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Age Identification System of Molar Dental Panoramic Image Processing with an Adaptive Region Growing Approach Method

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Abstract

Forensics plays a crucial role in law enforcement, particularly in cases when objects or human victims who are being identified forensically have suffered significant damage. Teeth have a high level of endurance, rendering them a highly effective means of identification, as they are capable of enduring various environments. Forensic odontology is a specialized discipline that focuses on utilizing dental evidence to establish the identity of individuals in judicial processes. Age estimation is a crucial determinant in the field of forensic odontology. The development of an individual's teeth is typically strongly correlated with their age, and this can be determined by analyzing the dental pulp. The tooth pulp experiences either restriction or enlargement with age. This study focused on creating an image processing system specifically designed for analyzing dental pulp molar radiograph images. The system utilized the Adaptive Region Growing Approach (ARGA) method. Subsequently, the dental pulp images were classified utilizing the Support Vector Machine (SVM) methodology. The research process encompassed data collection, picture manipulation, feature extraction, and size classification of molar dental pulp. The algorithm attained an accuracy rate of over 80% in the findings. This was achieved by utilizing specific parameters, such as setting an adjustment threshold of OTSU 1.15 and applying a clip limit histogram equalization of 0.1 to categorize the data into four classes. The study concludes that the utilization of the Adaptive Region Growing Approach (ARGA) and Support Vector Machine (SVM) classification is highly effective for age assessment using panoramic radiograph pictures. This has the capacity to be widely utilized in the domain of forensic odontology, particularly in assisting in the identification of victims in law enforcement.

Keywords: Forensics; Odontology Forensic; Adaptive Region Growing Approach (ARGA); Support Vector Machine (SVM)

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1. Introduction

Forensics is the utilization of scientific expertise to analyse and interpret evidence in a legal setting, intending to aid criminal investigations and court procedures from a scientific perspective [1]. Various branches of forensic science are dedicated to investigating human-related issues and uncovering the enigma of crimes. These branches include criminalistics, toxicology forensic, odontology forensic, psychiatry forensic, hematology forensic, anthropology forensic, ballistics forensic, and molecular serology forensic [2]. Forensic Odontology is a method used by forensics to identify teeth. Teeth can sometimes serve as a viable method for identification due to their durability and resistance to damage [3].

Forensic Odontology is a scientific discipline that utilizes dental expertise to resolve legal cases associated with court processes [4]. The current technique used in forensic odontology relies on manual measurements, resulting in potential variations in the estimation outcomes and a lack of clarity. A deep learning-based automated system decreases processing time while providing consistent

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and replicable outcomes [5]. The development of a person's teeth is closely tied to age, as reflected in the dental pulp condition. As individuals age, the dental pulp decreases in size, while it increases in size in younger individuals [6]. From a medical perspective, age estimation can be determined by examining dental radiography pictures [7]. Artificial intelligence technologies facilitate the observation of dental radiography pictures through image processing during their development [8-11].

Age estimation using machine learning involves analyzing panoramic dental photos of specific types of teeth, such as mandibular and molar teeth [12,13]. Previous research utilized the Local Binary Pattern technique and manual examination of data. The study reported a precision level of 63.21% with a computational duration of 0.87 seconds. The lower precision results from the manual scanning of data and the inability to identify the complete pulp region [14]. Subsequently, a study utilizing Cone Beam Computed Tomography (CBCT) scans was conducted to ascertain the gender of individuals based on the maxillary sinus bones.

The study conducted dimensional calculations using CBCT images and found that measuring the maxillary sinus bone can be utilized for gender identification [15]. Furthermore, a study employed Computed Tomography (CT) images to detect lung nodules, serving as indicators for various lung disorders. The study employs the Binary Large Object (BLOB) technique and the Support Vector Machine classification approach, which yield impressive results and exhibit significant potential [16]. Several studies have explored panoramic images, examining gender identification through canine teeth and achieving a system accuracy of 80% [17]. Additionally, research in facial identification has utilized panoramic dental images, incorporating fuzzy and ID3 algorithm methods to achieve an accuracy rate of 65% based on data from 26 teeth. [18].

