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RESEARCH ARTICLE

Mandibular Landmark Determination Based on Statistical Features of Panoramic Radiograph Images Using Multi-Output Neural Network

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ABSTRACT

The mandible is crucial in orthodontic treatment, forensic identification, and clinical diagnosis. However, manually identifying mandibular landmarks is time-consuming and highly dependent on expert skill, necessitating a more reliable automated prediction method. Previous research has used linear and nonlinear regression methods, in which each model predicts a single landmark point, resulting in inefficiency. In addition, these methods only use the centroid of the binary image of the mandible as input. This research proposes a multi-output neural network model that is able to predict multiple mandibular landmark points simultaneously. The proposed neural network architecture in predicting mandibular landmark points is 11 neurons on the input layer, 22 neurons on the hidden layer, 32 neurons on the hidden layer, and 14 neurons on the output layer. The dataset consists of grayscale panoramic radiographs from the Dental and Oral Hospital, Faculty of Medicine, Universitas Airlangga, with 96 images for training and 6 for testing. Image features, including mean intensity, standard deviation, median, variance, skewness, kurtosis, entropy, contrast, homogeneity, energy, and correlation, were extracted and used as inputs to a multi-output neural network. The model predicted the reference points of the right condyle, left condyle, right coronoid, left coronoid, right gonion, left gonion, and menton. The results showed that the proposed model effectively predicted the reference points of the mandible, with the right condyle showing the highest accuracy. The highest prediction accuracy value, with a Successful Detection Rate (SDR) 12% and the Adam optimizer, was the right condyle point.

Keywords: Image features, Mandibular landmark points, Multi-output, Neural network, Panoramic radiograph

Introduction

Dental radiograph images are essential for clinical diagnosis, treatment, and surgical procedures. In recent years, efforts have been made to develop computerized systems for analyzing dental radiographs.^{1,2} This research aims to develop and

evaluate an accurate method for automatic dental radiograph analysis. Previous researches have explored various approaches, including the automatic segmentation of the mandibular canal using the residual fully convolutional network method. In the research,³ AlexNet deep learning was used for feature extraction. Mandibular parameter measurements

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on panoramic radiographs for gender identification.⁴ Previous researches indicate that the automatic analysis of dental radiographs is a challenging task. Automation systems aid in this process by establishing a repository of dental radiograph data, enabling quantitative evaluations for comparison, and enhancing algorithm development.⁵ In order to support further research, good management and analysis of dental radiographs is needed with the availability of adequate software and data collection.

To identify precise anatomical landmarks in the mandible, it is crucial to develop precise methods based on advanced techniques such as machine learning, medical image processing, and deep learning. These landmarks are crucial for diagnosis, treatment planning, identification, and structural reconstruction in various fields, such as orthodontics, maxillofacial surgery, and dental prosthetics. As the largest and strongest bone in the face, the mandible contributes to facial appearance and overall quality of life, such as chewing, speaking, and supporting the lower teeth. Consequently, the mandible has been studied in fields such as dentistry, orthodontics, and forensic science⁶ due to its complex anatomy, which makes identifying landmarks very difficult and requires expertise.⁷ These landmarks include key anatomical structures such as the condyle, coronoid, and ramus. These structures are crucial for clinical applications and anatomical reconstruction. Many current methods rely on manual identification by surgeons and orthodontists. Recent advances have enabled automated landmark prediction, allowing for faster and more consistent results. Mandibular parameters, particularly landmarks, have been measured in several studies using semi-automatic methods.^{8,9} These methods are based on predefined geometric definitions. These measurements are also widely used in forensics, particularly for human identification.^{10,11} Radiographic analysis is widely used in surgical planning, diagnosis, and treatment.¹² It is also used to assess facial soft tissue and mandibular structures. This allows doctors to perform precise analysis and treatment planning because it provides a comprehensive understanding of the patient's bones. In several studies, iterative Convolutional Neural Network (CNN),¹³ regression methods, and other techniques applied to cephalometric images, often evaluated with SDR, are crucial for finding precise landmark points in orthodontic treatment, dental implant placement, and surgical reconstruction. An automated prediction system can enhance diagnosis and treatment planning while minimizing human errors in medical procedures. Several techniques have been explored for landmark point prediction,

with deep learning methods being a prominent approach.¹⁴ Deep learning methods have demonstrated superior performance compared to human evaluation in healthcare.¹⁵⁻¹⁸

