CEPHALOGRAM LANDMARK DETECTION USING COORDINATE ATTENTION MODULE

Under Dr. Geetha S

For the Course of Medical Image Processing

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CONTENT

INTRODUCTION

In the fields of craniofacial analysis and orthodontics, the accurate identification of cephalometric landmarks is crucial for tasks like diagnosis, treatment planning, and result evaluation. Cephalometric analysis involves measuring and interpreting skeletal and dental connections using specific anatomical landmarks observed in radiographic images. Digital Image Processing has significantly impacted medical domains, including cephalometric analysis, leading to the development of automated approaches for landmark recognition. These automated methods are faster, more reliable, and less susceptible to human interpretation errors. Traditionally, cephalometric landmarks were identified manually, requiring meticulous attention and advanced anatomical understanding. However, with advancements in computing hardware, image processing, machine learning, and computer vision, there has been a paradigm shift from manual to computerized cephalometric analysis.

PROBLEM STATEMENT

Cephalometric analysis requires a doctor to identify and locate anatomical landmarks on cephalograms. However, the manual examination of these radiographs is characterized by their need for significant knowledge, subjectivity, and monotonous nature. The foundation of the field of cephalometry, which is concerned with comprehending the dimensions and proportions of the human head, is the recognition and localization of anatomical landmarks on cephalometric radiographs. Nevertheless, the painstaking and subjective nature of the traditional manual examination of these radiographs makes it error-prone and requires a high degree of competence. Thus, there is a need for a faster, reliable way to identify these landmarks automatically

SOLUTION

We introduce a novel approach using Coordination attention, a unique attention mechanism that is sensitive to positional information in combination with traditional Convolutional Neural Networks. This mechanism enhances the model's ability to capture both global and local context, addressing the spatial relationships of landmarks.

METHODOLOGY

Normalization of Coordinates:
Each landmark coordinate within the dataset undergoes a normalization process, scaling the values between 0 and 1. This normalization step makes it so that the model’s output is between 0 and 1 that can be scaled back to the image’s resolution as needed

Training and Inference:
For model input, the X-ray images are passed after resizing them to (600, 745) resolution. The output of the model is 38 points which represent 19 (x, y) pairs of coordinates

DATASET DESCRIPTION

The most common dataset used by researchers in this topic is the ISBI 2015 Grand Challenge Dataset. Many papers also use private datasets that they obtained from a medical institution and hence those are not publicly accessible. The IEEE International Symposium on Biomedical Imaging (ISBI) held on 2015 released a dataset containing 400 cephalograms obtained from a Hospital in Taipei, Taiwan. The resolution of these images is 1935 x 2400 pixels. The cephalograms are obtained from a wide range of age group ranging from 6 to 60. The dataset has 19 landmarks marked as (x, y) coordinates of pixels. It has a pixel spacing of 0.1 mm

DATASET DESCRIPTION

DATASET SPLIT: TO FACILITATE ROBUST MODEL TRAINING AND EVALUATION, THE DATASET IS STRATEGICALLY DIVIDED. A TOTAL OF 150 IMAGES ARE USED FOR TRAINING, 150 FOR VALIDATION, AND A SEPARATE SET OF 100 IMAGES FOR RIGOROUS TESTING. THIS DIVISION ENSURES A COMPREHENSIVE ASSESSMENT OF THE MODEL'S GENERALIZATION CAPABILITIES.