Furthermore, a study focused on the early detection of osteoporosis employed the Gray Level Cooccurrence Matrix (GLCM) and the Support Vector Machine classification method on mandibular x-ray images, resulting in an accuracy rate of 85.71% [19]. The focus of the age identification study lies in analyzing several components of the tooth, such as the pulp of premolars, canines, and molars, using panoramic photographs. A study investigating premolar pulp utilized the Statistical Analysis of Structural Information and Adaboost techniques,

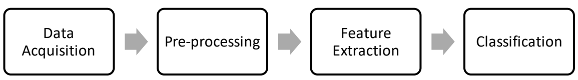


Fig. 1 Diagram of the System Process

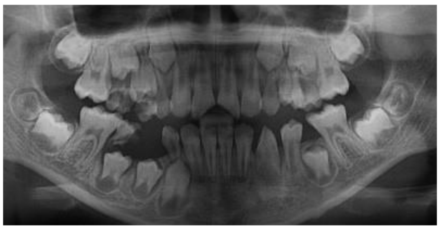


Fig. 2 Panoramic Image

achieving an accuracy rate of 84.6%. [20]. Subsequently, a study was conducted on canine pulp utilizing the Adaptive Region Growing Approach technique, yielding an accuracy rate of 63% [21]. Moreover, the primary source for this study is research conducted on molar pulp.

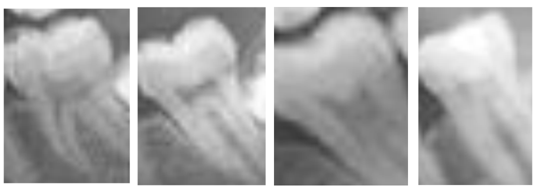
2. Research Methodology

The system designed is an age identification system based on the pulp area of molar teeth using radiological images. The system initiates with the image acquisition phase, collecting panoramic X-ray data, and proceeds to a crucial pre-processing stage aimed at enhancing the quality of the image targeted for research. Following this, the system engages in feature extraction using the ARGA approach and concludes with the classification procedure using SVM. The first part of this approach is data acquisition, then its followed by pre-processing data which will allow for feature extraction and lead to the classification stage. The system work procedure can be observed in Figure 1.

2.1 Data Collection

This study employed panoramic X-ray pictures from the Padjadjaran University Dental and Mouth Hospital with registration number 1387/LN6.KEP/EC/2019 of ethical exemption. The image shows the X-ray of each person that was obtained with the panoramic X-ray. An example of panoramic image data can be seen in Figure 2.

In this study, a total of 376 dental images were used, covering an age range from 14 to 60 years. The dental pictures are classified into four classes: Class I (age 14–25 years), Class II (age 26–37 years), Class III (age 38–49 years), and Class IV (age 50–60 years).



(a) (b) (c) (d)

Fig.3 Molar Dental Images. (a) Class I (age 14–25 years), (b) Class II (age 26–37 years), (c) Class III (age 38–49 years), and (d) Class IV (age 50–60 years)

Out of these, 282 images were utilized for training, while the remaining 94 were used as test images. The sample of data based on the class can be shown in Figure 3.

2.2 Pre-Processing

The process of preparing and refining data for inspection is known as pre-processing. This involves several steps, including cropping, RGB-to-grayscale conversion, and image segmentation. Cropping is a means of handling and reviewing evidence through teeth and mouth [25] or mapping the relationship of each pixel that depends on the pixel itself if you want to retrieve useful information or objects so that irrelevant things or pixels will be removed. Furthermore, RGB to Grayscale is a technique of transforming color images (Red, Green, and blue) at each pixel to one grey value to simplify image processing [26]. Then there is picture segmentation, which aims to break the image into multiple objects or group pixel regions based on similarities in color or form, and discover coherent image portions. [27].

