Current Status and Open Problems in Bone Age Estimation

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A B S T R A C T

Bone age is an effective indicator for diagnosing various diseases and to determine bone ages of livings. The earliest well-known studies belong to the Greulich-Pyle and Tanner-Whitehouse, as a result bone age development atlases were published using hand and wrist radiography. Atlases works well for the younger ages between 0-18, while they have deviations at elder ages. Kazuro Anhara and Takao Suzuki emphasized the importance of changes in pubic symphysis of pubic bones belonging to 20 to 40 years old cases who were not alive for further ages. All this researches focuses on the hand intensive works. However, automation of bone age detection using artificial intelligence techniques such as image processing of radiological images is important in order to prevent human side-effects on the evaluation, they are called automated methods. Some examples are automatic bone age estimation fully automatic with carpal bone segmentation using fuzzy classification, fuzzy-based radius model for bone age estimation including image preprocessing, and neural network applications mostly seen on the literature. It is obvious, artificial intelligence promises faster bone age estimation and to minimize different evaluations between experts. However, new studies are needed for applying new techniques (deep learning) efficiently and discovering new bones to estimate elder ages accurately in the field of forensic informatics especially.

1. Introduction

In this study, important studies on bone age estimation from the past to the present are examined and open problems that have not yet achieved sufficient results are mentioned.

Skeletal maturation varies according to the geography, gender and socio-economic status of the person. Estimation of bone age shows the degree of skeletal maturation. The age calculated from the date of birth of the person is the calendar age, and the bone age is the age determined by looking at the skeletal maturity rather than the calendar age. Bone age estimation is necessary in the diagnosis of some diseases. Age estimation is also important in judicial terms, and bone age estimation is required in many issues such as competence in crime and age correction. Especially in cases where children are registered late in the population in rural areas, or if the same identity information is maintained for the unregistered child after the death of the older child, it is important to estimate the real age of the person [1-2].

Studies have been carried out on alive and dead cases in determining the bone age. Kazuro Anhara and Takao Suzuki carried out the main study on anatomically examining the bones and estimating the age according to the changes on the bones. This study was accepted especially because it explains the morphological changes on the bone in detail. Radiological method is used to estimate the bone age of living individuals. In these methods, radiographic images obtained from the wrist bones in children aged 0-18 and from the shoulder, clavicle and pelvis bones in individuals over 20 years old are compared with the measurements in certain atlases and the age of the person is determined. This approach is the method used widely in the clinic and obtaining realistic results [3]. The most well-known systematic studies are the studies of Greulich-Pyle and Tanner-Whitehouse. Hand and wrist radiography was used in these studies. Because the hand and wrist are regions that have the necessary conditions for estimating the skeletal maturation process. In addition, considering that the majority of people use their right hand in their daily work, studies have focused on the left hand and wrist, under the assumption that the right hand can develop more than the left hand.

Bone age estimation is an issue concerning Forensic Informatics. Forensic problems that are tried to be solved by manually (autopsy or comparative results obtained from atlases on radiographic images) are time-consuming. For this reason, it is important to make computer-based analysis to solve forensic problems. Computer forensics is also considered as digital forensic or forensic information technology. Forensic Informatics is based on X-ray image analysis, Computed Tomography (CT) / Magnetic Resonance Imaging (MRI) and ultrasonography analysis [4]. Radiologists are responsible for visualizing the internal structure of the human body using electronic devices. These images are examined in more detail by the attending physician for medical diagnosis. Therefore, the digitized image should be well defined.

2. Manual Methods of Bone Age Estimation

2.1. Age Estimation by Regression Analysis on Pubic Symphysis

The study conducted by Kazuro Anhara and Takao Suzuki was applied on 70 pairs of pubic bones belonging to Japanese deceased cases. 33 pairs of these bones were obtained from Tokyo University Department of Anatomy and 37 pairs from Sapporo Medical College [5]. The study demonstrated that the pubic symphysis is a reliable indicator of age for the estimation of bone age between 20 and 40 years of age [5]. As a result of their morphology and experience, they focused on the following seven morphological features for the assessment of age in symphysis. These are: horizontal ridges and furrows, pubic tubercle, lower end, dorsal margin, superior Ossific nodule, ventral beveling, and symphysial rim.