Most research has focused on predicting landmark points in cephalometry, while research on mandibular landmark prediction in panoramic radiography remains limited. This includes predicting point mandibular landmarks: right condyle, left condyle, right ramus, left ramus, right gonion, left gonion, as well as the upper and lower mandibular body using the linear regression method. However, predictions using linear regression have shown low accuracy.¹⁹ Due to the suboptimal prediction results of the linear regression method, an analysis and comparison were conducted using non-linear methods. Research result accuracy improved in predicting the right condyle and right gonion landmark points using the polynomial method. The model used in the research¹⁹ includes each mandibular landmark point(x,y). Each landmark has its own model, resulting in a lengthy model development process. Additionally, in the research¹⁹ previous research, the input data consisted of centroid point values from binary mandibular images, limiting the image representation to a single feature. As a result, a more accurate and precise mandibular landmark prediction system is needed. This research aims to improve prediction accuracy by incorporating more diverse grayscale panoramic radiograph image features. Feature extraction affects the results of the detection process.²⁰ Additionally, instead of using separate models for each landmark, this research proposes a multi-output model capable of predicting multiple mandibular landmark points simultaneously.

Materials and methods

Dataset

The dataset for this research consists of panoramic radiograph images obtained from the Dental and Oral Hospital, Faculty of Medicine, Universitas Airlangga, Surabaya. A total of 102 panoramic radiographs were collected from male and female patients aged 19-70 years. The data was divided into 96 images for training and 6 images for testing. Landmark points, including the right condyle, left condyle, right coronoid, left coronoid, right gonion, left gonion, and menton, were manually annotated by a radiologist using the ImageJ application, as shown in Fig. 1a and Fig. 1b. These annotated landmark points were used as output data for training and testing. The input for this research consisted of grayscale

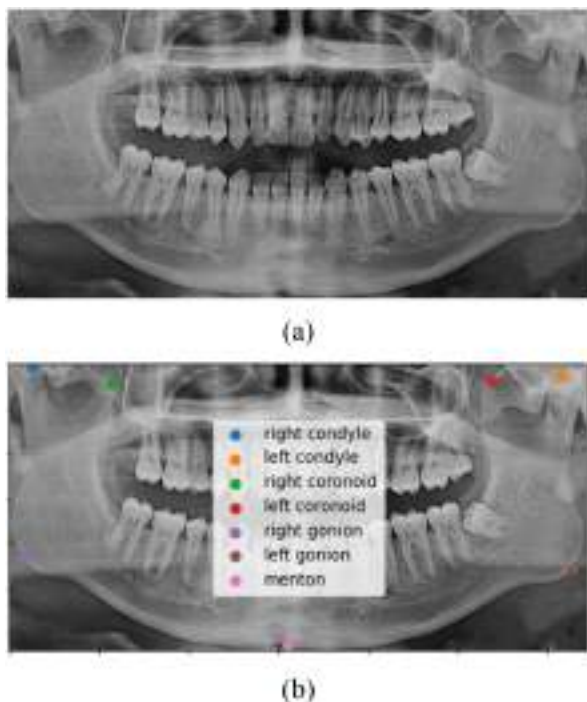


Fig. 1. Panoramic Radiograph.

panoramic radiograph image features Fig. 1. The Health Research Ethics Commission (KKEPK) Faculty of Dentistry, Universitas Airlangga, Surabaya, ethically tested the sample data with certificate No. 043/HRECC.FODM/II/2022.

Proposed method

The research stages are outlined in Fig. 2; features such as mean, standard deviation, median, variance, skewness, kurtosis, entropy, contrast, homogeneity, energy, and correlation are extracted from grayscale panoramic radiographs. These features are then used to train a prediction model with corresponding landmark point outputs. The trained model is evaluated by predicting landmark locations on panoramic radiographs and calculating the error based on Eq. (1).¹⁹ Eq. (1), x, y actual coordinate point, and x', y' prediction coordinate point.

$$R = \sqrt{(x - x')^2 + (y - y')^2} \quad (1)$$

The training process also involves the development of a neural network model. This research proposes a multi-output neural network for predicting mandibular landmark points. The model architecture, shown in Fig. 3, consists of an input layer with 11 neurons, corresponding to the extracted image features ($x_1 =$ mean, $x_2 =$ standard deviation, $x_3 =$ median, $x_4 =$ variance, $x_5 =$ skewness, $x_6 =$ kurtosis, $x_7 =$

entropy, $x_8 =$ contrast, $x_9 =$ homogeneity, $x_{10} =$ energy, $x_{11} =$ correlation), the proposed multi-output neural network consists of two hidden layers with 22 and 32 neurons, respectively. The output layer contains seven neurons, corresponding to the predicted mandibular landmark points (x, y), namely, right condyle, left condyle, right coronoid, left coronoid, right gonion, left gonion, and menton.

