Cephalometric Landmark Detection on Cephalograms using Regression CNN

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***Abstract*— Cephalograms are an imaging process used by orthodontics to determine the position of cephalometric landmarks. These cephalometric landmarks are essentials to be found before any treatment to the patient can be performed. In this research, a CNN architecture to detect 31 cephalometric landmarks was proposed. The results shows that Mean Absolute Percentage Error (MAPE) of our proposed method achieves a value of 1.856%. Better than detectron2 with 2.443%.**

Keywords—Cephalograms, Cephalometric Landmarks, CNN, Detectron2

I. Introduction

Teeth are parts of human body that have impact on how people look. The formation of human teeth can be influenced by many things such as genetic and jaw form. While orthodontics cannot change the genetic of the patient, but they can transform the form of the patient jaw via treatment with the help of cephalogram.

Research on imaging involving teeth has been an interesting topic. Recently, CT image of patient head that often used for surgery such as brain surgery[1], can be used to create the panoramic projection of the patient teeth[2]. However, panoramic images are often used to determine patient condition. Another imaging techniques involving teeth, cephalogram, shows the lateral side of the patient head that show cephalometric landmarks. By identifying those cephalometric landmarks, orthodontics can determine the shape of the patient jaw and determine the treatment needed.

However, depends on the case the orthodontic is working on, the number of cephalometric landmarks that need to be detected for the orthodontic to perform the treatment might be different. When annotating the cephalogram images, an experienced orthodontic can take up to 20 minutes to annotate 19 landmarks[3]. Inter-person and intra-person variance can also be a problem when annotating the cephalometric landmarks[4]. Thus, having automatic cephalometric landmarks detection might help orthodontics to shorten the time needed for the preparation phase.

Several studies performed on cephalometric landmarks detection shows that the number of cephalometric landmarks that is used are different in each study. The studies performed uses deep learning approaches to detects the landmarks[5]–[7] shows that deep learning achieves better than traditional machine learning[8]–[10]. There is also several study that utilizing Machine Learning such [11] and [12] that perform well. However, in this study, we explore the use and potential ability only on Deep Learning.

Deep learning architectures have different composition of layers and neurons. Detectron2 as an architecture shows good performances on various image processing tasks. Other architecture such as CephaNN[5], also proves that the architecture successfully produces high quality results on image processing tasks. In this study, we will compare our proposed architecture with detectron2 results.

II. Previous Study

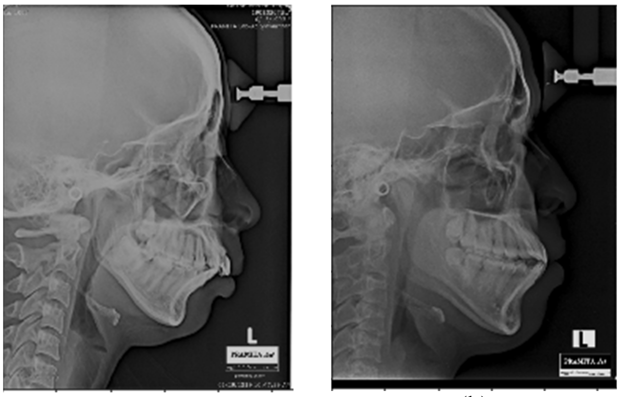
Studies for detecting cephalometric landmarks on cephalogram image have been done in recent years. Previous study [13] proposed Fully Automatic Landmark Annotation (FALA). This system produced an average of 1.2 mm error, with each point within the acceptable error range of 2 mm.

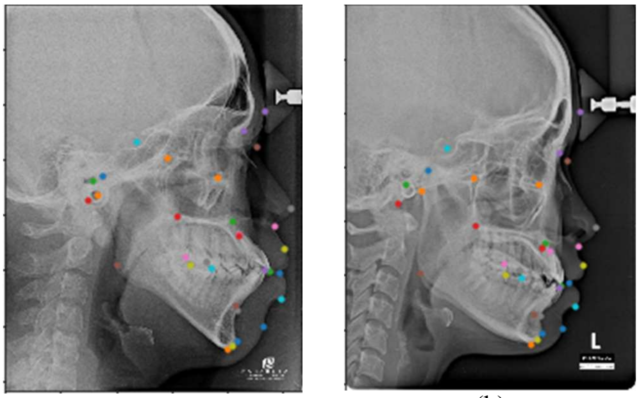
Other research [14] uses SVM as the base of the study. However, the method proposed in the study needs to rescale the image into 1/8 of the original image. Moreover, the method uses histogram of Oriented Gradient (HOG), which are needs to be extracted from the rescaled image. The results are not very satisfactory as there are still point that are beyond the acceptable error range of 2 mm.

Other study proposed a CNN architecture called CephaNN [5] that successfully detect up to 75-landmark dataset. This architecture is comprised of multi-head part and Attention part. The multi-head part is used to obtain coarse heatmaps of the landmark from the input. Whie the attention part fine tune the results.

