Middle Finger Bone Assessment for Age Identification

Ikke Amalia Risky
Departement of Informatics and Computer Electronics Engineering Polytechnic Institute of Surabaya
Surabaya, Indonesia
ikkeamalia@ce.student.pens.ac.id

Tri Harsono
Departement of Informatics and Computer Electronics Engineering Polytechnic Institute of Surabaya
Surabaya, Indonesia
trison@pens.ac.id

Riyanto Sigit
Departement of Informatics and Computer Electronics Engineering Polytechnic Institute of Surabaya
Surabaya, Indonesia
riyanto@pens.ac.id

***Abstract*— People who died because of natural disaster , airplane crash or vehicle accident are hard to identified. There are many parameters that used by forensic doctor to identify victims corpes. Bone is one of parameters that used by doctors to identify victims age, it provide accurate result compared to other diagnoses. But, it takes a long time for the doctors to identify manually. From those problems, we tried to develop an automatic system which can identify victims age using middle finger bone. An active shape model segmentation method applied in this system to extract middle finger bone. There are six parts of middle finger bone that used to analize age , proximal epyphisis, proximal metaphysis, middle epyphysis, middle metaphysis, distal epyphysis, and distal metaphysis. We measured the length of each parts to be input in age classification using k-Nearest Neighbor method. By using this method, 85% from 73 different experimental data has been succeeded to identified. We believe this can bring benefit for the future of forensic identification.**

Keywords*— *Forensic, identification, finger bone ,preprocessing, segmentation, active shape models, k-nearest neighbor.

I. INTRODUCTION

Forensic identification is important to revealed victims identity. There are many parameters that used by forensic doctors to identify the victims , such as tooth, fingerprint and hand bone . Identification person age using hand bone prove most accurate result for the chronological age of an unknown subject [1]. Forensic doctor used several parts of hand bone to assess person age. The parameters that mostly used by forensic doctors to analyse hand bone age are epyphysis and metaphysis. They compared the result of their identification to data reference from Greulich and Pyle book [2]. But, manual method which forensic doctors used to identify person age works slowly for each individual. In this paper we provide an automatic system to do age Assessment.

Age analysis using the finger bone has been widely studied by scientists. There are various parameters used by researchers to analyze age. Daniela Giordano [4] analyzed 8 parts of three finger bones, namely the thumb, middle finger and index finger. Giordano compared the width of the epyphysis and metaphysis parts. While Pietka [3] performed the same analysis, i.e comparing the width of the epiphyseal and metaphyseal bones, but using the middle finger bone. Pietka also analyzed the ossification stage that occurred to analyze age. Chen [7] analyzed the entire finger bone, chen analyzed the phalanx and epiphyseal / metaphyseal portions of the whole finger bones. In addition to using fingers, age analysis using epiphyseal and metaphyseal comparisons can be performed using the wrist bone [8]. Part of the handwrist analyzed is the radius bone, because the radius bone has a larger shape than the ulna. In this paper, we developed a system to assess bone age. The input of this system is hand bone x-ray image which researcher got from the hospital. The data will be processed in three stage, preprocessing, segmentation, and classification. Preprocessing is the first process, it purposed to enhance the quality of the data input. Preprocessing consist of three process, gaussian filtering, morphology and canny age detection. The next step is segmentation, the purpose of segmentation is to get the region of interest. In this paper, region of interest is meddle finger bone. The last process is classification. From the segmentation process, we get only middle finger bone and the length of ephyphysis and metaphysis. This feature will be the parameters in classification process. Region of interest will shown in fig 1 and fig 2 below.