Each landmark point is calculated using the average error as shown in Eq. (2).¹⁹ The predicted landmark points differ from the ground truth values. If the difference falls within a certain range, the prediction is considered accurate. In this evaluation, a 7-pixel tolerance is used as the standard, based on previous research, which has a value of 4 pixels.¹⁹ For example, the radial error is 3 pixels, meaning success. How to evaluate the level of accuracy by using the SDR Eq. (3), where N_a shows the number of accurate detections, and N shows the total number of detections.

$$MRE = \frac{\sum_{i=1}^n R_i}{n} \quad (2)$$

$$SDR = \frac{N_a}{N} 100\% \quad (3)$$

The training process for developing the multi-output neural network model was conducted using two optimization algorithms, Adam and RMSprop, both initialized with a default learning rate of 0.001. Each training session was performed for 10 epochs with a batch size of 2 and repeated three times to evaluate result consistency and determine the most accurate prediction outcomes. The mean absolute error (MAE) was employed as the loss function throughout the training. Table 1 summarizes the eleven features extracted from grayscale panoramic radiographs and used as model input. The coordinates of the corresponding landmark points are used as output. The output layer, with the same number of neurons as the landmark points, has two hidden layers with 22 and 32 neurons. While the output layer does not use any activation function, the hidden layers apply the ReLU activation function. The He's normal approximation is used to initialize the network weights, with the bias set to zero. No explicit regularization methods, such as dropout, are used due to the small dataset size and model complexity.

Results and discussion

The right and left condyles, coronoid, gonion, and menton were among the mandibular landmarks

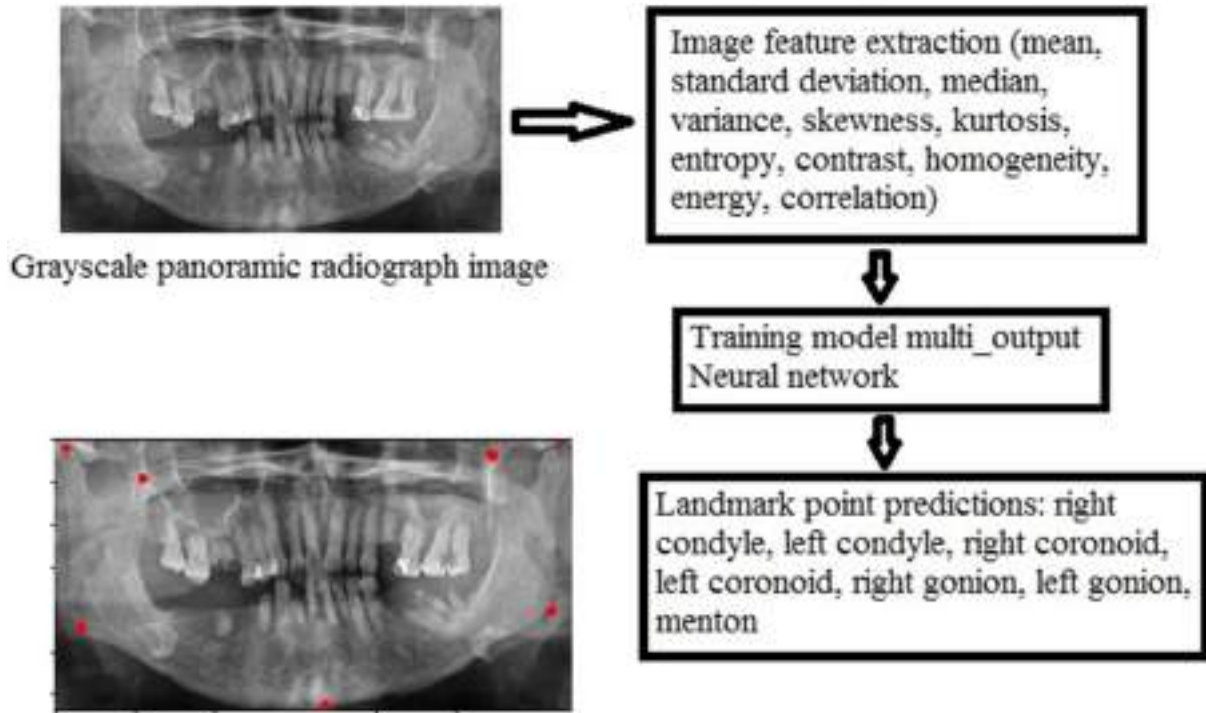


Fig. 2. Research Stages.