2.2. Description of Age Changes in Pubic Symphysis

2.2.1. Horizontal Ridges and Furrows

It has been determined in the study that: the situations where the protrusions on the symphysis surface are high and the grooves deep and sharp are very evident under the age of 20. By the age of 20-23, the grooves become shallow and the ridges relatively dull. This slimming continues until the age of 27. After the age of 28, with rare exceptions, this feature disappears completely and the symphysial surface becomes flat [5].

2.2.2. Pubic Tubercle

In individuals under the age of 23, there is epiphyseal cartilage between this tubercle and the pubic bone. However, after the age of 24, the tubercle completely merges with the pubic bone without exception.

2.2.3. Lower End

Before 22 or 23 years of age, the lower end of the symphysial surface is indistinguishable from the upper end of the lower pubic ramus. Between about 23 and 30 years of age, the lower part of the symphysial surface is surrounded by a narrow ridge, and after about 30 years of age, the ridge becomes wider and shows a triangular swelling in most cases.

2.2.4. Dorsal Margin

Up to the age of 19, there are no marginal ridge limiting the symphysial surface, and at around 20 years of age, a scar of the ridge appears on the dorsal border of the symphysial surface. In individuals older than 27 years of age, the formation of the ridge is almost complete, although still narrow along the entire length of the dorsal rim. In about half of the cases included in the study by Anhara and Suzuki, the back was enlarged after the age of 33 or 34. In current examples, 12 out of 22 (54.4%) show expanded margins.

2.2.5. Superior Ossific Nodule

This formation appears in the upper part of the pubic surface for a limited time. No nodules can be seen in individuals under the age of 20, but it is easily seen between the ages of 21-27 and then disappears again. Because the age changes of this nodule are relatively different, its occurrence or disappearance represents a good age indicator for the period from the early to late twenties.

2.2.6. Ventral Beveling

By age 22, the ventral border of the pubic symphysial surface joins the ventral surface of the pubic bone. In later ages, a narrow surface appears between the two surfaces. It is not defined for ages 23 to 27. Between the ages of 28 and 33, it occurs along the entire length of the pubic symphysis. In individuals older than 33 or 34 years of age, the upper part of the ventral curve disappears, but the variation of this change is relatively large.

2.2.7. Symphysial Rim

In older individuals, the surface of the symphysial is not very frequent, but is surrounded by a relatively wide and matt margin (rim). This finding can be seen in people over the age of 30, and its incidence increases after the age of 34. Therefore, the age of an individual with this phenomenon (rim) can be estimated to be in his/her mid-thirties or older, but this does not mean that the individual without the phenomenon is young.

2.3. Greulich and the Pyle Method

It is a method developed by Greulich and Pyle. These scientists obtained different radiographic images of children of different age groups, including left shoulder, elbow, hip and knee. The data collection process included approximately 1000 children's radiographs between 1931-1942. This study was published by Stanford University in 1959 under the title of Hand Bone Development Stages (Atlas of Skeletal Development of the Hand and Wrist) [4]. Since male and female mature at different speeds, two different atlases have been put forward. These atlases are the basic model used to analyze age-related changes in human bone structure. This method is called as GP method in the literature.

2.4. Tanner and Whitehouse (TW) Method

In this method developed by Tanner and Whitehouse, radiographs of the left hand and wrist were used again. In this method, bone joints were used as a determining feature in bone age estimation. The atlas of this study was published in 1962 (TW: TW1, TW2, TW3) [4]. In this method, the most accepted RUS (Radius, Ulna, Short Bone) scores are used. For the estimation of bone age, hand and wrist bones were considered as 8 main bones in total and 9 bones together with the ulna were considered. This method has been updated with studies conducted in various countries and the USA. Because the stages of bone development in the 1960s and the developmental stages of the 1990s differ [6]. The new method is named TW3.