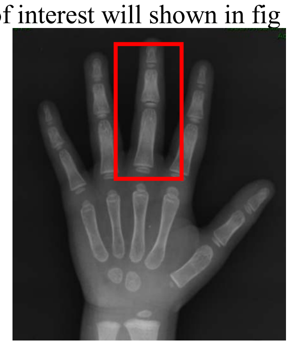


Fig 1. Middle Finger Bone

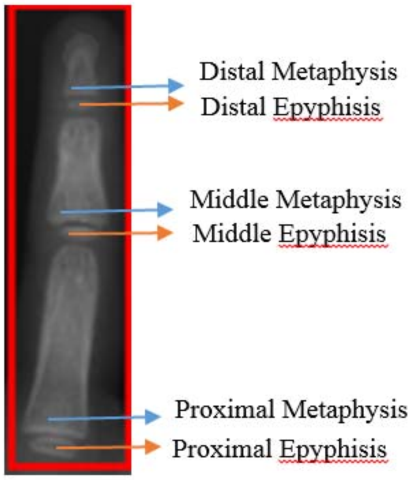


Fig 2. Detail of ROI, ROI consist of six parts.

II. RELATED WORKS

Bone age Assessment had been developed by many researches . Daniela Giordano [4] has built automatic skeletal bone age Assessment using Tanner and Whitehouse method (TW2) based on the integration between EMROI and CROI analysis, which ensures accurate bone age assessment for the entire age range (0-10). Then the bones in the EMROI are extracted by using the DoG (Difference of Gaussians) filter and enhanced using a novel adaptive thresholding obtained by histogram processing. Finally, the main features of these bones are extracted for the stage TW2 (Tanner Whitehouse) evaluation.

Aifeng Zhang [9] has built Automatic bone age assessment for young children from newborn to 7-year-old using carpal bones. Segmentation method that used by Zhang is thresholding. Fuzzy classification used to assess bone age based on selected features. This method has been successfully applied on all cases in which carpal bones have not overlapped. CAD results of total about 205 cases from the digital hand atlas were evaluated against subject chronological age as well as readings of two radiologists. It was found that the carpal ROI provides reliable information in determining the bone age for young children from newborn to 7-year-old.

Other researcher, R. Sigit [8] has built automatic system to assess bone age using hand-wrist bone. Active Contour Model segmentation applied to extract region of interest. Region of interest consist of two parts, first is hand-wrist epyphysis and second is metaphysis hand-wrist. After those important feature extracted, length of epyphysis and metaphysis will measured to assess bone age.

III. METHODOLOGY

This section will shown the design of the system. Fig 3 shown the block diagram of whole system.

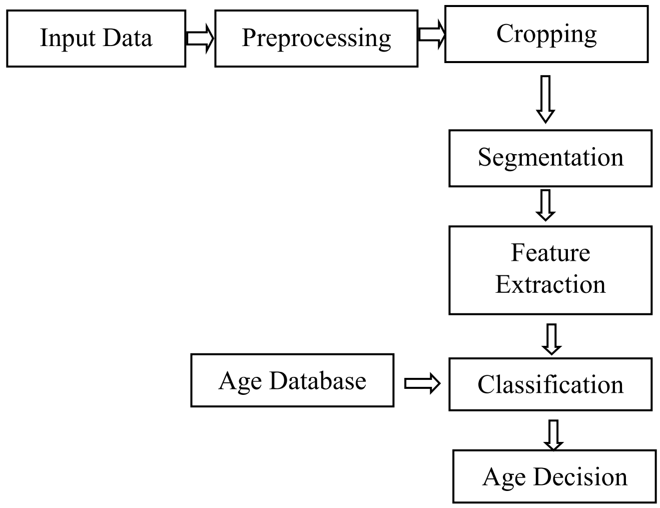


Fig 3. Block diagram of system

A. PREPROCESSING

X-ray image input has so many noise. We did preprocessing step to enhance quality of image input. Preprocessing consist of three steps, Gaussian filter, morphology and canny edge detection. Diagram block of preprocessing shown in fig 4.