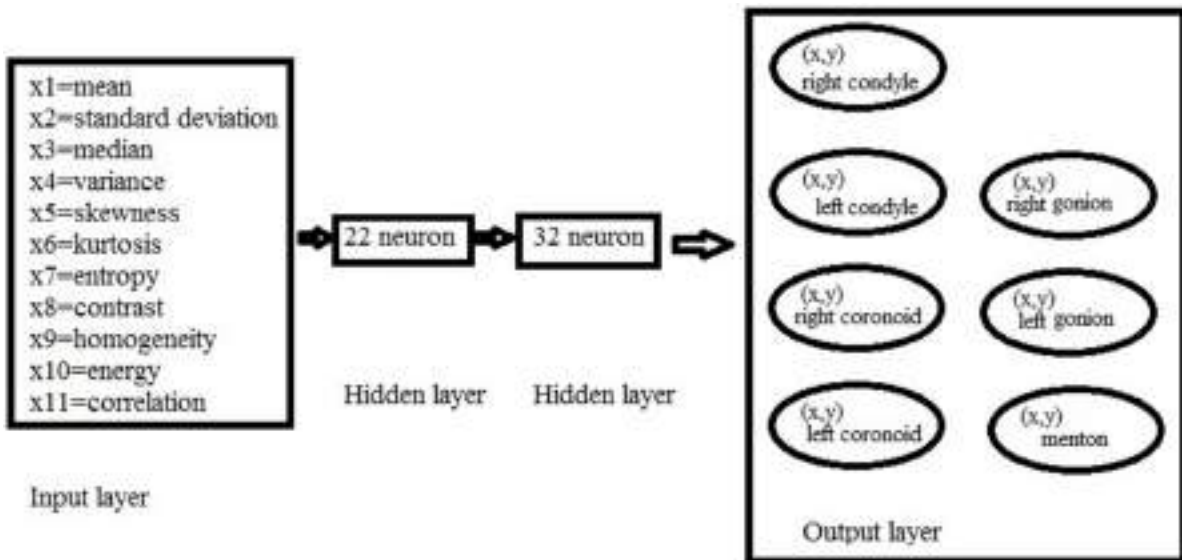
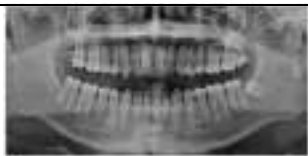
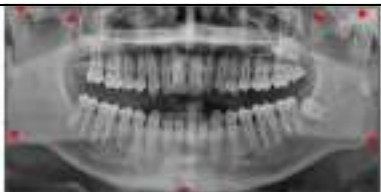
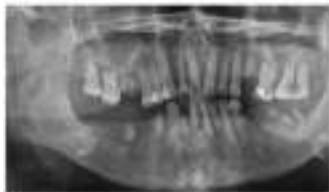
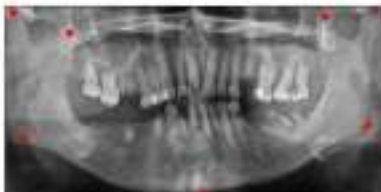


Fig. 3. Model Architecture.

predicted in this study using a multi-output artificial neural network. During the training phase, two optimizers, Adam and RMSprop, were used to run each experimental scenario three times. Table 2, separated into subtables (2a-2f), displays the prediction results generated by the Adam optimizer. Predictions of the seven landmarks in the test data are shown in each subtable, with red marks

indicating model predictions and blue marks indicating expert annotations. Some prediction errors remain, especially in some situations, which may be due to the limited training data. The left condyle remains the least accurately predicted landmark, while Table 2(b) displays the most accurate results with the lowest Mean Relative Error (MRE) of 23.45 pixels. On the other hand, the right condyle and right

Table 1. Feature extraction data.

