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Nonlinear regression analysis to predict mandibular landmarks on panoramic radiographs

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ABSTRACT

An automatic system for determining mandibular landmark points on panoramic radiography can reduce errors due to differences in expert professionalism and save time. Previous research has shown that the linear regression method is ineffective at predicting condyle and gonion landmark points in panoramic radiography. So, this research proposes an analysis of nonlinear regression methods (support vector machine (SVM) kernel=‘polynomial’, polynomial regression, and ensemble regression) for predicting condyle and gonion landmark points. There are four predicted landmark points, namely the right condyle, left condyle, right gonion, and left gonion. The nonlinear regression methods used are SVM, polynomial regression, and ensemble regression. The Dental and Oral Hospital, within the Faculty of Dentistry at Universitas Airlangga, provides the research data. The research encompasses 119 patients between the ages of 19 and 70, dividing 103 into training and 16 into testing. The research results show that the SVM method is only good at predicting the right condyle point with a mean radial error (MRE) of 4,724 pixels. Meanwhile, to predict the left condyle, right gonion, and left gonion points, it is better to use the polynomial regression method and ensemble regression with an order of success detection rate (SDR) of 37.5%, 18.75%, and 12.5%, respectively.

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1. INTRODUCTION

In clinical diagnosis, treatment, and surgery, dental radiography is essential. Recent years have seen efforts to develop dental radiographic image analysis systems for use in dentistry. Researchers have used mandibular shape analysis to diagnose conditions like osteoporosis and to estimate biological information like age, gender, and race. Modern orthodontic clinical diagnosis typically involves mandibular analysis. Manually marking mandibular landmarks takes a long time, and it is difficult to obtain accurate detection due to differences in doctors' professionalism. The linear regression method in research [1] predicted ten mandibular landmark points, including the left condyle point, the right condyle point, the left gonion point, the right gonion point, the left ramus point (2 points), the right ramus point (2 points), the lower mandible, and the upper mandible. The research results [1] showed that the linear regression method had good precision in predicting landmark points in the lower mandibular body; besides that, it had a prediction difference that was far from the ground truth. Previous studies found the linear regression method to be less precise in predicting landmark points on the condyle and gonion [2]. To perform dental implants in the mandible, accurate and automated measurements of the alveolar bone and mandibular canal are necessary [2]. To measure the mandibular canal, one must first perform a segmentation process known as mandibular segmentation [3].

Dental radiographs are necessary for dental care, diagnosis, and treatment planning. Radiographic analysis can provide an overview of the patient's bone, tooth, and soft tissue structures, as well as all the images for orthodontic analysis and treatment planning. During treatment planning, the clinical practice of manually tracing anatomical structures is a time-consuming and subjective process. Automatic landmark detection for cephalometric diagnosis and orthodontic treatment can be a solution to this problem. Here are several studies related to cephalometric landmark detection: These studies include the prediction of 19 cephalometric landmarks [4], the prediction of 19 cephalometric landmarks using the iterative deep convolutional neural network method [5], the prediction of mandibular landmarks on 3D cephalometric images [6], and the prediction of cephalometric landmarks using deep regression, with the best % successful detection rate (SDR) evaluation values being 86.91% (2 mm standard), 91.82% (2.5 mm standard), 94.88% (3 mm standard), and 97.90% (4 mm standard) [7]. The mandible, housing the lower teeth and used for chewing and speaking, is the strongest, largest, and most movable facial bone. Mandibular disorders affect appearance and quality of life. Dentistry, orthodontics, and forensics have conducted the most studies on the mandibular bones. Several studies have shown that there is a strong correlation between mandibular bone characteristics, such as morphometry and appearance, and biological variables, such as gender or age [8]. In an automatic mandibular examination, the system requires a segmentation stage and then determines 27 landmarks on the 3D mandibular cone-beam computed tomography (CBCT) [9].