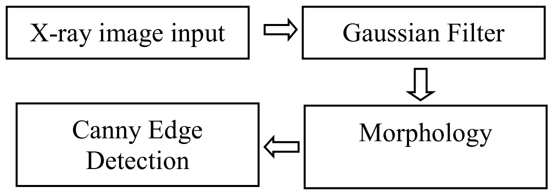


Fig 4. Block diagram of Preprocessing

Preprocessing steps :

1. Reducing noise using Gaussian filtering.
2. Morphology

Morpological image processing is a collection of non linear operation related to the shape or morphology of features in an image. Morphological operations, rely on ordering relative pixel values, and therefore especially suited to the processing binary image. In this paper, we applied erosion and dilation morphology. Erosion removes small-scale details from a binary image but simultaneously reduces the size of region of interest. Dilation has the opposite effect to erosion. It adds a layer of pixels to both inner and outer boundaries of region. The process of morphology can be seen in fig 5 and fig 6.

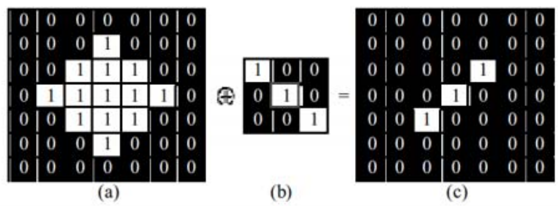


Fig 5. Operation of erotion

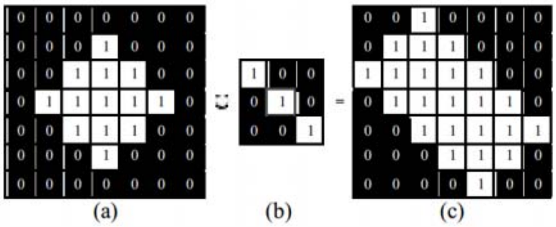


Fig 6. Operation of dilation

3. Canny Edge Detection

Canny edge detection is a technique to extract useful structural information from different vision objects and reduce the amount of the data to be processed. The process of canny edge detection algorithm can be broken down to 5 different steps :

- Apply Gaussian filter to image in order to smooth the image.
- Find the intensity gradients of the image
- Apply non-maximum suppression to get rid of spurious response to edge detection
- Apply double threshold to determine potential edge.
- Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

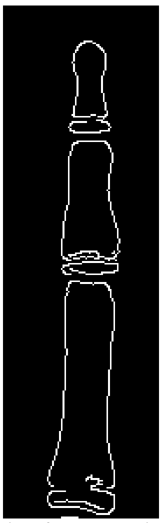


Fig 7. Result of canny edge detection

B. Active Shape Model Segmentation

Active shape model is a statistic model which developed by Tim Cootes [5] and used in medical field to analised the result of brain MRI (Magnetic Resonance Imaging) and identified bone from the result of X-Ray. Active shape model segementation consist of two process, there are training and fitting. The algorithm of training process explained below.

1. First, we have to choose some of data set to be training data. There are 30 images which choosen to be training data.
2. Initialize a landmark point for each training data. The landmark point are stack in the N-points vectors. N-points vector labelled manually by users. For each point (Xn, Yn) represent one feature of ROI. Total amount of landmark points is 49 points.

$$x = (x1, y1; \dots \dots .xn, yn) \dots\dots\dots\dots\dots\dots\dots (1)$$

Fig 8 and 9 showing the result of labelled training data.

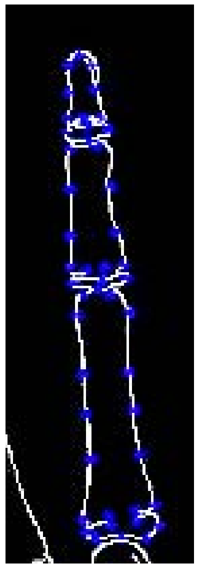


Fig 8. Labelled traing data.