Image	Input Features	(Image	Output (x, y)	
	$mean(x_1) = 109.89$ $std(x_2) = 38.42$ $var(x_3) = 1476.00$ $skewn(x_4) = 0.20$ $median(x_5) = 117.00$ $kurtosis(x_6) = 2.27$ $entropy(x_7) = 7.16$ $contrast(x_8) = 59.28$ $h.omoge(x_9) = 0.19$ $energy(x_{10}) = 0.02$ $correl(x_{11}) = 0.98$		right condyle= (50,6) left condyle= (1229,24) right coronoid= (227,43) left coronoid= (1075,38) right gonion= (29,434) left gonion= (1257,456) menton= (620,626)	
	$mean(x_1) = 111.48$ $std(x_2) = 41$ $var(x_3) = 1680.67$ $skewn(x_4) = 0.15$ $median(x_5) = 123.00$ $kurtosis(x_6) = 0.49$ $entropy(x_7) = 7.16$ $contrast(x_8) = 79.02$ $h.omoge(x_9) = 0.17$ $energy(x_{10}) = 0.02$ $correl(x_{11}) = 0.98$		right condyle= (27,21) left condyle= (1260,2) right coronoid= (219,90) left coronoid= (1091,35) right gonion= (63,442) left gonion= (1233,402) menton= (673,626)	

gonion have the largest MRE of 124.71 pixels against the ground truth data in Table 2(e). In addition, the estimated Menton landmark points are outside the image boundaries, as illustrated in Table 2(d).

Table 3 displays the results of mandibular landmark location estimation using the RMSprop optimizer. Table 3 is divided into six sub-tables(3a-3f), each of which displays prediction results on a different test dataset. Seven mandibular landmark locations are shown in each figure, with blue marks indicating expert interpretations and red marks indicating model predictions. Overall, most landmark points can be predicted by the model using the RMSprop optimizer. However, there are still some discrepancies in some situations, possibly due to insufficient training data. With the lowest MRE of 39.45 pixels, Table 3(b) displays the most accurate results. The three landmark points of the right gonion, right coronoid, and right condyle are in close agreement

with the ground truth data. Table 3 shows that the right condyle consistently exhibits high prediction accuracy across multiple trials. Furthermore, in Table 3(b), Table 3(c), and Table 3(d), the gonion landmark is predicted with relatively high accuracy. However, predictions for other landmark points differ significantly from the ground truth data. With the highest MRE of 239.94 pixels, Table 3(e) shows the least accurate results, where most of the predicted landmark locations differ significantly from the expert values.

Table 4 presents the MRE values for each landmark point obtained using the Adam and RMSprop optimizers. Based on Table 4, the Adam optimizer consistently achieved the lowest MRE values across all landmark point predictions. Table 5 displays the SDR evaluation results for both optimizers. Interestingly, while Adam achieved lower MRE values, Table 5 shows that the RMSprop optimizer had a

Table 2. Results of landmark point prediction using the adam optimizer.


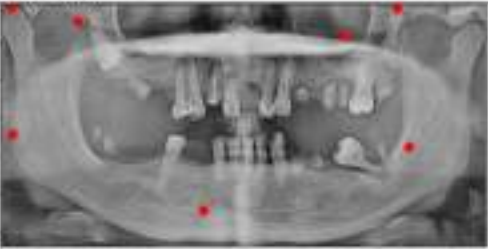

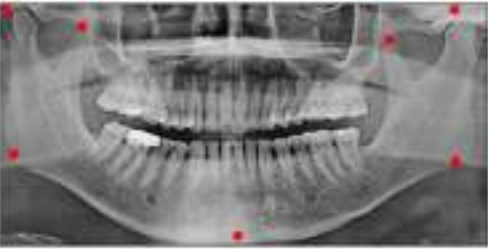
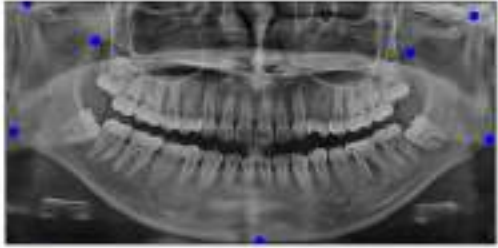
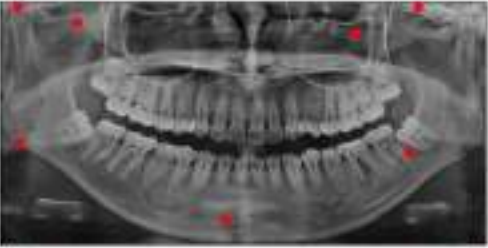
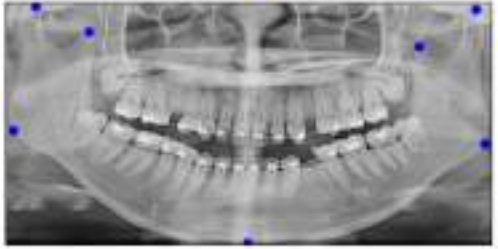