In orthognathic and aesthetic surgery, facial asymmetry is critical because congenital malformations, traumatic injuries, and oral cancer affect the shape of the face. Reconstruction of facial symmetry is the primary goal of many operations; therefore, it is very important to perform accurate measurements of symmetry deviation when planning surgery. That determines the steps for measurements by identifying landmarks on cephalometric radiographs. Researchers have developed various methods to accurately and automatically determine landmarks, such as the deep learning method [10], template matching [11], convolutional neural network (CNN) [12], and the faster region-based convolutional neural network (R-CNN) [13]. In the fields of dentistry, orthodontics, and forensics, many studies of mandibular bones exist because there is a strong correlation between the characteristics of mandibular bones and biological variables, such as gender or age. Researchers have determined gender dimorphism by measuring the distances between anatomical landmarks or examining the mandibular shape. Clinical applications of cephalometric analysis in surgical planning include diagnosis and treatment, evaluation of facial soft tissues, and evaluation of the mandible or lower jaw [14]. Cephalometric analysis is necessary because it provides an interpretation of the patient's bone structure and an overall picture for the surgeon in orthognathic surgery (OGS) [15]. In research [16], they determine gender by measuring each landmark on the mandibular bone, specifically the mandibular landmark points, using geometric parameters [17]–[19]. Researchers have extensively studied the geometric measurements of mandibular landmarks to estimate gender and age in forensic settings [20]–[24]. Understanding the variations in anatomical structures is crucial for radiological pathological diagnosis, which requires specific knowledge of anatomical landmarks. During implant surgery, knowledge of the morphological and anatomical variations associated with mandibular anatomical landmarks is required, especially because the inferior alveolar nerve bundle is in various locations and undergoes many changes. The individual identification process of gender, race, and age requires radiological examination methods [25], [26].

According to the review above, determining mandibular landmarks is extremely important in dentistry. Previous research on the process of determining mandibular landmarks has used various methods, one of which is linear regression, but it has a high error at the gonion and condyle landmark points. Therefore, the next research suggests evaluating nonlinear regression methods for predicting condyle and gonion points. This research analysis nonlinear regression methods for predicting mandibular condyle and gonion points. Because some individuals have different ramus and mandible lengths, this research proposes a nonlinear method. The structure of writing this scientific article is as follows: the first part provides the background to the research, the second section identifies the dataset source, research proposal, explains how to evaluate the performance of the method, the third section discusses the research results, and the fourth section conclusion.

2. METHOD
2.1. Dataset
The data was collected from the Dental and Oral Hospital at the Faculty of Medicine, Universitas Airlangga, Surabaya. The patient data includes 119 men and women from 19 to 70 years old based on selection from expert radiologists. The research divides the panoramic radiography data into 103 for training and 16 for testing. Expert radiologists determined landmark points for the condyle and mandibular gonion from 119 panoramic radiography data points. Because it adapted to the model architecture, this research scaled all panoramic radiography data to 224×224. The dataset includes condyle landmark points in Figure 1(a) and gonion in Figure 1(b).

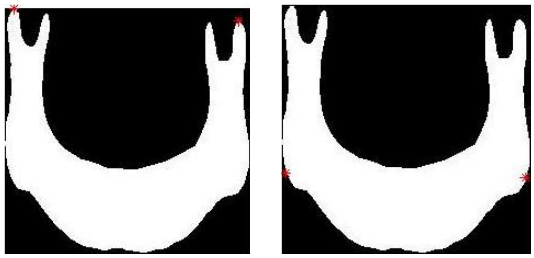

(a) (b)

Figure 1. Landmarks (a) condyle and (b) gonion

2.2. Proposed method
According to research [1] on the process of determining landmark points, a linear regression method is proposed, and the points determined are the condyle, ramus, gonion, and mandibular body. Research [1] found that the prediction results for landmark points with a large error were gonions, specifically 10 pixels. Therefore, this research proposes the prediction of condyle and gonion landmark points on mandibular panoramic radiography. Figure 2 illustrates the stages of this research. Expert radiologists determined the point of the condyle and mandibular gonion from all 119 panoramic radiograph images. The research divided all the data from 119 panoramic radiographs into 103 images for training and 16 images for testing. This research trained data from 103 panoramic radiography images containing landmark points using the support vector machine (SVM) (kernel=‘polynomial’), polynomial regression, and ensemble regression methods to create forecasting models. This research analysis each model’s landmark point prediction results and seeks the most appropriate prediction value.