EVALUATION METRICS

Mean Radial Error (MRE): Mean Radial Error is the mean of squared error between predicted and ground truth coordinates. While evaluating, often MRE is used after converting the pixel values to millimeters using a conversion factor S which depends on the scanner used to take the radiogram.

$$SE_{px}(Squared\ Error) = (\hat{x} - x)^2 + (\hat{y} - y)^2$$

$$SE_{mm} = ((\hat{x} - x) \times S_x)^2 + ((\hat{y} - y) \times S_y)^2$$

$$R = \sqrt[2]{SE_{mm}}$$

$$MRE = \frac{\sum_{i=1}^{N} R_i}{N}$$

Where,

$x, y = ground\ truth\ coordinates$

$\hat{x}, \hat{y} = predicted\ coordinates$

$S_x, S_y = pixel\ spacing\ factor$

EVALUATION METRICS

Successful Detection Rate (SDR): In landmark detection tasks, a threshold is used to measure the performance of the detection system alongside a distance metric. SDR is used to give an idea about how many landmarks were identified within a maximum range of some threshold T. Mathematically, it can be written as follows:

$$SDR\ (\%) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} Check(R^{i,j}, T)}{N \times M} \times 100$$

Where,

$$Check(X,T) = \begin{cases} 1 & if\ X \leq T \\ 0 & otherwise \end{cases}$$

$N = number\ of\ images$

$M = number\ of\ landmarks$

COMMON THRESHOLDS THAT ARE USED BY MOST PAPERS ARE 2.0 MM, 3.0 MM, 4.0 MM

ARCHITECTURE USED

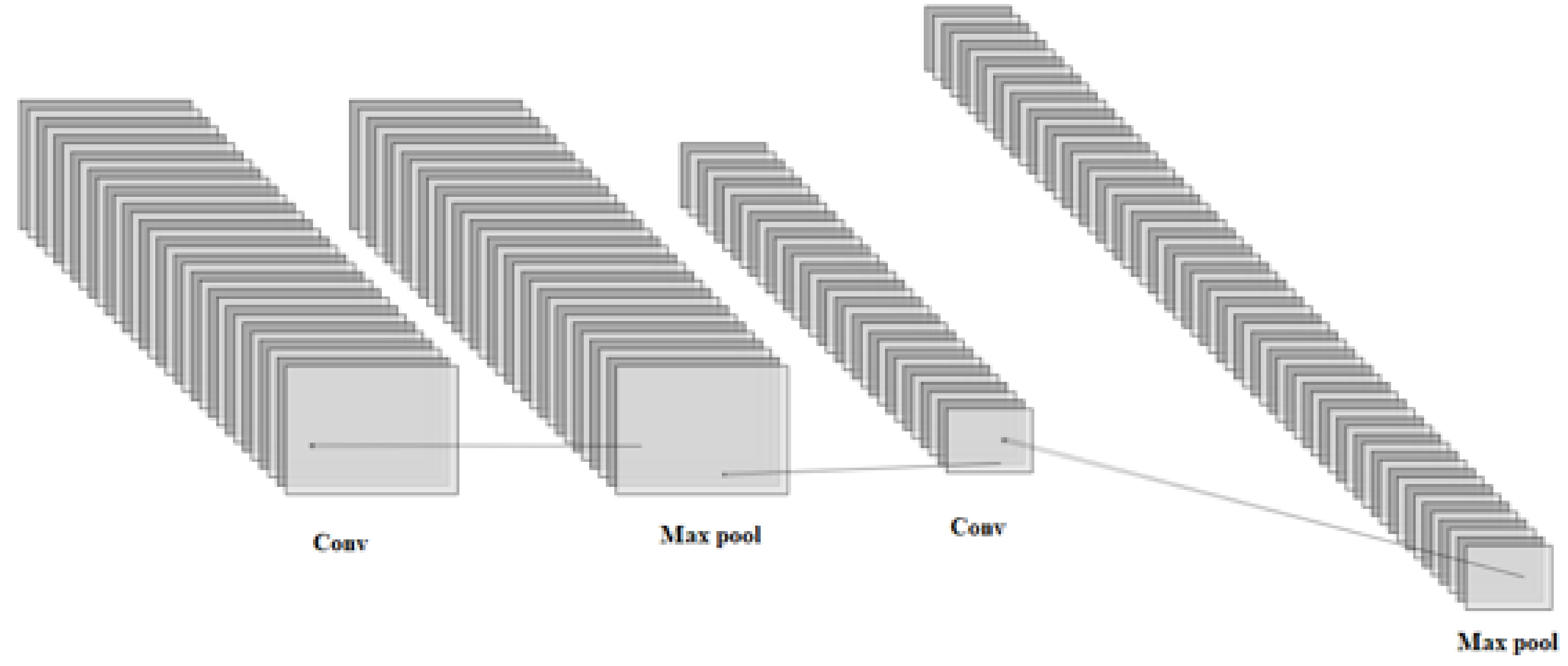

Fig. 1: CNML block taken from [25]

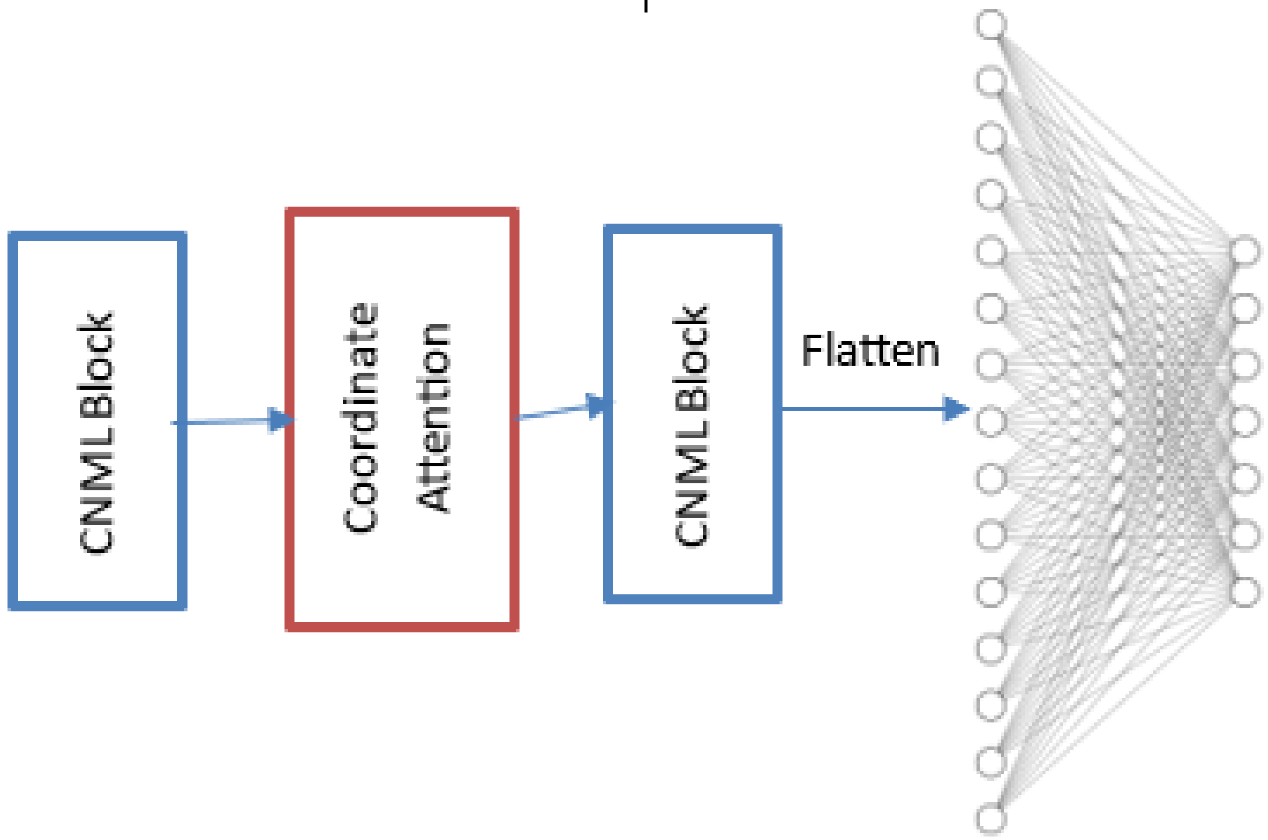

Fig. 2: Overall Architecture. Coordinate Attention block from [27]

