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# Fully automated method for dental age estimation using the ACF detector and deep learning

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**Abstract**

**Background:** Dental age estimation plays an important role in identifying an unknown person. In forensic science, estimating age with high accuracy depends on the experience of the practitioner. Previous studies proposed classification of tooth development of the mandibular third molar by following Demirjian's method, which is useful for dental age estimation. Although stage of tooth growth is very helpful in assessing age estimation, it must be performed manually. The drawback of this procedure is its need for skilled observers to carry out the tasks precisely and reproducibly because it is quite detailed. Therefore, this research aimed to apply computer-aid methods for reducing time and subjectivity in dental age estimation by using dental panoramic images based on Demirjian's method. Dental panoramic images were collected from persons aged 15 to 23 years old. In accordance with Demirjian's method, this study focused only on stages D to H of tooth development, which were discovered in the 15- to 23-year age range. The aggregate channel features detector was applied automatically to localize and crop only the lower left mandibular third molar in panoramic images. Then, the convolutional neural network model was applied to classify cropped images into D to H stages. Finally, the classified stages were used to estimate dental age.

**Results:** Experimental results showed that the proposed method in this study can localize the lower left mandibular third molar automatically with 99.5% accuracy, and training in the convolutional neural network model can achieve 83.25% classification accuracy using the transfer learning strategy with the Resnet50 network.

**Conclusion:** In this work, the aggregate channel features detector and convolutional neural network model were applied to localize a specific tooth in a panoramic image and identify the developmental stages automatically in order to estimate the age of the subjects. The proposed method can be applied in clinical practice as a tool that helps clinicians to reduce the time and subjectivity for dental age estimation.

**Keywords:** Aggregate channel features detector, Convolutional neural network, Dental age estimation, Forensic sciences, Medical image classification

## Background

Forensic age estimation may be required by the authorities in criminal, civil, or asylum procedures when birth records or other official identity documents, which reflect the age of an individual, are not accessible. The estimation typically includes a predicted age and probability measurement of a person observed who attained a particular legally relevant age barrier. Most established methods for age estimation employ medical imaging of several human body components, such as the teeth, and long and carpal bones, which are still developing in children and young adults. Dental age estimation is said to be a reliable technique for estimating the age of an unknown person. Several studies have focused on

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it (Chandramohan et.al., 2015), especially using radiographic methods (Panchbhai 2011) such as tooth mineral evaluation (Nolla 1960), measurement of open apices in teeth (Cameriere et.al., 2006), volume assessment of teeth (Kvaal et.al., 1995), and tooth development (Demirjian et.al., 1973). However, a report stated that all teeth are fully developed by the time a person reaches the age of 15 years, except for permanent third molars (Hassanali 1985). In addition, 18 years are specified as a cut-off age for distinguishing between adults and children in legal procedures, according to the 1989 United Nations Convention on the Rights of the Child. As a result, the development of permanent third molars is necessary for determining the age of an individual when they fall in the category of adolescents and young adults (Duangto et.al., 2017). Due to the complexity of this process, experienced observers are needed to estimate the stage of tooth development for young adults.

At present, the convolution neural network (CNN) is used widely for medical image analysis. Regarding dental research, especially for problems of dental caries in bitewing and panoramic images (Cantu et.al., 2020; Lakshmi and Chitra 2020; Lee et.al., 2021; Lian et.al., 2021; Megalan Leo and Kalpalatha Reddy 2021; Megalan Leo and Kalpalatha Reddy 2020; Panyarak et.al., 2022; Suttapak et.al., 2022; Vinayahalingam et.al., 2021). In dental age estimation, some studies applied CNN to estimate age using full panoramic images (Atas et.al., 2022; Hou et.al., 2021; Vila-Blanco et.al., 2020; Zaborowicz et.al., 2021; Zaborowicz et.al., 2022). Semiautomated techniques have been proposed for classifying the stage of the manually cropped lower third molar images (De Tobel et.al., 2017; Merdietio Boedi et.al., 2020). Some previous studies proposed a fully automated method that can localize the third molar automatically. Banar et al. proposed a fully automated method that can localize the third molar before classifying its developmental stages (Banar et.al., 2020). Their study revealed that the proposed method could yield moderate accuracy. Milošević proposed a fully automated estimation of chronological age from panoramic dental X-ray images, without the staging process (Milošević et.al., 2022). However, the age range in their subjects was 19 to 90 years.

From 2021, the research team in this study (Upalananda et.al., 2021) has proposed employing deep learning technology to estimate ages between 15 and 23 years old using a semiautomated approach. The experimental results demonstrated that the proposed technique could reach better accuracy than that in previous studies. However, it was still a manual process. To make clinical practice more convenient, a fully automated method needed to be developed. The purpose of this study was to develop a fully automated system, based on the staging method of Demirjian, for the left mandibular third molar in order to reduce time and subjectivity in dental age estimation.