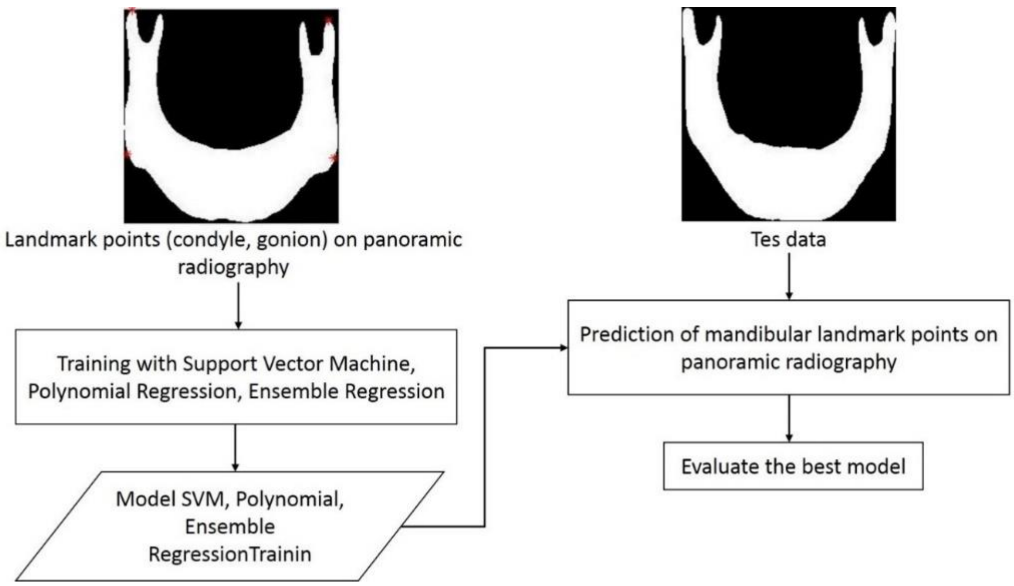


Figure 2. Proposed research

The method used to create the model is nonlinear (SVM with kernel='polynomial', polynomial regression, and ensemble regression). The SVM method is a training process to solve Equation with 1, w is the weight, $\Phi(x)$ is the basis or kernel function, and b is the bias parameter. The kernel in the SVM used is the polynomial in (2) [27].

$$y(x) = w^T \Phi(x) + b \quad (1)$$

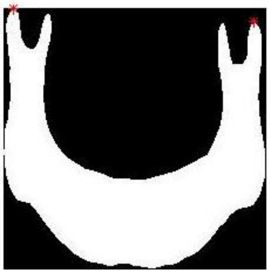
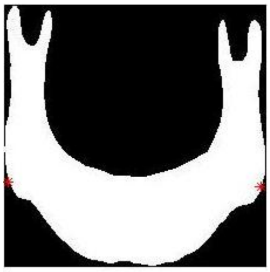
$$k(x_i, x_j) = (\gamma {x_i}^T x_j + r)^d, where \gamma > 0 \quad (2)$$

The polynomial regression method is a training process to solve (3) [28]. $p(x)$ is a polynomial of decreasing power with length p with $n + 1$.

$$p(x) = p_1 x^n + p_2 x^{n-1} + \ldots + p_n x + p_{n+1} \quad (3)$$

The predicted landmark points are the left and right parts of the mandible on panoramic radiography as in Table 1. Each landmark point will have predicted coordinates (x, y), The total predicted points are four coordinates (left condyle, right condyle, left gonion, and right gonion).

Table 1. Predicted landmark points

Section	Image	Left	Right
Condyle		(x, y)	(x, y)
Gonion		(x, y)	(x, y)

2.3. Evaluation

This research evaluates the performance of the resulting model using mean radial error (MRE), as done in [10]. MRE can be calculated using (4) and (5).

$$R = \sqrt{\Delta x^2 + \Delta y^2} \quad (4)$$

$$MRE = \frac{\sum_{i=1}^{n} R_i}{n} \quad (5)$$

Because the prediction results for landmark points are different from the ground truth. If the difference is within a certain range, it means it is correct within that range. In the experiment, the ranges used as standards were 2, 3, and 4 pixels. For example, if the prediction error is in the range of 3 pixels, it means it is successful in the 3 and 4 pixel standards but wrong in the 2 pixel standard. Another way to evaluate is to use the success detection rate (SDR) as stated in (6), where Na represents the number of successful detections and N represents the total number of detections.

