh as low as 5.5 pounds [**22**] [**23**]. These machines help to reduce the retakes of bone images and can be carried anywhere which makes them ideal for hospital, home-health, humanitarian and out-of-office use. Using hardware–software interfacing, these machines may be connected with the cloud technologies [**18**] to build an "Internet of Medical Things" [**24**]. These medical equipment can be connected to the internet either through radio or Wi-Fi [**17**] based technology framework using the communication models as mentioned in Section **Error! Reference source not found.**.

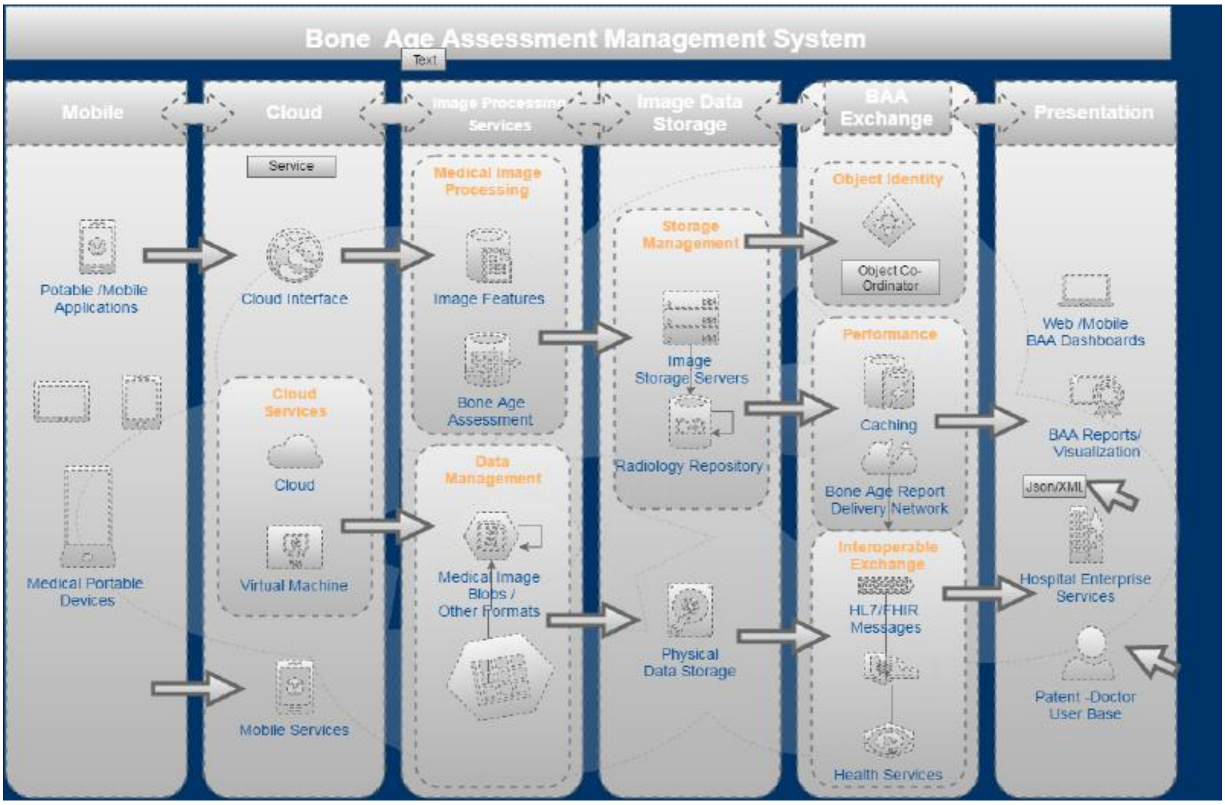

Figure 1. Bone Age Assessment System Layers

2.2 Cloud Interface Layer

The Cloud Interface layer should be composed of the service portal that connects various mobile medical devices. It means that it should have service dashboards which can manage remote medical sensors or equipment endpoints. This service interface will also be connected with the image processing and storage layers. A medical "transaction" in the medical cloud [**25**] is defined as an event that includes uploading and downloading medical data operations for offline usage and it may also have API calls [**26**] made from the Bone Age Assessment applications for completing the workflow of BAA.