2.5. Current Status in Turkey

The Forensic Age Estimation (Adli Yaş Tayini Kitabı - AYT) book published by the Forensic Medicine Institute is used in age estimation. The features to be used in estimating the age of cases between the ages of 1 and 50 have been estimated. The age estimation report is prepared by estimating the height, weight, number of teeth and radiological features for the relevant age and comparing it with the findings of the case for which age estimation is desired. It was observed that there was a significant difference between the age estimated by the AYT book and the real age, such as 1.21 years for boys and 2.17 years for girls [7]. In addition, research continues on new approaches and methods in estimating bone age.

2.6. Evaluation of Age Estimation in Forensic Medicine by Examination of Medial Clavicular Ossification from Thin Section Computed Tomography Images

In the study conducted by Murat Serdar Gürses et al., 1041 Thorax Computed Tomography images obtained between January 2012 and February 2014 at the radiology department of Uludağ University were used [8]. These images belong to cases between 10 and 35 years old. This study is basically based on the staging method developed by Schmeling and Kellinghaus. These stages seen on the clavicle are expressed as follows: Figure 1 for Stage 1, Figure 2 for Stage 2, Figure 3 for Stage 3, Figure 4 for Stage 4 and Figure 5 for Stage 5.

2.6.1. Stage 1: The ossification center is not followed:

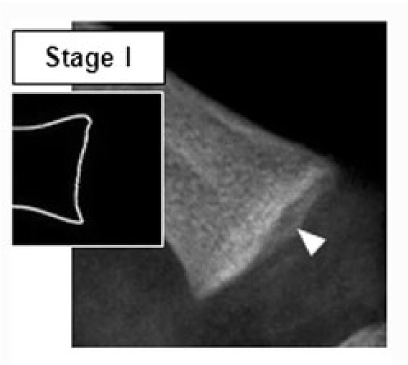

Figure 1. Clavicle at Stage I

2.6.2. Stage 2: The ossification center is ossified; the epiphyseal cartilage is not ossified.

2.6.2.1. Stage 2a: The longitudinal epiphyseal measurement is one-third or less compared to the transverse measurement of the metaphyseal tip.

2.6.2.2. Stage 2b: The longitudinal epiphyseal measurement is one-third to two-thirds greater than the transverse measurement of the end of the metaphysis.

2.6.2.3. Stage 2c: The longitudinal epiphysis measurement is more than two-thirds compared to the transverse measurement of the metaphyseal tip.

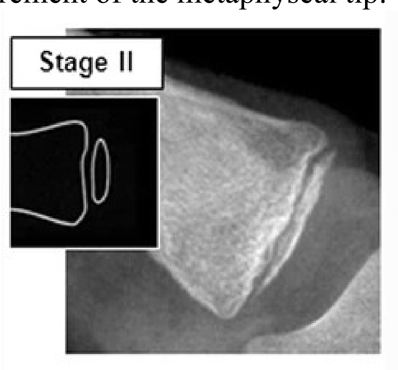

Figure 2. Clavicle at Stage II

2.6.3. Stage 3: The epiphyseal cartilage is partially ossified.

2.6.3.1. Stage 3a: Pineal-metaphyseal fusion completes one-third or less of the old space between epiphysis and metaphysis.
2.6.3.2. Stage 3b: The epiphysis-metaphysis fusion completes more than one-third to two-thirds of the old space between the pineal and metaphysis.
2.6.3.3. Stage 3c: The epiphysis-metaphysis fusion completes more than two-thirds of the old space between the pineal and metaphysis.