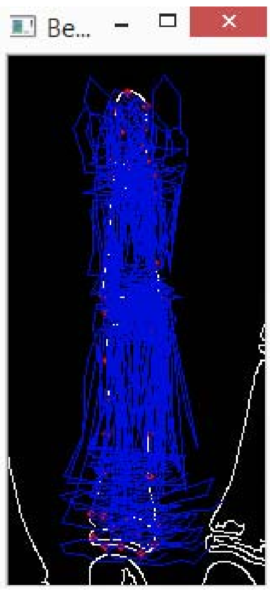


Fig 9. 30 Training data

3. After we have all the landmark point of training data, we have to aligned all the training data to be convergence with the reference shape. Aligning shape stage is modeled by performing statistical tests on the point coordinates that have been labeled in the training set. Here we use an adjustment with scaling, rotation, and translation. So that the adjustment results obtained as quickly as possible and minimized the number of weights of distance between points equivalent in different forms.

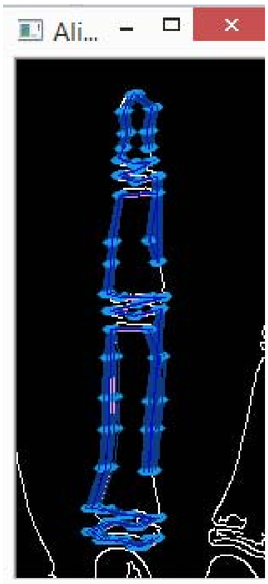


Fig 9. Result of aligned training data.

4. Calculate the mean shape

$$X = \frac{1}{s}\sum_{i=1}^{s} Xi \quad \text{.......................................(2)}$$

5. Calculate matrix covariance

$$X = \frac{1}{s-1}\sum_{i=1}^{s}(Xi - X)(Xi - X)' \quad \text{..............(3)}$$

6. Calculate eigenvalue and eigenvector, and select eigenvector which have a high value to reduce the dimension of the data. This process called principal component analysis.

```
========================Eigenvector=======================================
[0.6330362, 1; 0.60483605, 0; 0.32367373, 0; 0.27880639, 0; 0.21365272, 0; 0.018
874999, 0; -0.070268042, 0; -0.052244339, 0; -0.08460249, 1; -0.027117424, 0; 0.
16427752, 0; 0.37517092, 0; 0.64098382, 0; 0.64091921, 0; 0.28371403, 0; -0.5427
4887, 0; 0.45835689, 1; -0.38204733, 0; 0.49131206, 0; -0.1515715, 0; -0.0672086
78, 0; -0.16024949, 0; -0.33076566, 0; 0.44136697, 0; 0.58034772, 1; -0.18478681
, 0; 0.34541544, 0; -0.42408502, 0; -0.44317615, 0; 0.083626136, 0; -0.016108852
, 0; 0.45654956, 0; 0.56486762, 1; -0.51667708, 0; 0.043287203, 0; -0.20715222,
0; 0.2388688, 0; -0.25695205, 0; -0.27901804, 0; 0.45266998, 0; 0.42149082, 1; -
0.6112197, 0; 0.50104386, 0; -0.39872551, 0; -0.65063071, 0; 0.3552852, 0; 0.118
6601, 0; -0.043452155, 0; -0.15638629, 1]
===========================Eigenvalue=====================================
[20.644932, 0; 4.841392, 0; 2.1659448, 0; 0.68966758, 0; -0.14445691, 0; -0.4882
8152, 0; -1.709201, 0]
```

Fig 10. Sets of eigenvectors and eigenvalue.

7. After we got mean shape and eigenvector from training process, we go to the next step called fitting.Fitting is a process to match mean shape with a new image input. The algorithm of fitting process explained below.
   1. Initialise b = 0.
   2. Generate initial model instance started from mean shape. So the first iteration we just generate mean shape.

$$x = (X' + \sum_{i=1}^{s} bi.Ui) \quad \text{...............................(4)}$$