However, it must be noted that there will be a need for optimizing the number of transactions that are performed. This can be done mainly by buffering and aggregating medical data and at the same time by making less frequent calls to the API.

2.3 Image Database Layer

Today, there is a plethora of database technologies and sheer number of implementations of the same concept of database management systems makes difficult to reach at a decision for its selection [27] . As mentioned in requirement analysis table, there is a need for scalable and fault tolerance features in database system with flexibility in design of structure of tables on the fly. The read/write operations must be able to support the heavy volume of both images and video medial data steaming on heterogeneous mobile devices [20].

The most suitable database for a system to be used by medium scale medical organization is PostgreSQL [**30**] and for a large scale organization, an advanced database like Cassandra [**32**] may be preferred.

2.4 Bone Age Assessment Exchange Layer

Mobile cloud technologies can only be realized, if the system is able to integrate location based services along with the exhaustive range of platforms and technologies that may be based on java, python, .NET, Ruby on Rails. The current solution in the market is to build a system having RESTful API function calls to render the data either in XML or JSON format. This full system, illustrated here, confirms to the health standards of message exchange, delivery, security, privacy and structure. The main benefit of using a RESTful service such as Python Django, Flask-Restful, Jersey, DropWizard, LoopBack is that, it is based on HTTP services and is virtually operational on almost all the platforms but Python (Django) based API would be most suitable for a small to mid-sized organization considering it is relatively easier to setup and maintain.

2.5 BAA Image Processing Layer

Since the attempt here is to put forward a cloud based bone age assessment system proposal, the Table **2** gives matrix that provides information on the possible features that may be put to use for building algorithm for pre-processing steps on the medical images. The table 3 provides a comparative view on the bone age assessment algorithms and the last part shows how some of the existing bone age algorithms may be improved.

Table 2. Image Features Table

S. No	Texture Model	Features that may be helpful in BAA
1	GLCM [**41**] [**7**]	It represents a matrix that have the co-occurrence of values at time given time within offsets range of gray scale values. Many studies show the use of these features to detection edges /cracks and change of texture in the bones for detecting Osteoporosis etc
2	High Order GLCM [**42**]	In this feature extraction the offsets all-encompassing through 180 degrees (i.e. 0, 45, 90, and 135 degrees) at the same distance are computed as used to differentiate between one type of ROI and second type of ROI.
3	SGLCM (Spatial Gray Level [**43**] Dependence Matrices)	Statistical properties of pixel pairs at several distances, within an image having different Gray Scales
4	Gray Level Difference Statistics [**44**] [**43**]	Statistics related to the differences in gray levels of the image. These statistics may include min, max, average gray difference.
5	Fractals Geometry [**45**] [**46**]	The fractal dimension of an image typically will have some correlation with type of Region of Interest (ROI). This feature can help us identify distinct bone tissue pattern for detecting bone related issues.
6	FoS [**47**]	Mean ,Variance , skewness , kurtosis
8	SFM [**48**] Statistical Feature Matrix	In this the main features include periodicity , contrast , roughness , Coarseness
9	FPS Power Spectrum (FPS) [**48**]	In this the main features include two features viz., radial sum and angular sum
10	Neighborhood gray Tone Difference [**49**]	Coarseness , Contrast , Business , Complexity and strength
11	Factual Difference Textual Analysis (FDTA)	Hurst Co-efficient H^{k} k=1,2,3,4
12	SURF, BRIEF, BRISK, FREAK [**50**]	Group of Features having similar principals as steps as SIFT for detecting local features of an image.