ARCHITECTURE USED

THE CNML BLOCK CONSISTS OF CONVOLUTIONAL LAYERS FOLLOWED BY MAX POOLING LAYERS TO CAPTURE THE SEMANTIC RELATIONSHIP BETWEEN THE FEATURES ACROSS THE IMAGE. MAX POOLING HELPS RETAIN THE ESSENTIAL FEATURES. SINCE OUR TASK AT HAND IS TO PREDICT LANDMARKS, AN ATTENTION MECHANISM THAT IS POSITION SENSITIVE IS WELL SUITED AND HENCE WE ARE USING COORDINATE ATTENTION. IT IS A VARIANT OF THE SQUEEZE-AND-EXCITATION (SE) MODULE. THE SE MODULE DOES CROSS-CHANNEL ATTENTION WHEREAS COORDINATE ATTENTION DOES INTER-CHANNEL X AND Y POOLING AND HENCE IT PRODUCES LOCATION SENSITIVE CONTEXTUAL FEATURES.

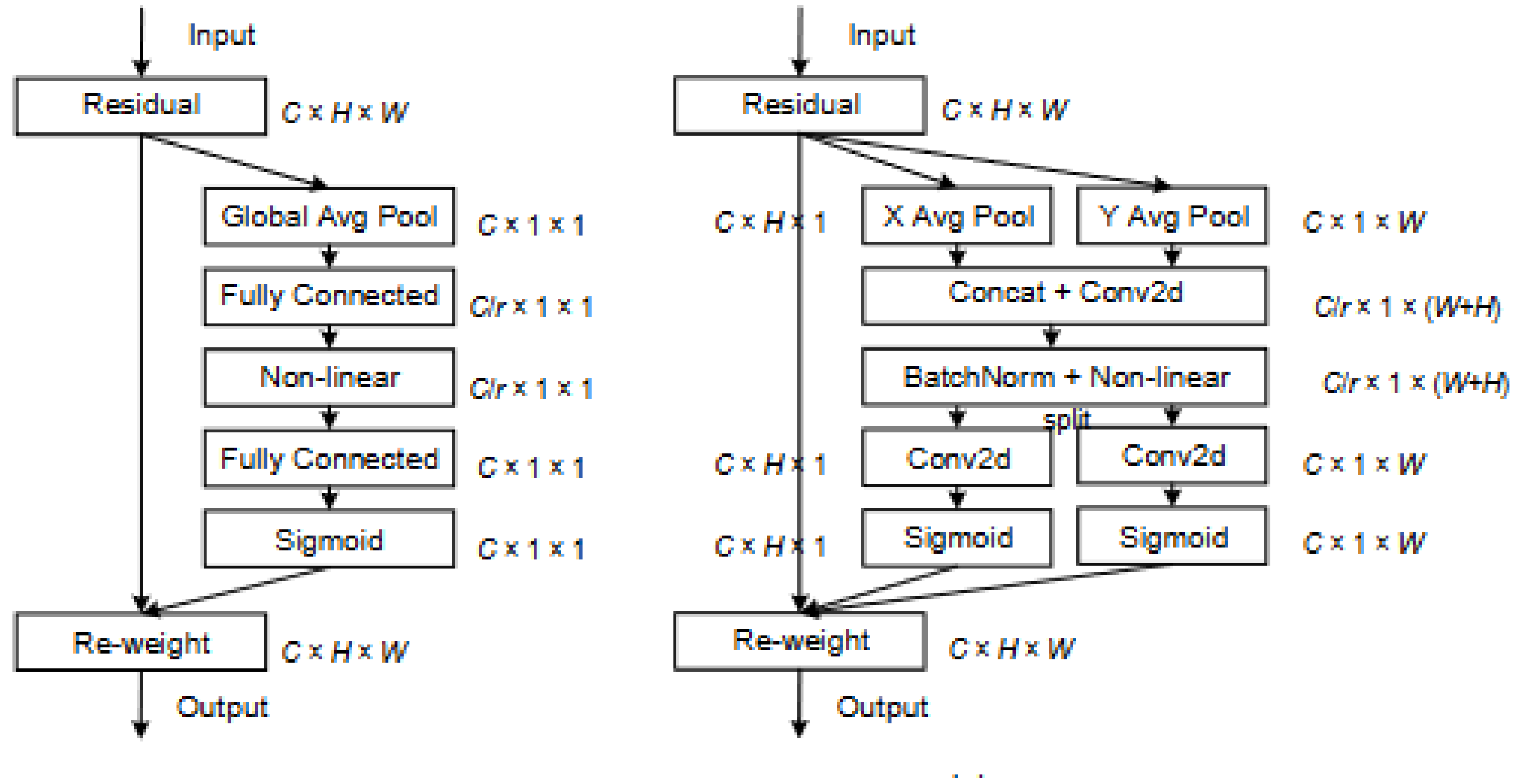

Fig. 4: SE module vs Coordinate Attention module [27]

CHALLENGES FACED

Proximity and Similar Visual Features: The model encountered difficulties in accurately detecting landmarks such as pogonion, menton, gnathion, and soft tissue pogonion. These landmarks share close proximity, leading to visual similarities in the images and ultimately similar features. The model struggled to differentiate between these closely situated landmarks, impacting its performance in achieving precise predictions.

Need for a lager open-source dataset: Some of the images in the ISBI Grand Challenge dataset were blurry around the edges of the subject's head. Also, the dataset only contains 400 images of which only 150 were used for training (and as is the standard for that dataset across other researchers using it)

RESULTS

Our model has obtained an SDR of 57.00% within 2 mm of MRE,, 83.36% for 3 mm, 93.26% for 4 mm. The model seemed to struggle with landmarks like pogonion, menton, gnathion, soft tissue pogonion as their proximity is near each other and hence they share similar visual features in the image.

Model	SDR (%)		
	2 mm	**3 mm**	**4 mm**
Lee et al. [19]	82.11	**92.28**	**95.96**
Wang et al. [14]	73.37	84.46	90.67
Tim et al. [29]	74.95	80.56	89.68
Ours	57.00	83.36	***93.26***