$$SDR = \frac{N_a}{N} 100\% \quad (6)$$

3. RESULTS AND DISCUSSION

This research analysis the best nonlinear regression methods (SVM kernel=‘polynomial’, polynomial regression, and ensemble regression) for predicting mandibular landmark points. There are four predicted landmark coordinate points, namely the left condyle, the right condyle, the left gonion, and the right gonion. Figure 3 shows the prediction results for mandibular landmark points using the SVM kernel=‘polynomial’ method; the prediction results are green, and the ground truth points are red. Figure 3(a) predicts the right condyle point with an error of 1.81 pixels, so it has good accuracy in the 2, 3, and 4 pixel standards, and the left condyle has an error of 2.48 pixels and has good accuracy in the 3 pixel standard and 4 pixels. Figure 3(a) predicts that the right gonion point has a high error of 11.92 and the left gonion has an error of 13.05, so both are not correct in predicting. Figure 3(b) shows that none of the landmark points are correctly predicted; the right condyle, left condyle, right gonion, and left gonion points have an error of 5.22, 5.15, and 6.93 pixels, 6.79 pixels. Figure 3(c) shows that none of the landmark points are correct in predicting; the right condyle, left condyle, right gonion, and left gonion points have an error of 4.28, 10.97, and 23.01 pixels, respectively, and 18.62 pixels. Figure 3(d) shows that none of the landmark points are correctly predicted; the right condyle, left condyle, right gonion, and left gonion points have an error of 8.14, 6.35, and 34.29 pixels, respectively, and 23.94 pixels.

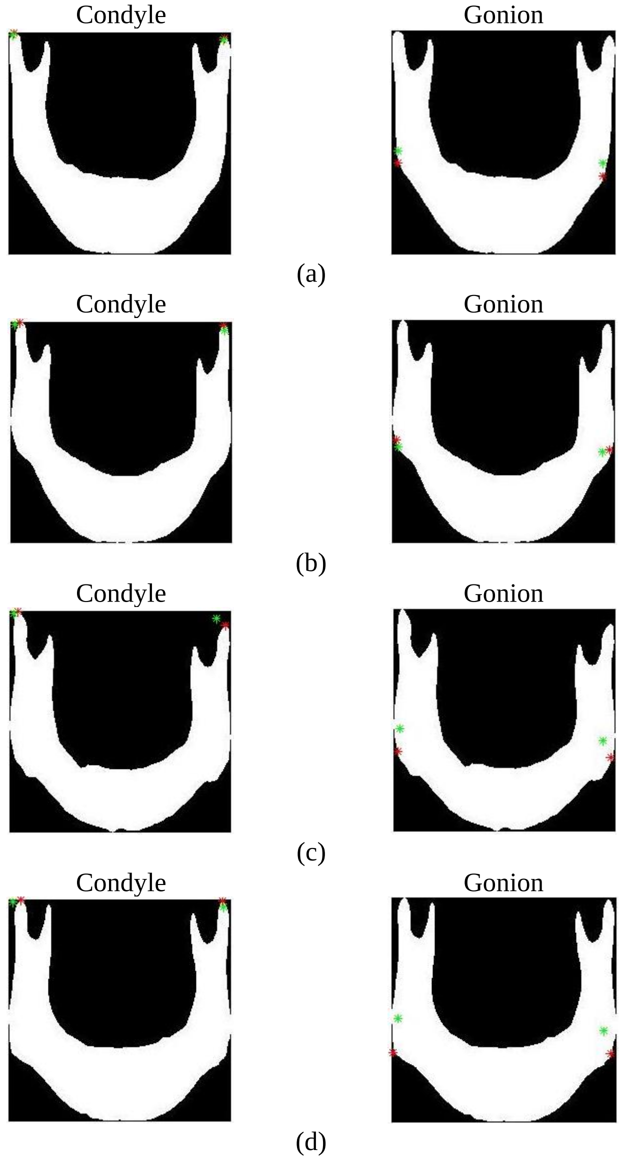


Figure 3. Landmark point prediction results with SVM: (a) first test, (b) second test, (c) third test, and (d) fourth test

Figure 4 shows the prediction results for landmark points using the polynomial regression method. Figure 4(a) shows that the right condyle point has an error of 2.50 pixels and has a standard accuracy of 3 and 4 pixels; the left condyle point has an error of 3.07 pixels and has a standard accuracy of 4 pixels; and the right and left gonion points are both inaccurate in predicting with sequential errors of 11.77 and 11.88 pixels. In Figure 4(b) only the right condyle point has accuracy in predicting with a standard of 3 pixels, 4 pixels, and an error value of 2.99 pixels, the other points are not correct in predicting, namely the left condyle point, right gonion, and left gonion values. The sequential errors are 4.74, 23.66, and 9.94 pixels. Figure 4(c) shows that the right and left condyle points are correct in predicting the standard 2 pixels, 3 pixels, and 4 pixels with error values of respectively 0.74 pixels and 1.50 pixels, and neither of the right and left gonion points are correct. The error values for the right and left condyle points are 7.14 pixels and 6.75 pixels, respectively.