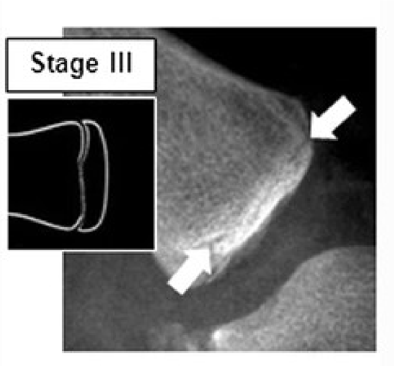

Figure 3. Clavicle at Stage III

2.6.4. Stage 4: The epiphyseal cartilage is completely ossified; the epiphysis scar is visible.

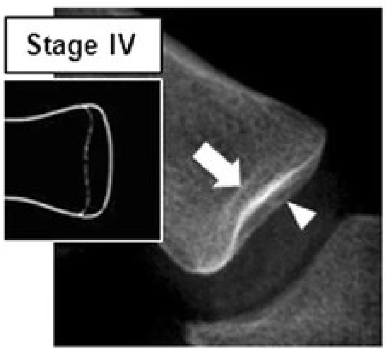

Figure 4. Clavicle at Stage IV

2.6.5. Stage 5: Pineal cartilage is completely ossified; Pineal scar is no longer visible.

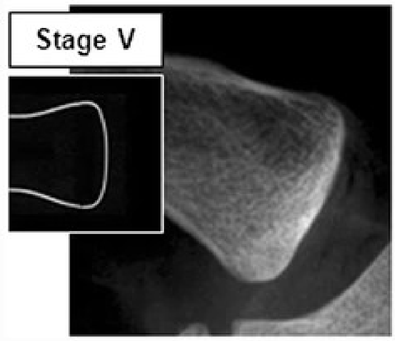

Figure 5. Clavicle at Stage V

In this study, two radiologists, one with 15 years of experience and the other with 5 years of experience, examined the CT images at 2-week intervals, and the results of which they reached a consensus were determined, and age was estimated. Located in this study, two radiologists, Turkey's estimated age than before yet on CT images, before they are given to age estimation on CT images. It was stated that the age of the cases from which the images were obtained was not previously known by either of the two radiologists. In cases where there is a developmental difference between the left and right clavicle, the side with more development is taken as a basis.

As a result, evaluation of clavicle ossification was possible in 725 cases. Comparisons between male and female data mostly revealed statistical differences in the 4th stage. However, such a difference was not observed in other stages.

3. Automatic Methods for Bone Age Estimation

3.1. Automatic Bone Age Assessment for Young Children from Newborn to 7-Year-Old Using Carpal Bones

In this study by Zhang et al, a carpal ROI (Region of Interest) analysis and bone age estimation study with fuzzy classification were performed for fully automated carpal bone segmentation. In this study, a model was developed and tested using x-ray images obtained from 205 children [9]. Figure 6 shows the stages of detecting the carpal bones through the hand x-ray image.