Detectron2[15] recently have been used by facebook to perform various image processing task, such as object detection, object masking, keypoint detection, and semantic segmentation. The results shows that the architecture successfully done the given task.

However, none of the mentioned research have done 31 landmarks annotated by our orthodontics. Thus, based on the previous research mentioned here, we propose a method to detect the 31 cephalometric landmarks.


(a) (b)
Figure 2. Cephalogram data used in this study


(a) (b)
Figure 1. Annotated cephalograms

III. Research Method

A. Data

The data we used in this research are taken from Airlangga University, Indonesia. The cephalometric landmarks were annotated by orthodontics on 68 data. Figure 1 shows the data we used.

Figure 1 shows the cephalograms we used in this study. The data we collected consists of 68 cephalograms with various resolutions. Thus, we resized all the resolution of all cephalograms into 718x536 as the majority of the cephalograms have those resolutions. Each cephalograms are then annotated by orthodontics to mark the 31 cephalometric landmarks. Figure 2 shows the annotated cephalograms.

As shown in Figure 2, all the landmarks are annotated on each cephalograms. Each of the landmarks have different color from one another. This annotated cephalogram will be used as our ground truth for the proposed CNN

B. Proposed CNN architecture

To detect the cephalometric landmarks, we propose a CNN architecture that consists of convolution layers, maxpooling layers, and dense layers. Figure 3 shows the architecture that we built.

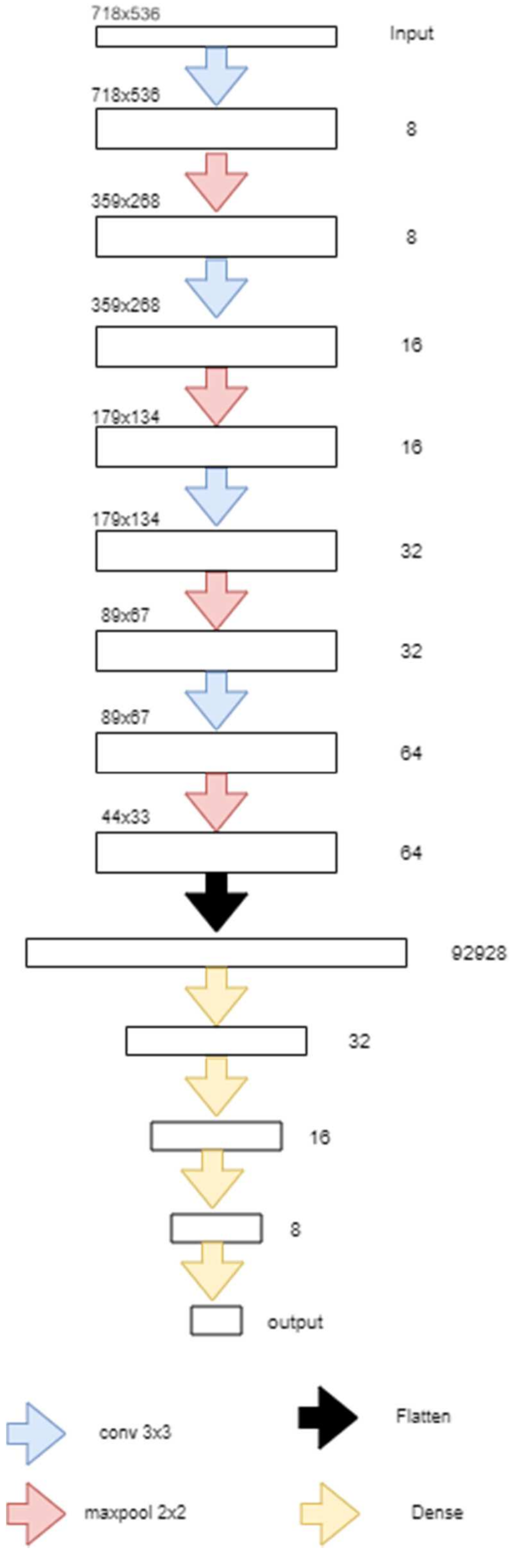


Figure 3. Proposed architecture

The architecture shown on Figure 3 consists of 4 convolution layers, 4 maxpooling layers, and 3 dense layers. The dense layers are needed since we will perform regression to predict the coordinate of each landmark on each cephalogram. The error function that we used is Mean Absolute Percentage Error (MAPE). Equation 1 shows the calculation of MAPE.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \qquad (1)$$