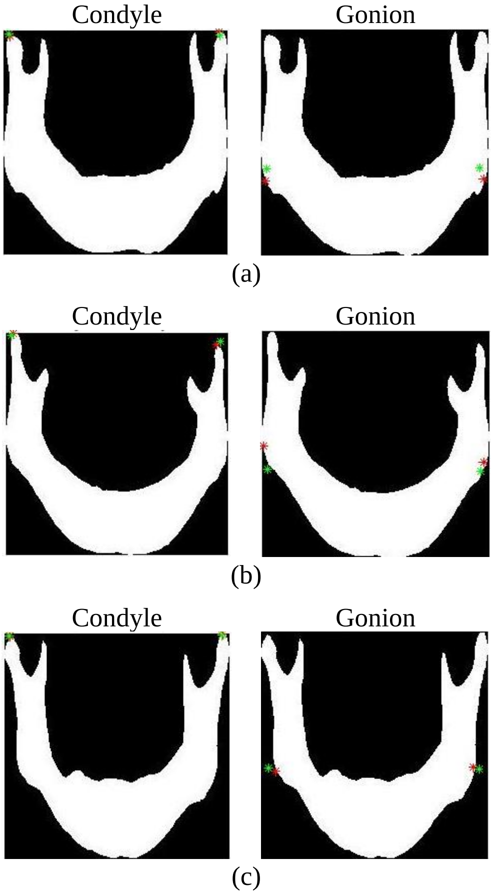


Figure 4. Landmark point prediction results with polynomial regression: (a) first test, (b) second test, and (c) third test

Figure 5 shows the predicted results for landmark points using the ensemble regression method. Figure 5(a) shows that the correct landmark point in predicting is the left condyle point with an accuracy of 3 and 4 pixels standard, error 3 pixels, the right gonion point with accuracy only 4 pixels standard, error 3.57 pixels, the right condyle point, and the left gonion is inaccurate in predicting with sequential errors of 4.72 and 21.93 pixels. In Figure 5(b) the correct landmark point for predicting is the left gonion at a standard of 4 pixels, the error is 3.17 pixels, while the right condyle, left condyle, and right gonion points have an error of 6.13, 5.94, and 6.66 pixels. Figure 5(c) shows that the right and left condyle points, with sequential errors of 1.12 pixels (exact within the standards of 2, 3, and 4 pixels) and 3.03 pixels (exact within the standards of 4 pixels), are the landmark points that have accuracy in predicting. Meanwhile, the errors for the right and left gonion points are 5.49 pixels and 7.81 pixels, respectively.

Figure 6 is the result of predicting landmark points that have high errors using several methods (SVM kernel='polynomial', polynomial regression, and ensemble regression). Figures 6(a) and 6(b) have high error values at the right condyle point, right gonion, and left gonion, respectively 8.14, 34.29, and 23.94 pixels using the SVM method. At the left gonion point, the polynomial regression method has an error of 19.48 pixels, and the ensemble regression method has an error of 31.76 pixels. Figures 6(c), 6(d), and 6(e) show the results of landmark point predictions using the SVM kernel='polynomial,' polynomial regression, and ensemble regression methods, which have high errors. According to the SVM method, Figure 6(c) has a height error of 13.52 pixels at the right condyle point. Figure 6(d) is the prediction result using the polynomial regression method at the right condyle point. The predicted result is negative, so it does not appear, and the error is 16.34 pixels. Figure 6(d) shows the prediction result for the right gonion point, which has a high error of 29.04 pixels using the polynomial regression method. Figure 6(e) shows the right condyle's landmark point using the ensemble regression method, the right gonion has a sequential error of 14.88 or 24.58 pixels. The prediction results in Figures 6(f), 6(g), and 6(h) show a high error using the SVM method, with the left gonion point showing 27.26 pixels and the left condyle point showing 19.18 pixels. In Figure 6(g) the polynomial regression method has an error of 21.22 pixels at the left condyle point and 22.19 pixels at the left gonion point. Figure 6(h) shows that the ensemble regression method has an error of 22.77 pixels at the left condyle point.