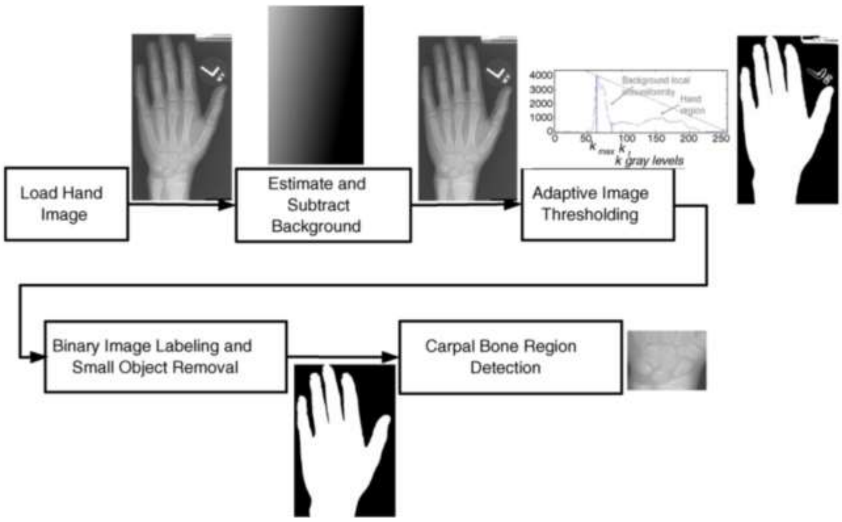

Figure 6. Procedure steps to determine the carpal bones from the X-ray image of the hand

The method applied in this study consists of 7 stages. The first step is to extract carpal bones from hand x-ray images. In the second step, filtering is applied to remove unwanted phenomena (background, shadow, etc.) on the image. In the third stage, the edges of the carpal bones are clarified with the edge detection algorithm. In the fourth stage, bones other than carpal bones are removed from the image. In the fifth stage, carpal bones are determined according to the model shown in Figure 7.

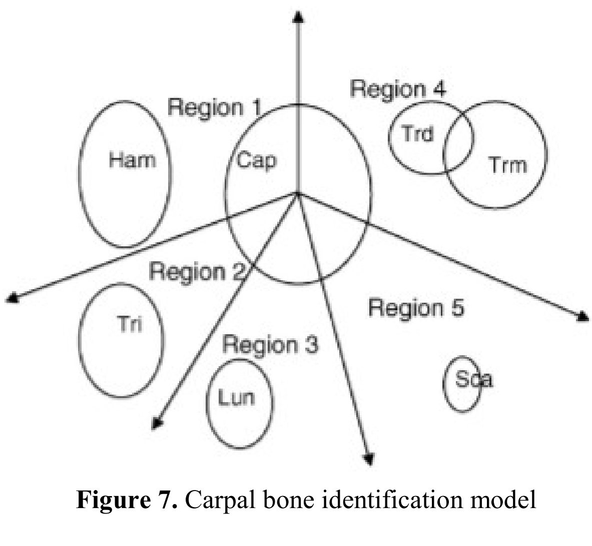

Figure 7. Carpal bone identification model

In this model, the polar coordinate system containing the center of the capitate as the starting point is divided into five regions. Based on priori anatomical information, capitate, hamatum, tricuitrum, lunatum, scaphoid, trapezium, and trapezoideum carpal bones are located in each of these five regions.

Figure 8 shows the ROI image of seven carpal bones obtained from the X-ray image of the hand.

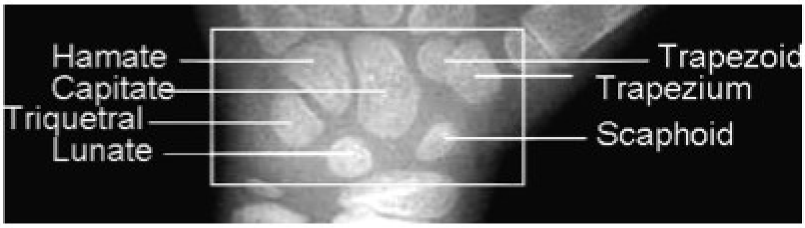

Figure 8. Identification of the carpal bones in the X-ray image of the hand

Figure 9 shows the developmental stages of the carpal bones of Asian men from newborn to 7 years old. The numbers on the images represent the age groups from which the images were acquired.