Where :
X' = mean shape
Ui = eigenvector

   3. Find the best align (translation, rotation , and scalling) x to image input.
   4. Invert pose parameters to project y = T-1 (Y). Where Y is image input.
   5. Update model parameter

$$b = U^T(y - X') \quad \text{.......................................(5)}$$

6. Repeat from step 2 until convergence. Fig 11 showing the result of active shape models segmentation.

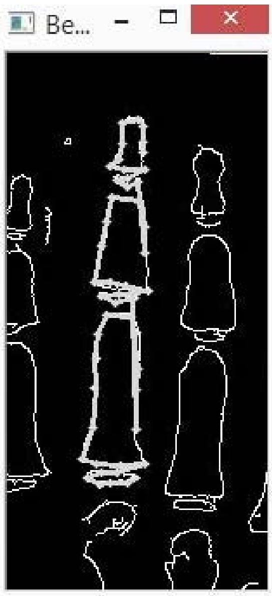
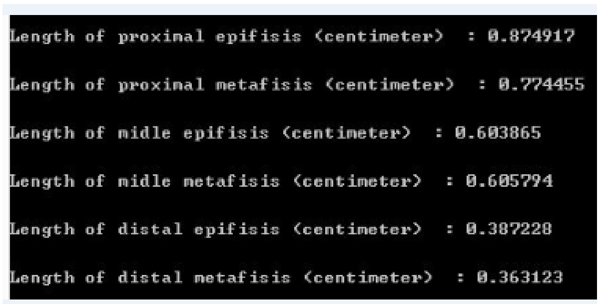


Fig 11. Result of active shape model segmentation.

C. Feature Extraction

In this paper, the result of middle finger bone segmentation were analyzed to determine human age. There are six features that analyzed to determine age, six parts consist of the length of proximal epyphysis, proximal metaphysis, middle epiphysis, middle metaphysis, distal epyphysis and distal metaphysis. We measured the length of each parts using Euclidean distance. Fig 12 showing the result of feature extraction.



```
Length of proximal epifisis (centimeter)  : 0.874917
Length of proximal metafisis (centimeter)  : 0.774455
Length of midle epifisis (centimeter)  : 0.603865
Length of midle metafisis (centimeter)  : 0.605794
Length of distal epifisis (centimeter)  : 0.387228
Length of distal metafisis (centimeter)  : 0.363123
```

Fig 12. Result of feature extraction

D. K-Nearest Neighbor Classification

An instance based learning method called the K-Nearest Neighbor or K-NN algorithm has been used in many applications in areas such as data mining, statistical pattern recognition, image processing. Successful applications include recognition of handwriting, satellite image and EKG pattern. This algorithm is a method for classifying objects based on closest training examples in the feature space . K-Nearest Neighbors (KNN) classification divides data into a test set and a training set. For each row of the test set, the K nearest (in Euclidean distance) training set objects are found, and the classification is determined by majority vote with ties broken at random. If there are ties for the Kth nearest vector, all candidates are included in the vote.

In this paper, kNN classification used to classify length of ephypisis and metaphysis to get age decision. Here is step by step on how to compute kNN algorithm :

1. Determine parameter K = number of nearest neighbor.
2. Calculate the distance between the query-instance and all the training samples.
3. Sort the distance and determine nearest neighbors based on the K-th minimum distance.
4. Gather the category Y on the nearest neighbors.
5. Use simple majority of the category of nearest neighbors as prediction value of query-instance.

IV. EXPERIMENTAL RESULT

In this section, we will provide the result of active shape model segmentation and kNN classification. The segmentation method works well in this system. As we can see in fig. 13 below. In this paper, we apply ASM segmentation for all data test. A whole parts of region of interest can be reach with ASM method. In this paper, training data for ASM segmentation is 30 data. Fig 13 and 14 showing some of result ASM segmentation.

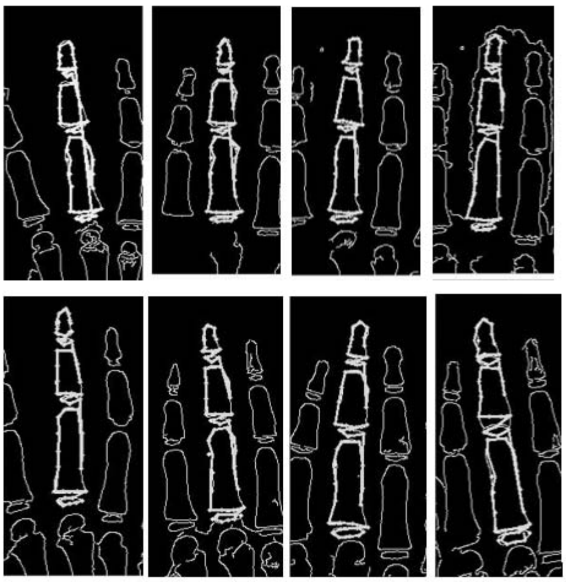


Fig 13. Result of ASM segmentation 3 - 8 years old.