Bold = best; Italic + Bold = Second Best

Table 1: *Results and Comparison*

DISCUSSION

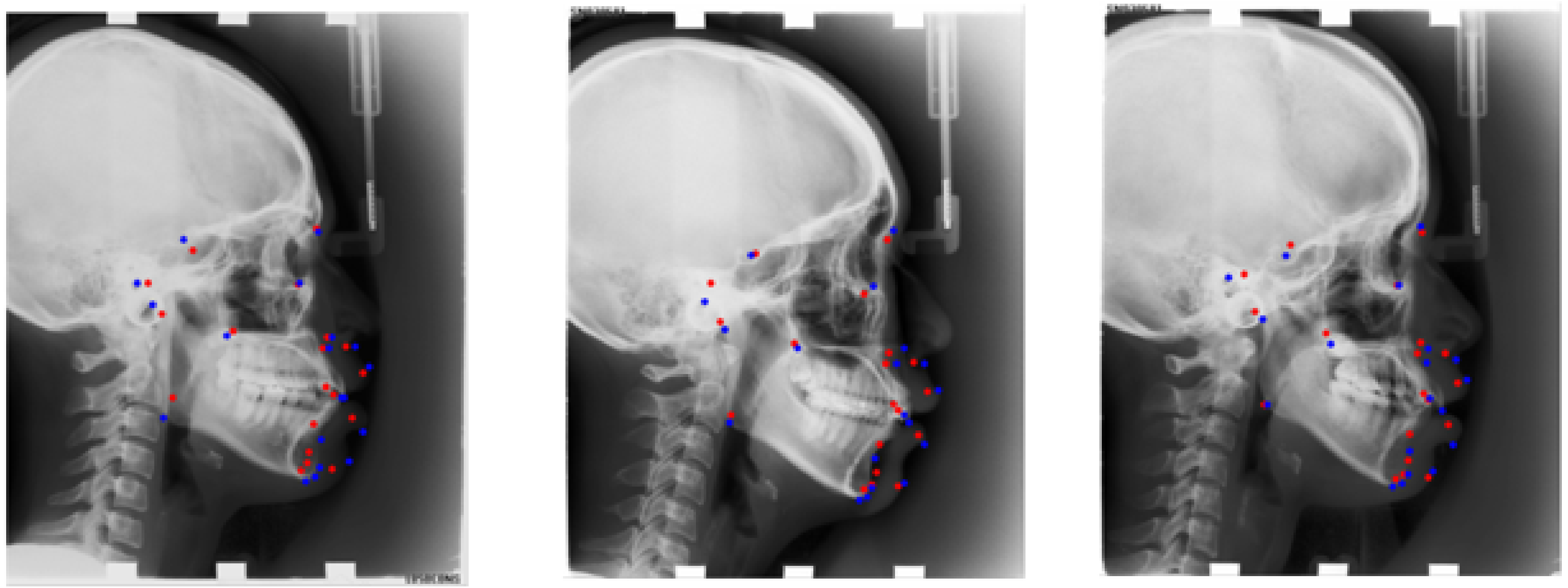

Fig. 5: *Sample Outputs. Red = Predicted, Blue = Actual*

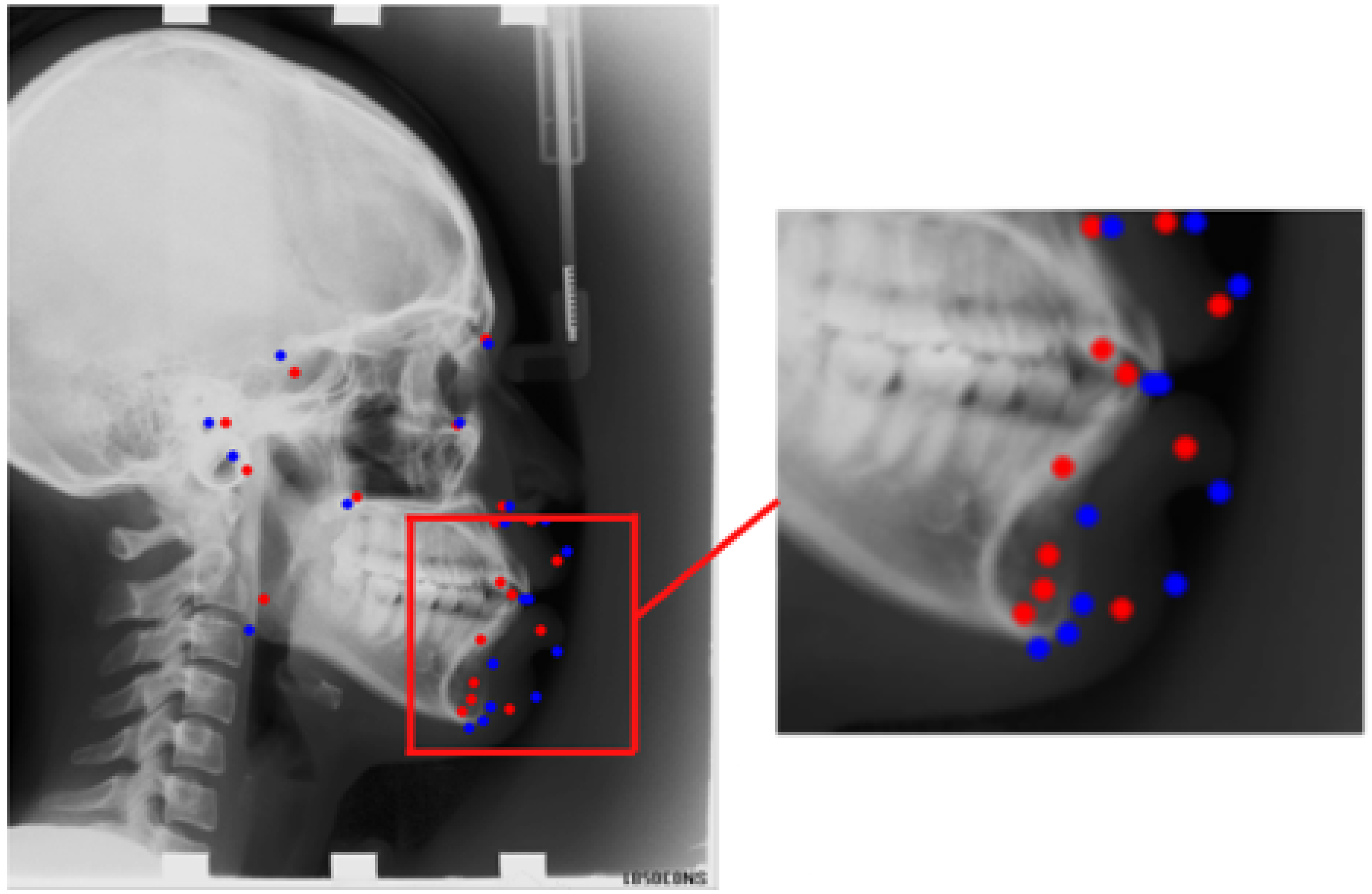

Fig. 6: *Zoomed view of the area with the lowest SDR landmarks. Red = Predicted, Blue = Actual*

AS MENTIONED BEFORE, GNATHION AND NEARBY LANDMARKS ARE HAVING HIGHER DEVIATION THAT THE REST ON AVERAGE. THIS IS DUE TO THEIR CLOSE PROXIMITY AND SIMILAR FEATURES. THIS CAN BE VISUALIZED ON THE ZOOMED IMAGE ON THE RIGHT

CONCLUSION

THROUGHOUT THE PROJECT, WE OBSERVED THAT THERE IS A SEVERE LACK OF OPEN-SOURCE DATA FOR THE TASK OF CEPHALOMETRIC LANDMARK DETECTION. TO ADD TO THIS DATA INSUFFICIENCY, THERE IS SEVERE LACK OF DIVERSITY TO IT AS THE MOST POPULAR DATASET WAS FULLY COLLECTED FROM ONLY ONE MEDICAL INSTITUTE FROM TAIWAN. SO, THERE IS A PRESSING NEED FOR A DATASET THAT IS SUFFICIENTLY LARGE, DIVERSE, OPEN-SOURCE

OUR FUTURE WORK MAY INCLUDE THE FOLLOWING:
-THE PROPOSED MODEL STRUGGLES IN THE 2 MM MRE RANGE, WHICH IS THE DESIRED RANGE FOR CEPHALOGRAM LANDMARK DETECTION [26]. THIS CAN BE OVERCOME BY CREATING PATCHES DATASET FROM THE ORIGINAL DATASET SIMILAR TO WHAT SOME METHODS HAVE DONE [25, 29].
-TO PERFORM ABLATION STUDY ON THE EFFECTIVENESS OF THE COORDINATE ATTENTION MODULE OVER THE SQUEEZE-AND-EXCITATION MODULE
-A SOLUTION TO THE DEVIATION IN LANDMARKS LIKE POGONION, GNATHION, ETC THAT ARE CLOSE TO EACH OTHER AND SHARE SIMILAR VISUAL FEATURES

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