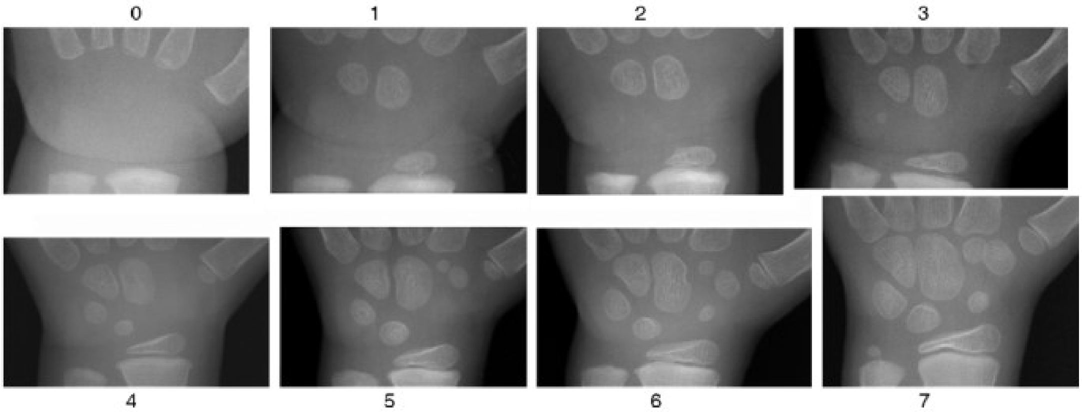

Figure 9. The developmental stage of the carpal bones in Asian males from newborn to 7 years of age

When examined chronologically, as can be seen in Figure 9, the first carpal bones detected are capitate and hamatum (seen on second image in Figure 9). Therefore, these two carpal bones were selected for analysis in this study. In the sixth stage, the extracted features were selected and in the last stage, age estimation was made by passing to the fuzzy classification stage.

3.2. Distal Radius Bone Age Estimation Based on Fuzzy Model

In the study by Sadiah Jantan et al., A fuzzy-based radius model for bone age estimation including image preprocessing and feature extraction is defined. In this study, it was aimed to estimate the bone age by using a fuzzy model based on distal radius bone features. 333 left hand digital X-ray images were included in this study. X-ray images are of 167 Asian-American boys and 167 Asian-American girls aged 0-18 [10].

The study basically consists of 5 stages. These are extraction of ROI, pre-processing of ROI (removal of background, shadow, etc. noise by applying filters), extraction of features, and estimation of age according to the classification result by inserting it into the fuzzy classifier at the last stage. The method followed is shown schematically in Figure 10.

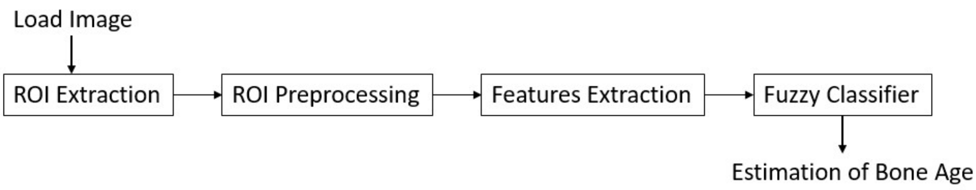

Figure 10. Flow chart of age estimation with Fuzzy Logic

Based on the results, it has been confirmed that the ratio of the radius to the distal end is an important parameter for explaining the state of bone growth before a child reaches the age of 14.

3.3. A Novel Method Using Neural Networks for Age Estimation in Children

In the study conducted by Harun Çelik and Semra İçer, it was aimed to estimate bone age from wrist x-ray images in children using Artificial Neural Network (ANN). The ANN developed in this study can automatically determine the age. 42 reference images were used for boys and girls in the study. First, the development of the elbow and forearm epiphyses in these images was examined, then ANN was trained with the features of these epiphyses and a system capable of automatic age estimation was developed [11].

In this study, the elbow and forearm epiphyses, which are considered to be more proportional to potential growth, were taken into account. While the transverse growth of these two epiphyses up to a certain age is a distinctive feature, growth occurs more towards the neck at later ages. For this reason, both transverse growth and longitudinal growth developments were taken into account in the calculations.