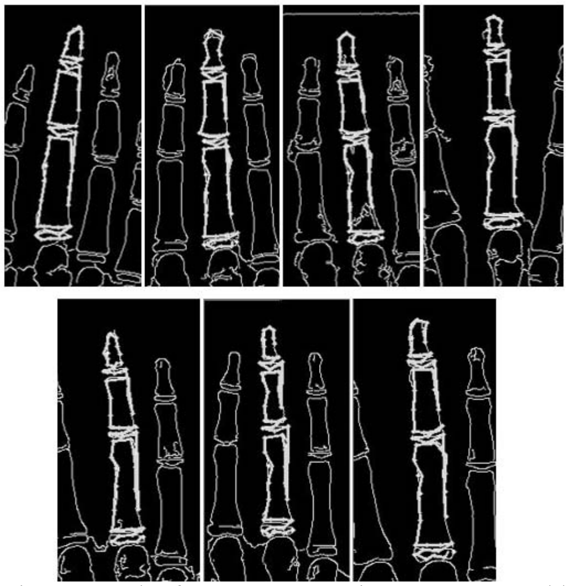


Fig 14. Result of ASM segmentation 9 – 15 years old

Fig 13 and 14 showed the result of active shape model segmentation. For this paper, we tested 73 different age data. From all data, segmentation using active shape model has done successfully. The method is able to reached the edge of middle finger bone.

In this research, feature extraction is performed by calculating the width between the epiphyseal and metaphyseal bones. As described in the previous chapters, the shape of the active shape model consists of 49 points connected into a single contour shape. So to obtain features in the form of epiphyseal and metaphyseal widths, calculated the distance between two points using Euclidean distance formula. The output of the calculation is then converted into centimeters. Table 1 and table 2 show the results of epiphyseal and metaphyseal measurement from greulich and pyle book.

Table 1. Epyphyseal measurement from geulich and pyle book

Age	Reference			Testing		
	PE	ME	DE	PE	ME	DE
3 years	0.6	0.4	0.2	0.35	0.338	0.218
3 years	0.7	0.5	0.4	0.56	0.435	0.314
4 years	0.75	0.55	0.45	0.7	0.435	0.29
4 years	0.8	0.5	0.45	0.63	0.507	0.389
5 years	0.85	0.7	0.5	0.56	0.435	0.341
6 years	0.95	0.7	0.55	0.68	0.41	0.362
7 years	1	0.8	0.6	0.82	0.635	0.461
8 years	1.1	0.85	0.7	0.68	0.704	0.58
9 years	1.15	0.9	0.8	0.92	0.71	0.504
10 years	1.1	0.9	0.8	0.7	0.531	0.58
11 years	1.2	1	0.8	0.66	0.555	0.555
12 years	1.3	1.1	0.85	0.7	0.678	0.603

Age	Reference			Testing		
	PM	MM	DM	PM	MM	DM
13 years	1.3	1.15	0.9	0.73	0.652	0.557
14 years	1.4	1.2	1	0.65	0.605	0.556
15 years	1.5	1.2	1	0.8	0.755	0.652
	Error(%)			30.44767		

Table 1 above is a table of long epiphyseal test results from the system. There are two information on the reference column and the test result column. The reference column shows the proximal width of epiphyseal (PE), middle epifisis (ME) and distal epiphyses (ED) on the scans of Greulich and Pyle's book. While the test results column shows the test results from the system. Based on the above table, it can be seen that the percentage error measurement system by 30%.