2.3 Adaptive Region Growing Approach

The Adaptive Region Growing Approach (ARGA) is an image segmentation method that utilizes models to characterize image regions' homogeneity and simple form features. This method allows for the adjustment of image segmentation parameters based on the properties of the processed picture [28]. In this work, the Adaptive Region Growing Approach (ARGA) method was employed to facilitate the segmentation process when searching for pulpal areas in images. This approach selects some pixels from the pre-processed image as seed pixels [29]. The pixel seed will next decide the neighboring pixels by picking the eight neighbors around it. Through the merging process, the seed pixels and their neighbors will generate an image that is the focus of inquiry. One of the key features of ARGA is the clip limit histogram Equalization, a contrast value that reduces image oversaturation, especially in homogeneous areas.

2.4 Classification: Support Vector Machine

A support Vector Machine is an image processing tool whose purpose is to analyze classification and regression; it may also be used to extract information or data [30]. The main notion of SVM is to determine the best decision surface (Hyperplane) for each data point [31]. SMV states that weight times the basis function with addition to the bias should equal zero. In general, the simple SVM equation/model can be seen in equation (1):

$$w \bullet f(x) + b = 0 \tag{1}$$

SVM employs a linear model as a decision boundary where x is the input vector, w is a weight parameter, f(x) is a basis function, and b is a bias.

In this study, SVM is utilized to classify training data and test data. It begins by inputting the training image featuring extraction results and subsequently determining the type of kernel employed. The kernel determination transfers non-linear panoramic image data into dimensional space. Three types of kernels are used: linear, Gaussian, and polynomial [32]. Following this, the type of SVM coding is determined, namely, one against one or one against all. Subsequently, training data is conducted, and ultimately, testing data is carried out by comparing it with the training image.

3. System Testing and Analysis

3.1 System Testing

In testing the designed system, three scenarios are carried out to identify its performance, strengths, and weaknesses. In the first scenario, the system is examined using test photographs with variations in the OTSU threshold values to optimize the segmentation process. The goal is to obtain pulp images that match the best accuracy. In the second scenario, the system is tested using photos with varied clip limit settings and histogram equalization to enhance image contrast and produce clear pulp images with maximum accuracy. The final scenario examines the system utilizing test images with multiple SVM kernel types to discover the kernel that matches the linear and non-linear data types with the best accuracy. This test assesses system performance and discovers ideal parameters to attain the best accuracy.

3.2 The Result of System Testing

In testing the system, 376 photos were employed, with 282 images used as training data and 94 as test data. Taking test photographs is done randomly with 24 data points from each class. This test consists of four different scenarios. The first scenario tries to discover the ideal adjustment value for the system,

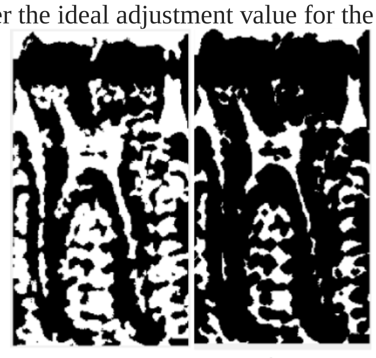


Fig. 4 The Difference of Image in different Thresholds; (a) Adjustment 1.09 (b) Adjustment 1.15

Table 1. Testing Accuracy Value Using Threshold Parameters

Adjustment Threshold OTSU	**Accuracy (%)**
1.09	54.26
1.11	62.77
1.13	68.08
1.15	80.85
1.17	72.34

which will then be analyzed. The second, third, and fourth scenario attempts to discover the ideal values for the clip limit in histogram equalization, the type of kernel, and the type of coding utilized in the system.

3.2.1 Result of Threshold ARGA Effect

The test employs the optimal pulp image obtained through various testing processes by adjusting the OTSU adjustment threshold. Its purpose is to assess the system's accuracy across different threshold values. The selected adjustment values are 1.09, 1.11, 1.13, and 1.15, chosen for their effectiveness in achieving precise pulp image segmentation. If the adjustment value is too small, then some of the teeth other than the pulp will be segmented, but very few sections will be detected if it is too large. Testing this situation requires the parameter clip limit histogram equalization 0.1 and the SVM polynomial kernel type. When the pulp area is adjusted, the accuracy changes. The difference in pulp area based on the ARGA threshold may be shown in Figure 4.