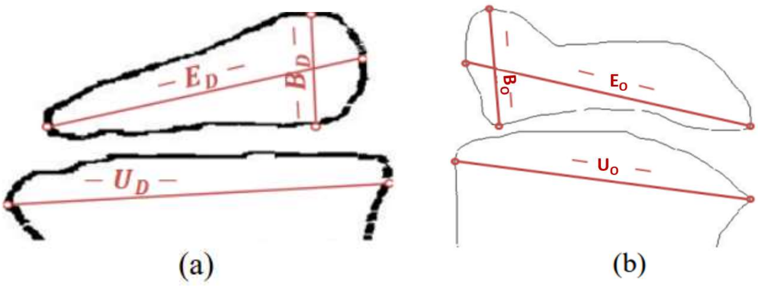

Figure 11. (a) Tip and epiphysis of the elbow bone, (b) tip and epiphysis of the forearm bone

Figure 11 shows the tip and epiphysis of the elbow bone (a) and the tip and epiphysis of the forearm bone. Where parameters are as follows:
U_D: the longest transverse end of the elbow end,
E_D: the widest length between the two transverse ends of the elbow epiphysis,
B_D: longitudinal widest length of the elbow epiphysis,
U_O: the longest transverse to the tip of the forearm bone,
E_O: the widest length between the two transverse ends of the forearm epiphysis,
B_O: the longest longitudinal length of the forearm epiphysis,

The researchers decided to look at the relationship between age and these epiphyses to determine whether it is sufficient to look at the forearm bone in age estimation. For this purpose, they calculated the change of epiphyseal development values corresponding to every age in boys and girls. They tried to reveal age estimation ability with correlation analysis. According to the result of correlation analysis, it was accepted as a perfect fit when the correlation coefficient was +1, and when it was -1, it was accepted that there was an inverse relationship between variables.

Table 1. Correlation analysis according to gender

	Boy	Girl
E_D / U_D	0.9046	0.8819
B_D / U_D	0.9422	0.9705
E_O / U_O	0.9573	0.9406
B_O / U_O	0.9793	0.9539

Analysis results showing the relationship between calculated epiphyseal growth values and bone age are given in Table 1. When the results in this table are examined, there is a relationship between the width and length of the epiphysis with a rate of over 90% in males and over 88% in females.
The ANN used in the study was designed with multiple layers. It has five neurons in input layer, two neurons in hidden layer and one neuron in output layer. In the experiments, the model with the Mean Squared Error (MSE) was preferred. The algorithm scheme of the system is as shown in Figure 13.
As a result, the system developed with this method was tested on 32 wrist images of different ages, whose bone age was estimated by two experts before, and predicted the bone age with an average error of 0.52 years. Thanks to this developed system, age estimation can be made quickly for children.