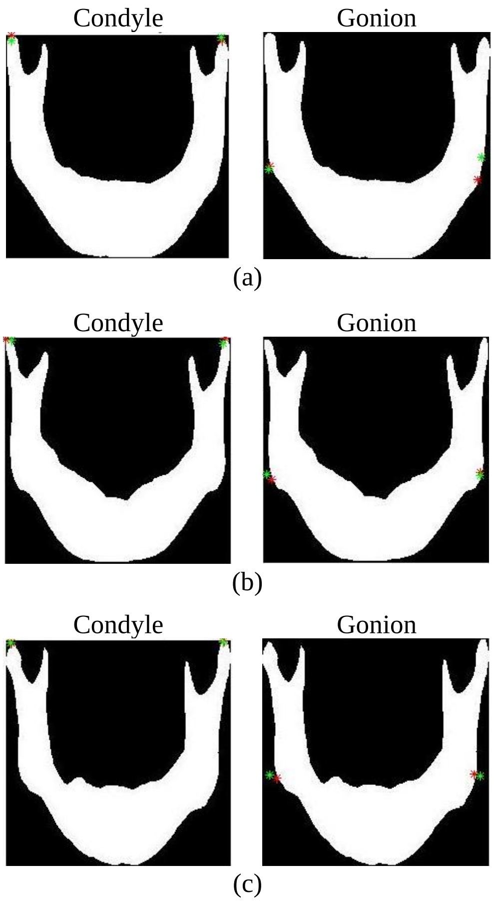


Figure 5. Landmark point prediction results with ensemble regression: (a) first test, (b) second test, and (c) third test

Table 2 shows the outcomes of testing landmark point predictions with SVM kernel='polynomial', polynomial regression, and ensemble regression. In Table 2, the one with the highest MRE is the SVM at the right gonion point of 17.316 pixels. All SVM, polynomial regression, and ensemble regression methods have a small MRE of less than 5 pixels for the right condyle point. Table 2 shows that polynomial regression, with a standard of 4 pixels, has the highest accuracy in predicting the right condyle landmark point, with a prediction accuracy of 50%. The ensemble regression method has accuracy in predicting the left condyle point from all standards (2, 3, and 4 pixels), respectively 18.75%, 25%, and 37.5%. At the right gonion point, the most accurate prediction is the ensemble regression method at the standard 4 pixels, with an accuracy of 18.75%. The polynomial regression method best predicts the left gonion point with an accuracy of 6.25% (standard 3 pixels) and 12.5% (standard 4 pixels).