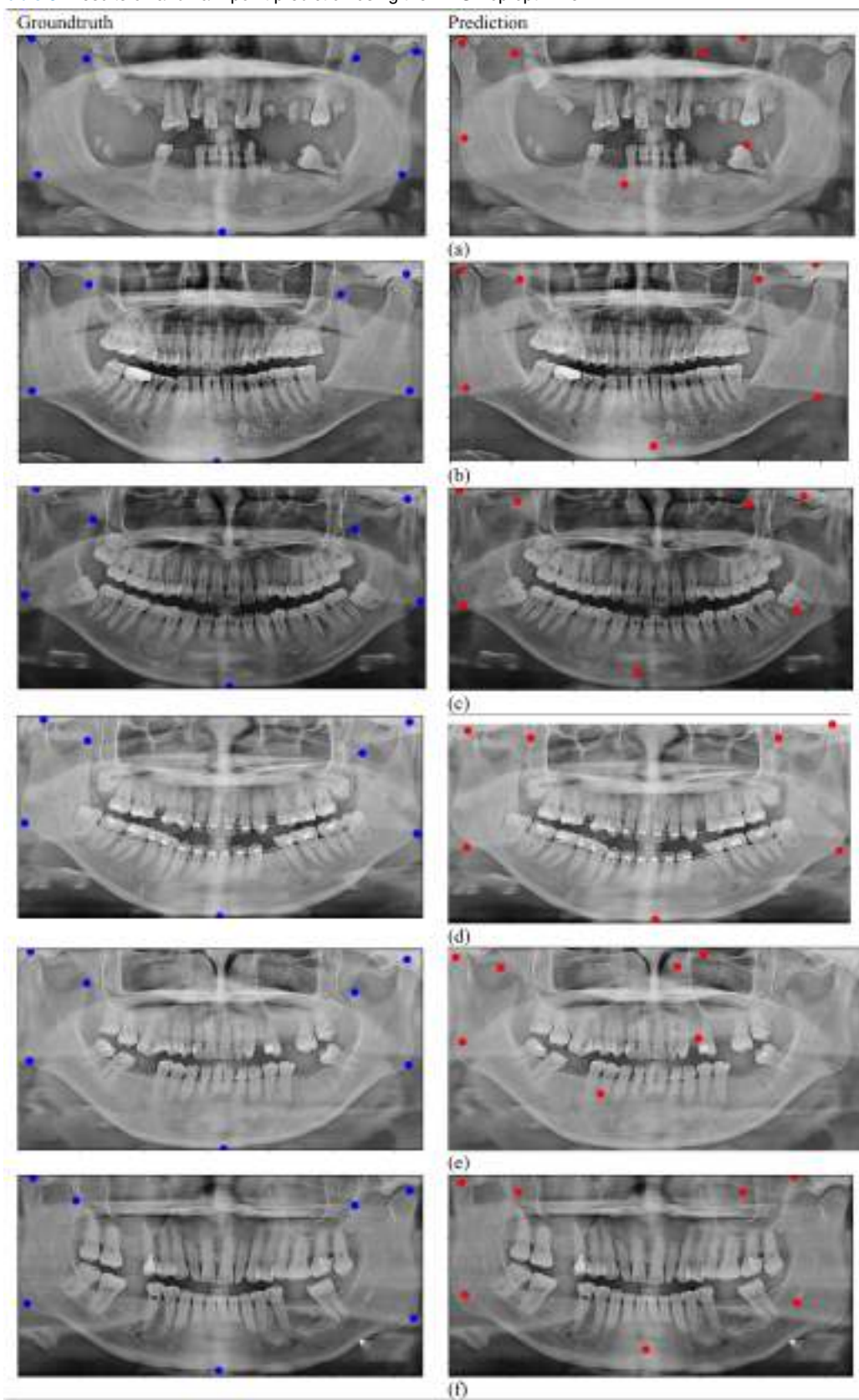
Groundtruth	Prediction
	
	(a) 
	(b) 
	(c) 
	(d) 
	(e) 
	(f) 

Table 3. Results of landmark point prediction using the RMSProp optimizer.