The highest accuracy, 80.85%, was achieved with an adjustment value of 1.15, where 76 out of 94 test data points were correctly identified. Conversely, the lowest accuracy, 54.26%, was observed with an adjustment value of 1.09, where only 51 out of 94 test data points were correctly identified. This variation in accuracy is attributed to the influence of the OTSU adjustment threshold value on the dental pulp segmentation process, the focal point of our research. A value of 1.09 led to the inclusion of other dental locations outside the pulp during the seed pixel search procedure, resulting in poor image segmentation. On the contrary, an adjustment value of 1.15 allowed the seed pixel to accurately recognize the edge of the pulp. The results show that 1.15 is the most accurate adjustment whilst 1.09 is the most inaccurate. The results of the performance system are shown in Table 1.

3.2.2 Result of Clip Limit Histogram Equalization Effect

The histogram equalization clip limit value, updated as a parameter of the ARGA technique for each image, determines visual contrast in homogeneous areas. The values used in this test are 0.01, 0.05, 0.1, and 0.15. The test employs the OTSU adjustment threshold parameter 1.15, polynomial kernel type, and one-against-one SVM coding type. The maximum accuracy number is obtained at the clip limit histogram Equalization of 0.1, which is 80.85%, with the correct test data being 76 out of 94. At the same time, the smallest accuracy value is reached at the clip limit histogram Equalization of 0.01, which is 51.06%, with the number of correct test data as high as 48 out of 94.

The discrepancy in accuracy findings is due to the influence of dental image contrast, which is defined by the clip limit histogram Equalization setting. At a value of 0.01, the tooth image contrast is low so that the tooth pulp is not visible, whereas at a value of 0.1, the tooth image contrast is high so that the tooth pulp is visible. The higher the clip limit, the higher the accuracy. The results of evaluating the clip limit histogram equalization can be shown in Table 2.

3.2.3 The Results of SVM Kernel Type Effect

The tested kernels include Gaussian, linear, and polynomial types. The Gaussian kernel is applied when the data cannot be separated linearly, while the linear kernel is suitable for linearly separable data. Polynomial kernels are chosen for their flexibility and adaptability. The test utilizes the parameter adjustment threshold OTSU 1.15 and clip limit histogram Equalization 0.1. The highest accuracy, 80.85%, is achieved with the polynomial kernel type, Whereas, the lowest accuracy is attained with the linear kernel type, which is 76.59%. The discrepancy in accuracy outcomes is attributed to the influence of the SVM kernel type on the hyperplane, which separates classes in the classification process. The linear kernel type, in this test, produces the least accurate results, which can be attributed to cropping image data with multiple resolution sizes. Variations in resolution within photos of the same class may lead

Table 2. Accuracy of Changing the Clip Limit Histogram Equalization

Threshold OTSU	***Histogram Equalization***	**Accuracy (%)**
1.5	0.01	51.06
	0.05	76.59
	0.1	80.85
	0.15	79.78

Table 3. The System Accuracy Based on Kernel Type of SVM

Threshold OTSU	***Histogram Equalization***	**Kernel Type**	**Accuracy (%)**
1.15	0.1	*Gaussian*	79.78
		Linear	76.59
		Polynomial	80.85

to unequal and incompatible data categorization findings. With different methods come different accuarcies and the linear kernel type is seen as the most accurate. The outcomes of testing this scenario can be found in Table 3.

4. Conclusions

Based on the results of testing and analysis in this study, it can be concluded that the Adaptive Region Growing Approach method and Support Vector Machine classification can effectively establish an age range using panoramic radiograph image processing. This study indicates that numerous parameters can influence system performance which is measured based on accuracy. These parameters are OTSU adjustment threshold value, clip border histogram equalization value, and SVM kernel type. The system exhibits optimal performance with a test accuracy exceeding rate 80%. However, it falls short of maximum performance due to the utilization of a dental panoramic image of insufficient quality, resulting in an obvious pulp shape.

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Additional Information