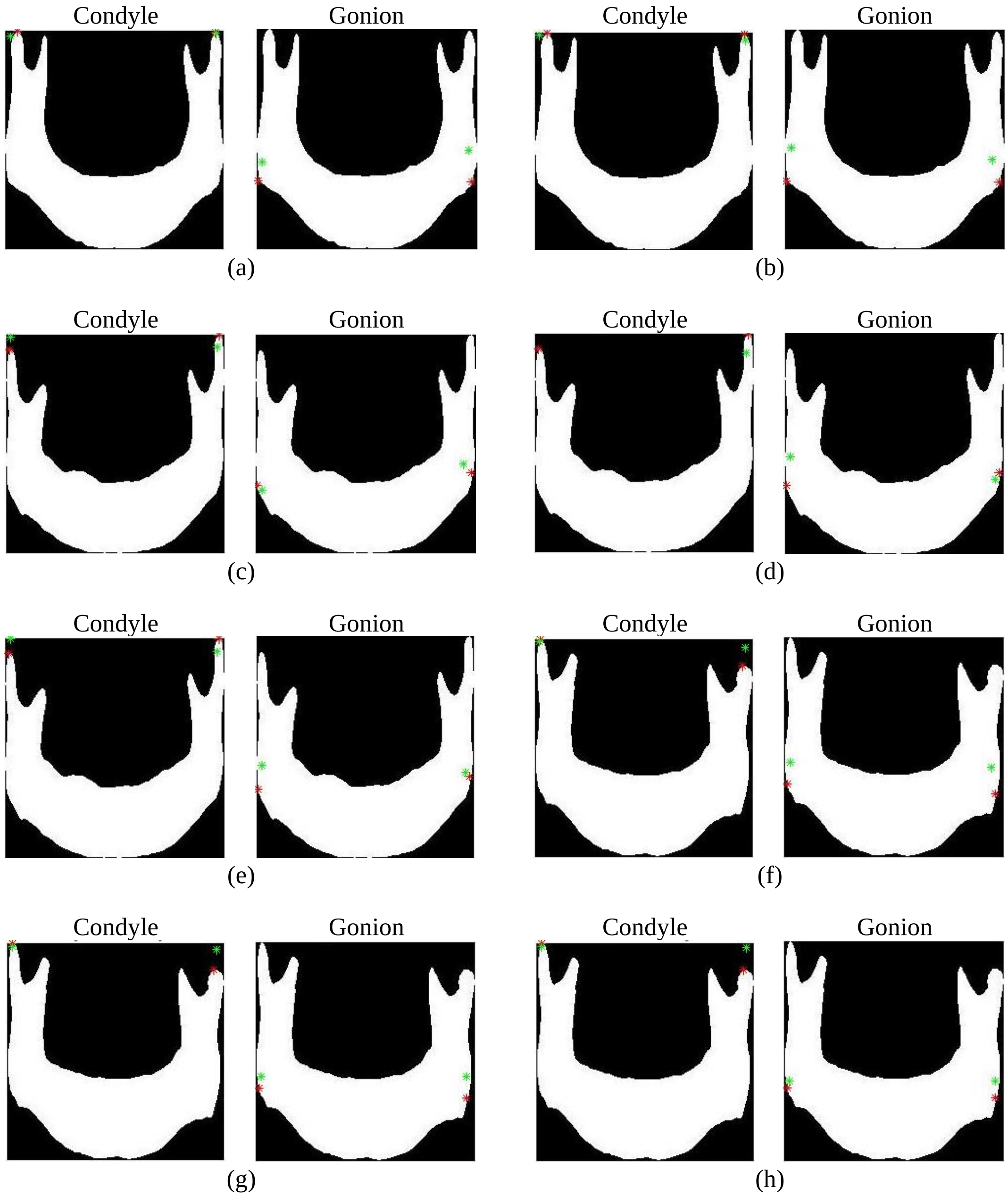


Figure 6. Landmark point prediction results with high error: (a) first test, (b) second test, (c) third test, (d) fourth test, (e) fifth test, (f) sixth test, (g) seventh test, and (h) eighth test

Table 2. Evaluation results of the landmark point prediction method

Section	Method	MRE (px)	SDR 2 px (%)	SDR 3 px (%)	SDR 4 px (%)
Condyle R	SVM	**4.724**	31.250	31.250	43.750
	Polynomial	4.976	6.250	43.750	**50.000**
	Ensemble	4.849	18.750	37.500	43.750
Condyle L	SVM	10.392	0.000	6.250	12.500
	Polynomial	7.573	12.500	12.500	37.500
	Ensemble	**7.278**	**18.750**	**25.000**	**37.500**
Gonion R	SVM	17.316	0.000	0.000	6.250
	Polynomial	10.618	0.000	0.000	0.000
	Ensemble	**10.363**	0.000	0.000	**18.750**
Gonion L	SVM	12.703	0.000	6.250	6.250
	Polynomial	**10.333**	0.000	**6.250**	**12.500**
	Ensemble	13.760	0.000	0.000	12.500

Each individual’s mandible condition varies in panoramic radiographic images, necessitating the use of polynomial or ensemble regression methods to predict the right and left gonion landmark points. In the panoramic radiography image, the condition of each individual's left and right ramus has different lengths, so when predicting the right condyle landmark point, you can use linear or nonlinear regression methods, but when predicting the left condyle point, it is better to use the nonlinear regression method.

4. CONCLUSION

This research analysis the nonlinear regression method for predicting mandibular landmark points (right condyle, left condyle, right gonion, and left gonion points). The nonlinear regression methods used are SVM kernel=‘polynomial’, polynomial regression, and ensemble regression. Experimental results show that to predict the right condyle landmark points can use the SVM, polynomial, or ensemble regression methods. Polynomial regression and ensemble regression are better methods for predicting landmark points for the left condyle, right gonion, and left gonion. Because each person’s ramus and mandible length are different, nonlinear regression is better at the gonion point. Suggestions for further research include experimenting with several nonlinear regression methods to predict gonion landmark points.

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