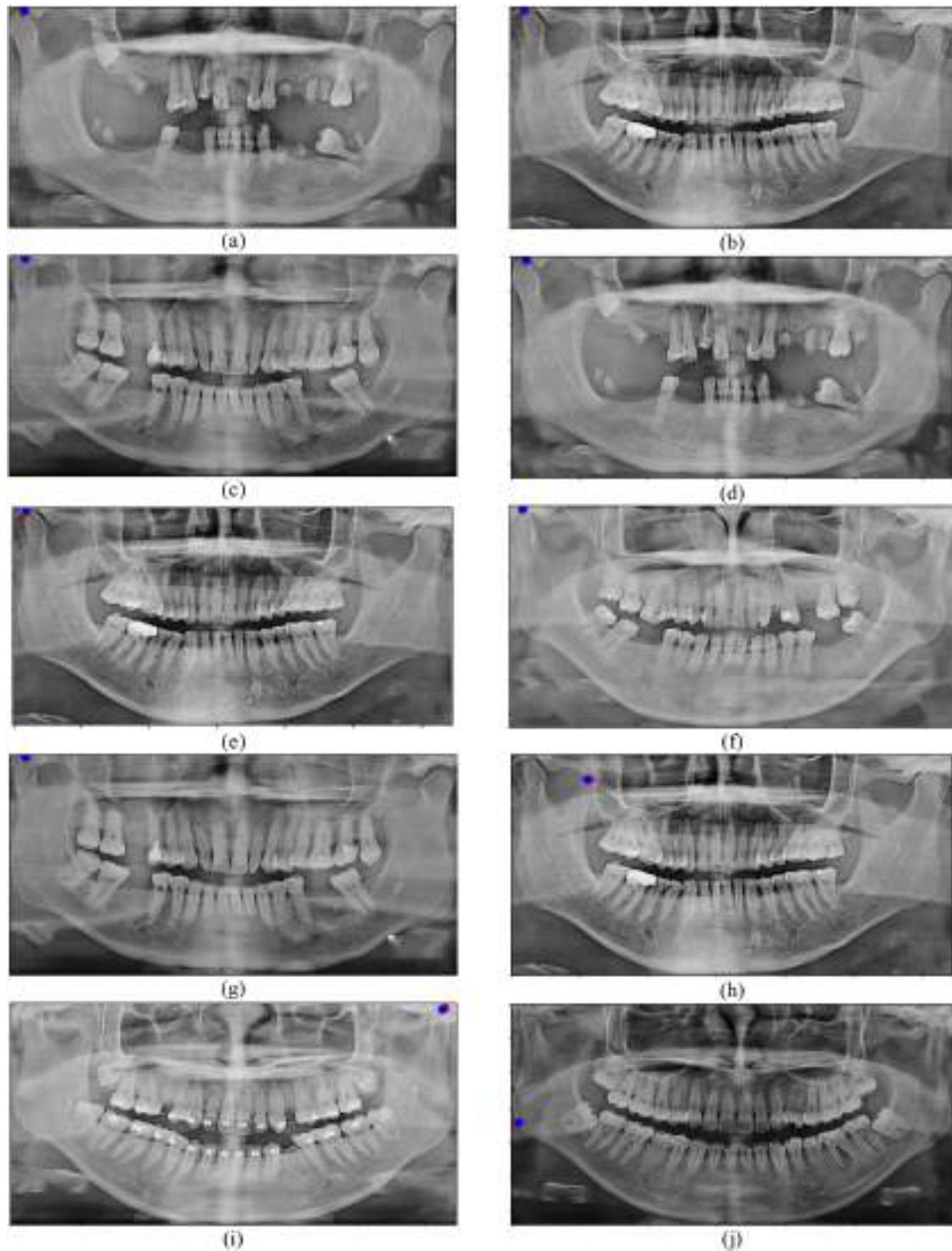


Fig. 4. Mandibular landmark point prediction results at a threshold of 7 pixels, Adam optimizer (a-c) and RMSprop (d-j).

higher overall success rate in predicting landmark points.

Fig. 4 illustrates the prediction results for mandibular landmark points with an SDR threshold of 7 pixels. In this visualization, blue dots indicate expert labels, while red dots indicate model predictions. Fig. 4(a)–4(c) show the prediction results using the Adam

optimizer, while Fig. 4(d)–4(j) show the prediction results using the RMSprop optimizer.

Based on the SDR calculations, the right condyle is the landmark with the highest prediction accuracy, as seen in Fig. 4(a)–Fig. 4(g). Of the two optimizers, Adam performed best in terms of SDR, as shown in Table 5. Table 6 compares the evaluation results for

Table 4. MRE landmark points.

Landmark Point	Optimizer	
	Adam (pixel)	RMSProp (pixel)
Right condyle	17.87	21.14
Left condyle	216.41	218.92
Right coronoid	56.41	46.01
Left coronoid	194.00	206.20
Right gonion	71.78	73.72
Left gonion	238.45	250.65
Menton	154.24	152.16

Table 5. SDR landmark points.