The BAA system should have in-built "Mathematical Ability Engine" that provides multiple ways to analyze the data. These capabilities need to have access to the mathematical graphical interface. This maths graph interface will be deriving its capabilities from python maths or Matlab libraries. The patients' medical image and demographic data can be processed on the fly whenever it is viewed. In this manner, image features' plots will also be generated and the frequencies will be filtered out, helping in an iterative analysis. However, it should also be noted apart from the afore mentioned features in Table 2, there is a need for building "computational" features based on distance between various bones from which clue on age of the subject may be computed. The gradual changes observed in the bone structure over time needs to be recorded as historical data, and the real time image data need to be compared to assess age. The changes in wrist bone, elbow bone need to be computed based on distance between reformer or anchor points. Some studies show the age of fusion of different types of hand bones (Table [3]) and "thickness of bone or cartilage" is used as a unit of measurement to assess the bone age. Using this fact bone age algorithms may be built [**52**].

Table 3. Bone Appearance Order [51**]**

S. No.	Appearance	Bone Description
1	1st Year	Capitate, H
		Harnate
		Cartilage
2	Fuse at puberty	Cartilage
3	2nd Year	Triquetral
4	3rd Year	Lunate
5	6th Year	Trapezium
		Scaphoid
6	12th Year	Pisiform

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The contemporary survey in this context can be summarized using Table 4 for understanding the methods required to build next generation BAA system.

Table 4. Review of Current Algorithms of BAA System

S. No.	BAA Methods	Description	Merit	Demerit
1.	Neural Network Classifiers Using Features of the RUS and Carpal Bones [**48**] [**59**] [**60**] [**61**]	Linear Regression Based Neural Network.	Easy and simple to implement with low overhead	Does not work with features that are non – linear in nature
2.	Neural Network Based on the Radius and Ulna [**48**] [**59**] [**60**] [**61**]	Linear Regression Based on Neural Network Logic	Difference is feature sets , the radius and Ulna act as better discriminator	Ignores the nonlinear dataset of features related to ulna, radius.
3.	Neural Network Analysis Based on the Epiphyses and Carpal Bones for bone age assessment [**48**] [**59**] [**60**] [**61**]	NN Back propagation, NN based Radial basis function and SVM [**62**] or Support vector machine	All methods have high level of accuracy. And SVM [**62**] has the lowest overhead.	Multiple layers of NN may add some level overhead.
4.	Automated Web Based System Using Histogram Method [**63**] [**11**] [**47**]	Using Histograms as features for identifying feature difference	Based on frequency values of the bone features, simple and easy to implement	May become slow , if histograms have large number of bins
5.	Digital Hand Atlas [**5**] [**10**]	Standard Reference Database for building Bone Age Assessment System	Well known , standard reference	Standard atlas based on demographics need to considered
6.	Fuzzy Method / Classifiers [**64**]	In this methods feature values are classified based on fuzzy method / PCA [**64**] / classifier.	Handles complex , overlapping ,imprecise features values of bones to arrive at accurate fuzzy class of objects	Fuzzy membership functions do not represent, match real conditions.
7	Deep Learning Neural Network [**65**]	Deep learning (also known as deep structured learning, hierarchical learning or deep machine learning) is a branch of machine learning based on a set of algorithms that attempt to model high level abstractions in data.	It reduces the need for feature engineering, one of the most time-consuming parts of machine learning practice	It requires a large amount of data, only then it will compete with other algorithms. Secondly, It is extremely computationally expensive to train. The most complex models take weeks to train using hundreds of machines equipped with expensive GPUs
8	Fusion Rule Classifier [**66**]	Bone Age is computed as Weighted Average of 5 parts of bones , then validation is done using classifiers	Grouping of bone feature measurements supervised, hence time consuming.	The classifiers can be fine-tuned with multiple parameters.

III. ALTERNATIVE ALGORITHM OF BAA

It is apparent from the tables [2, 3, and 4] that the process of building an automated BAA consists of three phases viz, pre-processing, measurements of bones and machine learning phase. In this section, logical steps for various measurements of bone with respect to age are presented. The concept is based on point distribution and active shape modeling **[**67**]** **[**68**]**. For this, it is assumed that the age assessment will be done on the basis of Table 7, which mentions the order of appearance is more important, the size and the distances between the anchor/Landmark points are equally indicators of age. These steps illustrated increase the reliability of results and at the same time reduces the overhead as compared to the previous algorithms mentioned in the Table 4.