Table 2. Metaphyseal measurement from geulich and pyle book

Age	Reference			Testing		
	PM	MM	DM	PM	MM	DM
3 years	0.9	0.8	0.55	0.824	0.702	0.411
3 years	1	0.9	0.5	0.966	0.726	0.435
4 years	1.05	0.9	0.55	0.872	0.734	0.485
4 years	1.1	0.9	0.6	0.966	0.683	0.411
5 years	1.05	0.9	0.6	0.772	0.604	0.339
6 years	1.1	0.95	0.6	0.896	0.652	0.461
7 years	1.2	0.9	0.6	1.045	0.845	0.54
8 years	1.2	1	0.7	1	0.874	0.605
9 years	1.2	1	0.7	0.845	0.683	0.512
10 years	1.25	1	0.7	0.898	0.725	0.581
11 years	1.2	1	0.7	0.845	0.7	0.458
12 years	1.25	1	0.75	0.918	0.603	0.386
13 years	1.3	1.05	0.8	0.776	0.603	0.246
14 years	1.4	1.1	0.9	0.676	0.437	0.339
15 years	1.4	1.1	0.9	0.919	0.715	0.533
	Error (%)			27.79673101		

Table 2. above is a table of metaphysical length test results derived from the system. There are two information on the reference column and the test result column. The reference column shows the proximal width data of metaphysis (PM), middle metaphysical (MM) and distal metaphysis (DM) on the scans of Greulich and Pyle's book. While the test results column shows the test results from the system. Based on the above table, it can be seen that the percentage error measurement system of 27%.

Features derived from feature extraction processes include proximal widths of epiphyses, proximal metaphysis, middle epipisis, middle metaphysis, distal epiphyses and distal metaphysis. For all test data, the process of classification using kNN method. Where the value of variable k = 1. The classification process using kNN using the average data width of epiphyses and metaphysical as training data. Where the data training amounted to 50 data, ages 3 to 15 years. This training data will be matched with input data from the system. The result of classification using kNN can be seen in table 3.

Tabel 3. Classification result using kNN algorithm

Age Range	Testing Result	Success	Failed
3 Years	4 success, 0 failed	100%	0%
4 Years	7 success, 0 failed	100%	0%
5 Years	4 success, 0 failed	100%	0%
6 Years	4 success, 1 failed	80%	20%
7 Years	3 success, 0 failed	100%	0%
8 Years	5 success, 1 failed	83%	17%
9 Years	3 success, 1 failed	75%	25%
10 Years	6 success, 2 failed	75%	25%
11 Years	6 success, 1 failed	86%	14%
12 Years	4 success, 2 failed	67%	33%
13 Years	3 success, 0 failed	100%	0%
14 Years	5 success, 2 failed	71%	29%
15 Years	4 success, 2 failed	67%	33%
	Precentage	85%	15%

As we can see in table 3, the age classification using k-Nearest Neighbor method shows excellent performance. With the total of 50 data and 72 test data, the succession process is 85% and the percentage error is 15%. In the table above, it can be seen that the age range with the highest success rate is the age range 3 to 5 years. This is because at that age, there is not much variation in bone width and bone form variation as found in data age 9,10, 11,12, 14 and 15. In the age range 9 to 15 years, the percentage of error tends to be higher than With age range below 9 years. Because at this age, the width and shape of bones vary widely. There are some data showing age incompatibility with bone width. For example, an individual by the age of 15 can have a width or bone shape like an individual at the age of 10 years or even as 8 years of age. Or even vice versa. This is what causes the percentage error is higher in the age range of 9 to 15 years. Figure 15 shows a graph of the success precentage of age classification using the kNN method.