where,

n= number of predicted data

A_t= ground truth value

F_t= predicted value

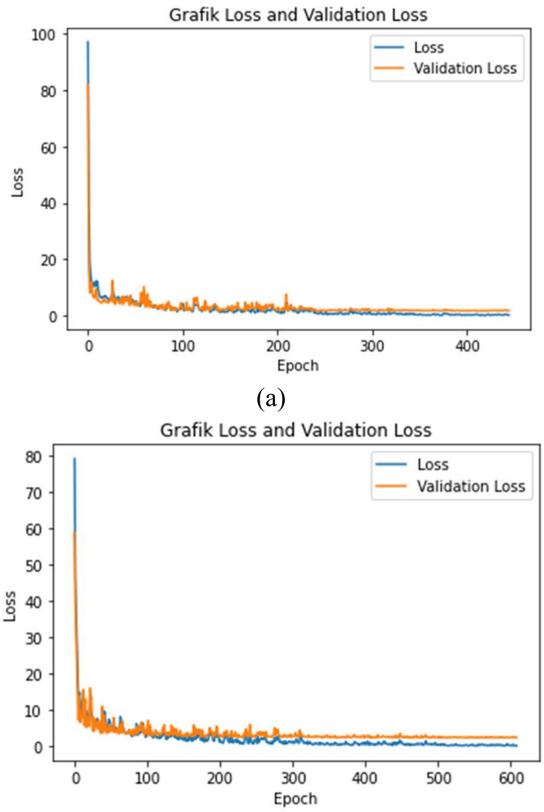
As shown on Equation 1, MAPE calculate the mean absolute percentage error. Since we will predict the coordinate of the landmarks, the number might be very small. Thus, a small miss on the prediction result may reproduce a high MAPE value. This is advantageous in this study to help the CNN we built to predict more accurately. Moreover, if the CNN architecture predicts low MAPE, then the coordinate of the ground truth and predicted values are very close.

C. Environment

The method was tested using a computer with the following specification:

- Intel(R) i9
- 64 GB of random-access memory (RAM)
- 64-bit Windows operating system

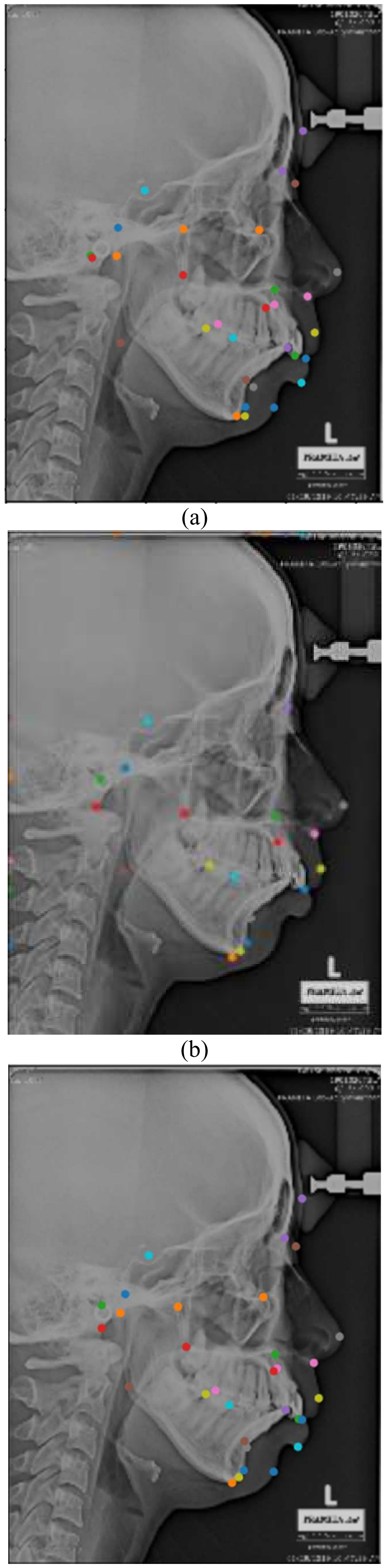
The method was implemented using Python 3 environment with Tensorflow 2.7.0 to build the CNN architecture.



(a)

(b)

Figure 5 training loss and validation loss of (a) proposed method (b) detectron2



(a)

(b)

Figure 4. Landmarks detection result of (a)proposed method, (b) detectron2, and (c) ground truth

IV. Result and Analysis

The result of our proposed method will be presented here. Figure 4 shows our proposed network and detectron2 landmarks detection results.

Figure 4 shows the training and validation loss of our proposed method and detectron2. Our proposed method achieved MAPE of 1.856 while detectron2 achieved 2.443. Figure 5 shows the predicted landmarks on the cephalograms.

Figure 5 shows how our proposed method and detectron2 performed. The results on Figure 5 (a) detect the landmarks better than the results of detectron2 on Figure 5 (b). We used dense layers on our proposed network to perform regression on the cephalograms. However, some landmarks are better detected by Detectron2. Thus, the proposed method can still be improved. In the end, our proposed architecture of CNN could outperform the Detectron2 with 1.856 of MAPE compared with 2.443 by Detectron2.

V. Conclusion

Cephalometric landmarks are essential for orthodontics to perform treatments. Thus, accurately detecting the cephalometric landmarks can determine the success rate of the treatment. Our proposed method shows that it can perform better than detectron2 on detecting the landmarks due to the use of dense layers. However, detectron2 still performs better in detecting some landmarks. Thus, we can conclude that this works can be improved in the future.

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