1) *Let "age_group" be variable representing Age Groups in set of Subjects*

age_group = {1, 2, 3 , N } in years .

2) *Let "ethnicity _group" be variable representing Ethnicity in set of Subjects*
ethnicity _group = {Indo-Aryan, Dravidian , Sino-Tibetan }
3) *Let "gender_enum" be the variable representing the Gender of the Subjects.*
4) *Let "bone_group" be variable representing bone part to be considered for analysis .*
bone_group = { Distal ,Middle, Phalanx I, Phalanx II, Phalanx III, Phalanx IV, Phalanx V, Carpal Bone , Radius , Ulna}
5) *Let m_shape be variable representing the mean shape of the bone part.*
6) *Let 't' be the transformation matrix of m_shape matrix*
7) *Let 'c' be the variable representing the centroid of each bone part.*
8) *Let 'cm' be the matrix representing the edge of the bone part at different rotations angles {30,60,90,120,150,180,210,240,270,300,320,350}*
9) *From each edge find distance from centroid of each bone part.*
10) *Find Co-relations between the various distances and build a Co-variance matrix.*

11) *Build a feature matrix and subject to supervised learning algorithm for predicting the age of the person. The feature labels or grouping is done on the basis of standardized digital atlas of hand and wrist.*
12) *Evaluate Performance in terms of accuracy.*

IV. CONCLUSION AND DISCUSSION

The Syrian refugee crisis has brought importance to BAA system into limelight due to its application in verifying the age credentials of refugees coming to European countries. In the current context, it has proved very useful due to its non-intrusive nature but its lack of portability is its greatest limitation. If this test could be done from a remote diagnostic location, it will become a great boon then this technology will work wonders for the people living in the remote corners of the country. It could be used for collecting medical imaging data from remote village clusters for diagnoses in super specialty hospitals located in any part of the world bringing the benefit of the best expertise in the world to their doorstep. However, this can become a reality only if the penetration of internet also increases at a fast pace with minimum level of band width resources (> 2G).

In this paper, an outline of the requirements for building bone age assessment system with latest technology stack and possibilities has been reviewed. Initially a requirement matrix was built and based on this matrix; the survey for each requirement was construed. It was found that major focus of the existing BAA systems is on waist, finger, and hand morphological feature values for computing the age of a subject. Many researchers have used machine learning algorithms like fuzzy classifier, neural network, SVM and fuzzy–neuro classifiers for building BAA system. But a very few systems are cloud and mobile enabled and they use parallelization for processing medical images in limited manner. Therefore, a new programming model that revolves around the usage of parallelization algorithms is the need of the hour. It is a known fact, that the main optimization of algorithms will come from software based stages rather than the hardware; hence, there is a need for new generation of compilers and interpreters that can process images in parallel. Such compilers will automatically detect the most used functions like IFFT of image processing and process in parallel, thus helping in building next generation of BAA systems.

It was also observed that hybrid approach of machine learning algorithms for improving the accuracy of the current BAA systems has been applied in a limited manner. It was also found that communication models for building mobile BAA should be a mix of multiple technologies like Bluetooth, Wi-Fi and other radio standard protocols. It was also analyzed that the system that could be compatible with legacy systems (RDBMS) should also be built for storing medical imaging data and the BAA system must support interoperable standards such as HL7 and FHIR. The purposed system attempts to fulfill these requirements. This paper is not a full specification document for building a mobile cloud enabled BAA system but enlists the basic infrastructure requirements for developing a portable system in terms of hardware and interoperable in terms of software. For future directions, we suggest that not only the above tabular information should be used for gathering firsthand information to develop BAA system but some detailed security aspects must also be surveyed with right kind of technology combinations to develop secured bone age assessment system.

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