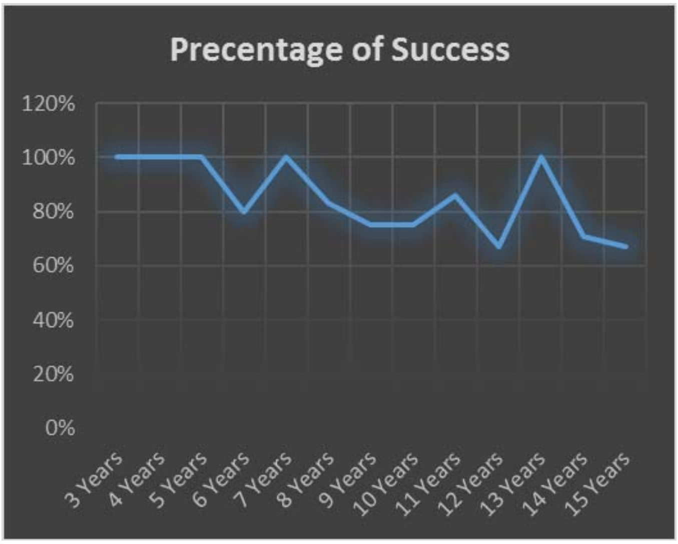


Fig 15. Success precentage of age classification

V. CONCLUSION

The proposed of this paper is built an automatic system to assess human age. There are four steps which has done , the process consist of preprocessing, segmentation, feature extraction and classification. Preprocessing step has done 100% , which is consist of Gaussian filtering, morphology and canny edge detection. After we do preprocessing, the next step is segmentation. In this paper segmentation using active shape model has done 100% and we got good result. The method successfully reach the boundary of middle finger bone. The last step is classification. In this part, we applied k-Nearest Neighbor classification. And the result came out with 15% error. It means percentage of successful is 85%.

VI. REFERENCES

[1] Mardiati,Endah. Hand-wrist Radiograph Analysis. Bandung. Fakultas Kedokteran Gigi Universitas Padjajaran.

[2] S.Idell Pyle, Alice W and William Walter Greulich. 1971. A Radiographic Standard Of Reference The Growing Hand and Wrist.The Press Of Case Western Reserve University, Cleveland.

[3] Pietka, E.: “Integration of computer assisted bone age assessment with clinical PACS.” Computerized Medical Imaging and Graphics, Volume 27, Issue 3, Page 217.

[4] D. Giordano, C. Spampinato, G. Scarciofalo and R. Leonardi, "An Automatic System for Skeletal Bone Age Measurement by Robust Processing of Carpal and Epiphysial/Metaphysial Bones," in IEEE Transactions on Instrumentation and Measurement, vol. 59, no. 10, pp. 2539-2553, Oct. 2010.

[5] Cootes, T. F., Hill, A., Taylor, C. J. , Haslam, J.: “The use of active shape models for locating structures in medical images.” Proc. First British machine Vision Conference, 245:407–412, 1990.

[6] C. W. Hsieh, C. Y. Chen, T. L. Jong, T. C. Liu, C. H. Chiu, “Automatic Segmentation of Phalanx and Epiphyseal/Metaphyseal Region by Gamma Parameter Enhancement Algorithm,” Meas. Sci. Rev., Vol.12, No 1, pp. 21–27, 2012.

[7] C. Y. Chen, L. J. Wu, C. W. Hsieh, T. C. Liu, T. L. Jong, “A novel image segmentation for phalanx and epiphyseal/metaphyseal based on hand x-ray films,” 2012 Proceedings of CVGIP, Taiwan, F3-12.

[8] R. Sigit et al., "Hand-wrist bone assesment for automatic age identification," 2016 International Electronics Symposium (IES), Denpasar, 2016, pp. 54-59.

[9] Aifeng Zhang , Arkadiusz Gertych, Brent J. Liu, “Automatic bone age assessment for young children from newborn to 7-year-old using carpal bones” 2007 Computerized Medical Imaging and Graphics 31 (2007) 299–31.

[10] Justiawan; SIGIT, Riyanto; ARIEF, Zainal. Tooth Color Detection Using PCA and KNN Classifier Algorithm Based on Color Moment. EMITTER International Journal of Engineering Technology, [S.l.], v. 5, n. 1, july 2017. ISSN 2443-1168..