Landmark Point	Optimizer (SDR 7 pixel)	
	Adam (%)	RMSProp (%)
Right condyle	12	11
Left condyle	0	2
Right coronoid	0	2
Left coronoid	0	0
Right gonion	0	2
Left gonion	0	0
Menton	0	0

Table 6. Evaluation comparison.

Method	SDR (%)
Regresi linear ¹⁹	Standard 4 pixels=39.08
Polynomial	Standard 4 pixels=50.00
This research proposal	Standard 7 pixels=12.00

mandibular landmark prediction based on panoramic radiographs. This study used full panoramic radiographs, which more accurately depict the actual clinical situation, in contrast to previous studies¹⁹ that used binary images of the mandible. In this study, the observed SDR reached 12.00% at a tolerance of 7 pixels. This difference may be explained by the higher complexity and uncertainty of full panoramic radiographs. Consequently, this study provides a benchmark for assessing landmark prediction ability in a more practical clinical imaging environment.

Conclusion

In this study, a multi-output neural network based on grayscale image data was used to predict mandibular landmark points on panoramic radiographs. With a maximum SDR of 12%, the results showed that the model could identify mandibular landmarks. The right condyle was the most accurately predicted landmark of all the locations assessed. These results indicate that the proposed method may be useful as an aid for automatic landmark identification. To improve the prediction accuracy and ensure its application in clinical situations, further improvements are needed.

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Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- Author(s) signed an ethical considerations approval.
- Ethical Clearance: The project was approved by the local ethical committee at University of Airlangga, Surabaya, Indonesia.

Authors' contributions statement

Conceptualization: NN; methodology: NN and AH; software: NN; validation: ERA, AA, and RW; resources data: ERA, AA, and RW; writing—original draft preparation: NN; writing—review and editing: NN, AH, KJ, and RW.

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تحديد معالم الفك السفلي بناءً على السمات الإحصائية لصور الأشعة البانورامية باستخدام الشبكة العصبية متعددة المخرجات

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الخلاصة

يلعب الفك السفلي دوراً مهماً في تحديد وتشخيص وعلاج تقويم الأسنان. يتطلب تحديد نقاط معلم الفك السفلي يدوياً خبرة كبيرة ووقتاً، مما يتطلب نظام تنبؤ آلي دقيق وفعال. استخدمت الدراسات السابقة أساليب الانحدار الخطي وغير الخطي، حيث يتنبأ كل نموذج بنقطة معلم واحدة، مما يؤدي إلى عدم كفاءة الوقت. بالإضافة إلى ذلك، تستخدم هذه الأساليب فقط مركز ثقل الصورة الثنائية للفك السفلي كمدخل. تقترح هذه الدراسة نموذج شبكة عصبية متعدد المخرجات قادر على التنبؤ بنقاط معلم الفك السفلي المتعددة في وقت واحد. تتكون بنية الشبكة العصبية المقترحة في التنبؤ بنقاط معلم الفك السفلي من 11 خلية عصبية على طبقة الإدخال، و22 خلية عصبية على الطبقة المخفية، و32 خلية عصبية على الطبقة المخفية، و14 خلية عصبية على طبقة الإخراج. تتكون مجموعة البيانات من صور الأشعة البانورامية ذات التدرج الرمادي من مستشفى طب الأسنان والفم، كلية الطب، جامعة إيرلانجا، مع 96 صورة للتدريب و6 صور للاختبار. استُخرجت خصائص الصورة، بما في ذلك متوسط الشدة، والانحراف المعياري، والوسيط، والتباين، والانحراف، والتفرطح، والإنتروبيتا، والتباين، والتجانس، والطاقة، والارتباط، واستُخدمت كمدخلات لشبكة عصبية متعددة المخرجات. تنبأ النموذج بالنقاط المرجعية للقامة اليمنى، والقامة اليسرى، والإكليل الأيمن، والإكليل الأيسر، والعظمة اليمنى، والعظمة اليسرى، والمينتون. أظهرت النتائج أن النموذج المقترح تنبأ بفعالية بالنقاط المرجعية للفك السفلي، حيث أظهرت اللقمة اليمنى أعلى دقة. وكانت أعلى قيمة لدقة التنبؤ عند نسبة 12% من دقة التنبؤ باستخدام مُحسِن آدم هي نقطة اللقمة اليمنى.

الكلمات المفتاحية: ميزات الصورة، نقاط المعالم السفلية، متعدد المخرجات، الشبكة العصبية، التصوير الشعاعي البانورامي.