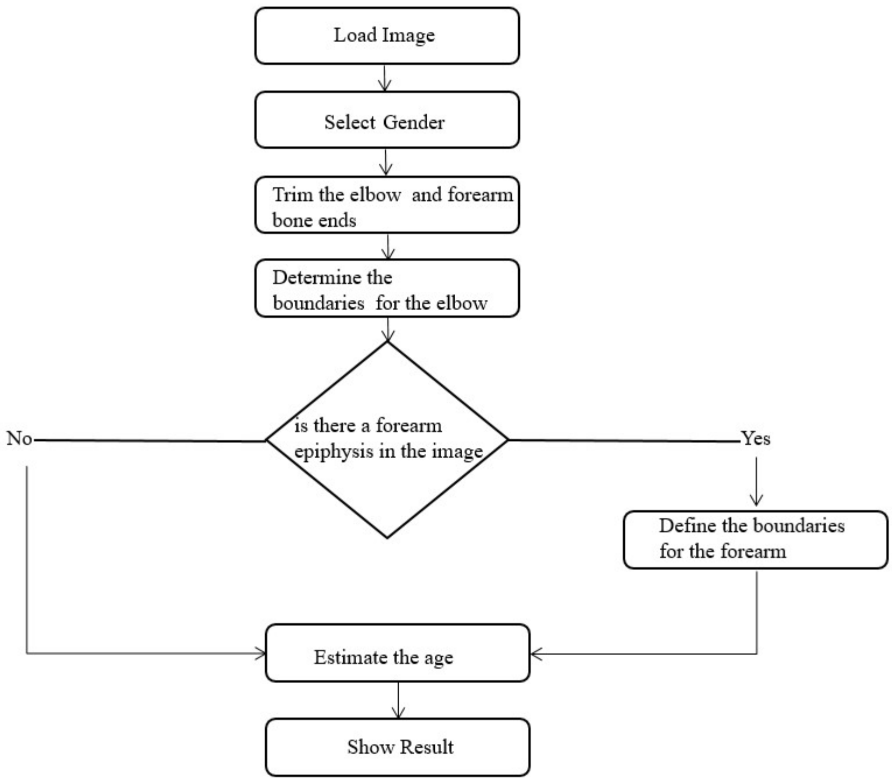

Figure 13. System operating model

3.4. Use of Artificial Neural Networks to Estimate Radiological Bone Age from Hand - Wrist X-Ray Images

Esra Hasaltın and Erkan Beşdok developed a semi-automatic system for bone age estimation using ANN. X-ray images of 307 pediatric cases without growth disorders were used in the study. 144 of these images belong to female and 163 to male cases [12]. Carpal bone areas were used in the study. In the calculation of the areas of the carpal bones, the borders of the bones were first marked by an operator and these marked points were transformed into a cubic spline curve.

5 different models have been applied in artificial neural network design.

- *Model 1*: 7 neurons in input layer (carpal bones), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 2*: 8 neurons in input layer (7 carpal bones and 1 calendar age), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 3*: 8 neurons in input layer (7 carpal bones and 1 gender), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 4*: 7 neurons in input layer (carpal bones belonging to female cases), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)
- *Model 5*: 7 neurons in input layer (carpal bones belonging to male cases), 5 neurons in hidden layer and 1 neuron in output layer (predicted bone age)

Performance analysis of three different learning algorithms has been performed and the performance of various learning algorithms on the data set has been evaluated. These learning algorithms are; Resilient Propagation - RP is Levenberg-Marquardt (LM) and batch gradient descent with momentum (GDM) - variable learning rate (GDX).

Different transfer functions were used in the artificial neural network structure according to the learning model. In the LM algorithm, the sigmoid transfer function in the hidden layer and output layers, tangent hyperbolic in the hidden layer in the RP algorithm, the sigmoid transfer function in the output layer, linear in the hidden layer and sigmoid transfer function in the output layer in GDX algorithm were applied. The authors stated that they also experimented with different transfer functions, but they used the ones that gave the best results in this study. Of the data set consisting of 251 cases, 150 were used for learning and 101 for testing. In studies where male and female cases were evaluated separately, 110 were used as learning and 27 test data for male cases, and 90 learning and 24 test data for female cases.

Bone age was estimated by an expert radiologist by evaluating the X-ray images according to the Greulich-Pyle atlas. The information about the learning method and other cases were given to different ANN models and the results were evaluated comparatively. According to the results obtained, LM algorithm gave the best result in all models according to MSE error criteria. Then RP algorithm took second place and GDX algorithm ranked third. In the test data, the RP algorithm gave a better result.

4. Conclusion

Artificial intelligence is promising for the future in order to estimate the age from radiological images quickly and to minimize the different evaluations between experts. However, new studies are needed for the development of this technique, which is very new in the field of forensic informatics. In the literature, it is seen that computer-aided automatic bone age estimation applications are generally carried out with X-ray images of the hand and wrist. However, the hand and wrist development is largely completed after the age of 18, which is inadequate in estimating the age of the cases between the ages of 18-50. For this reason, computer-based systems and radiological image processing techniques will fill the knowledge gap in this field in terms of the development characteristics of bones in different ages, genders and races.

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