## Methods

### Data preparation

This study was approved by the review board of the Human Experimentation Committee, Faculty of Dentistry, Chiang Mai University, Chiang Mai, Thailand (document No. 50/2019). Panoramic dental X-ray images were collected from the Faculty of Dentistry, Chiang Mai University, Chiang Mai, Thailand, as shown in Fig. 1a. Those with low image quality were badly misaligned or had missing mandibular third molars or jawbone pathology were excluded. This study focused on the application of dental age estimation using Demirjian's method in a group of young individuals aged 15 to 23 years, and only covered stages D to H of mandibular third molars (Fig. 1b), in accordance with a previous study (Duangto et.al., 2017). A total of 1000 panoramic images from 454 males and 546 females, 200 per stage, were selected and assessed by an expert observer, who had more than 10 years' experience in assessing dental radiographs for age estimation. The intra- and inter-operator agreements were evaluated using Cohen's kappa statistic, as reported in a previous study by the authors (Upalananda et.al., 2021). The intra- and inter-observer agreements were 0.898 and 0.833, respectively. According to the guidelines of Landis and Koch (Landis and Koch 1977), their level of agreement was nearly perfect. Next, the images were divided randomly into two groups for each stage, with 160 and 40 images in the training and validation group, respectively. Therefore, 800 images were used to train the model, and 200 images were utilized to test how well the trained model performed.

Three procedures made up the proposed technique. First, the lower left third molar in the panoramic image was located automatically and cropped. Second, the cropped image was categorized into the last five stages (D to H) of Demirjian's method. The final step was estimated age based on stage classification. Figure 2 illustrates the proposed workflow of the technique.

### Localization procedure of the lower left third molar

To localize the lower left third molar on a panoramic image, the aggregated channel features (ACF) detector (Dollár et.al., 2014) was used for detecting and localizing the position of specific teeth. For images in the training group, bounding boxes (BBs) were created to cover the lower left third molar. The ACF detector was trained to recognize the features inside the BB. For testing or implementation, the lower left third molar was located automatically from the testing group in the new images, using the optimized detector after the training procedure, by

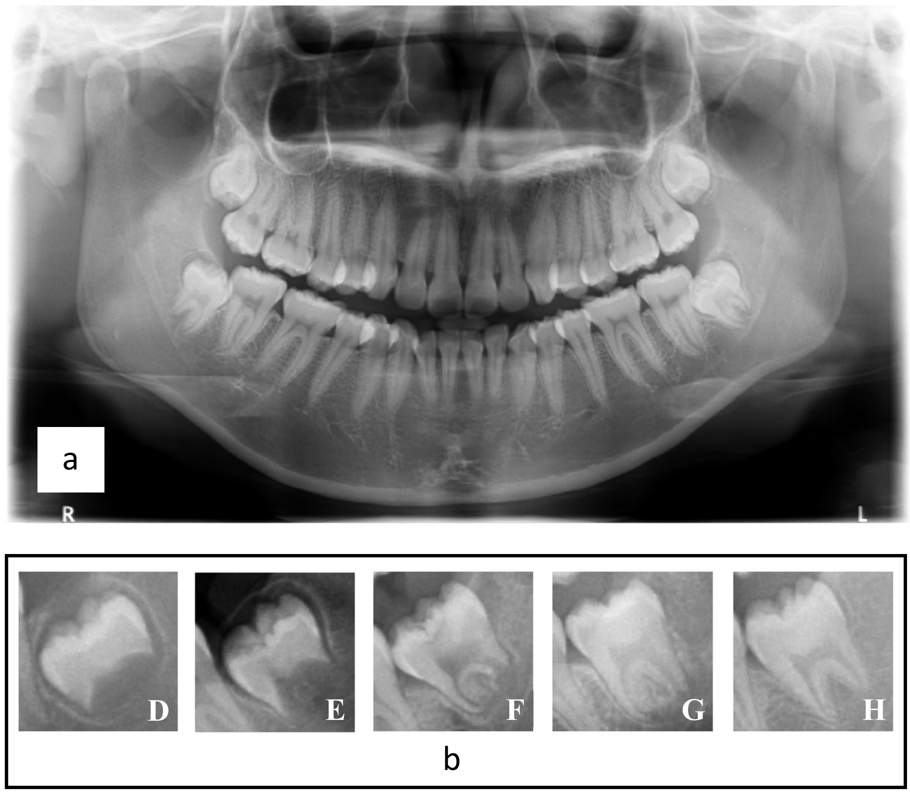

**Fig. 1** Examples of images used in this study. **a** A panoramic image and **b** cropped images that covered the lower left third molar including stages D to H

creating a BB around the potential location. If more than one feasible BB was created, the lower left third molar was chosen from the farthest left-hand side (the farthest right-hand side of the image). The lower left third molar was then cropped by using the location of the selected BB.

### Developmental stages of the classification procedure

To prepare data for training the classification model, the lower left third molars in 800 training images (160 images per stage) were cropped manually as shown in Fig. 2. The CNN model was used in this study to classify the cropped lower left third molars automatically in D to H stages. The transfer learning technique (Pan and Yang 2010) was used to accelerate and improve the performance using the pre-trained network. GooLeNet (Szegedy et.al., 2015) was used in a prior study by the authors (Upalananda et.al., 2021), and it produced successful outcomes. In this study, ResNet50 (He et.al., 2016) was applied and compared with the previous report. Twenty percent of the training data was separated in order to validate the classification performance during each training epoch. The network was trained using the Adam optimizer (Kingma and Ba 2015) and a hyperparameter tuning strategy. Data augmentation, which entails scaling, rotation, and translation, was used to increase the amount of data because of its limited availability. After the training process, the trained model was used to classify the cropped images.

The classification results were compared with the expert-evaluated ground truth in order to evaluate the classification performance. In this study, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy were reported as shown in Eqs. (1) to (5):

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{1}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{FP} + \text{TN})} \tag{2}$$

$$\text{PPV} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{3}$$

$$\text{NPV} = \frac{\text{TN}}{(\text{FN} + \text{TN})} \tag{4}$$

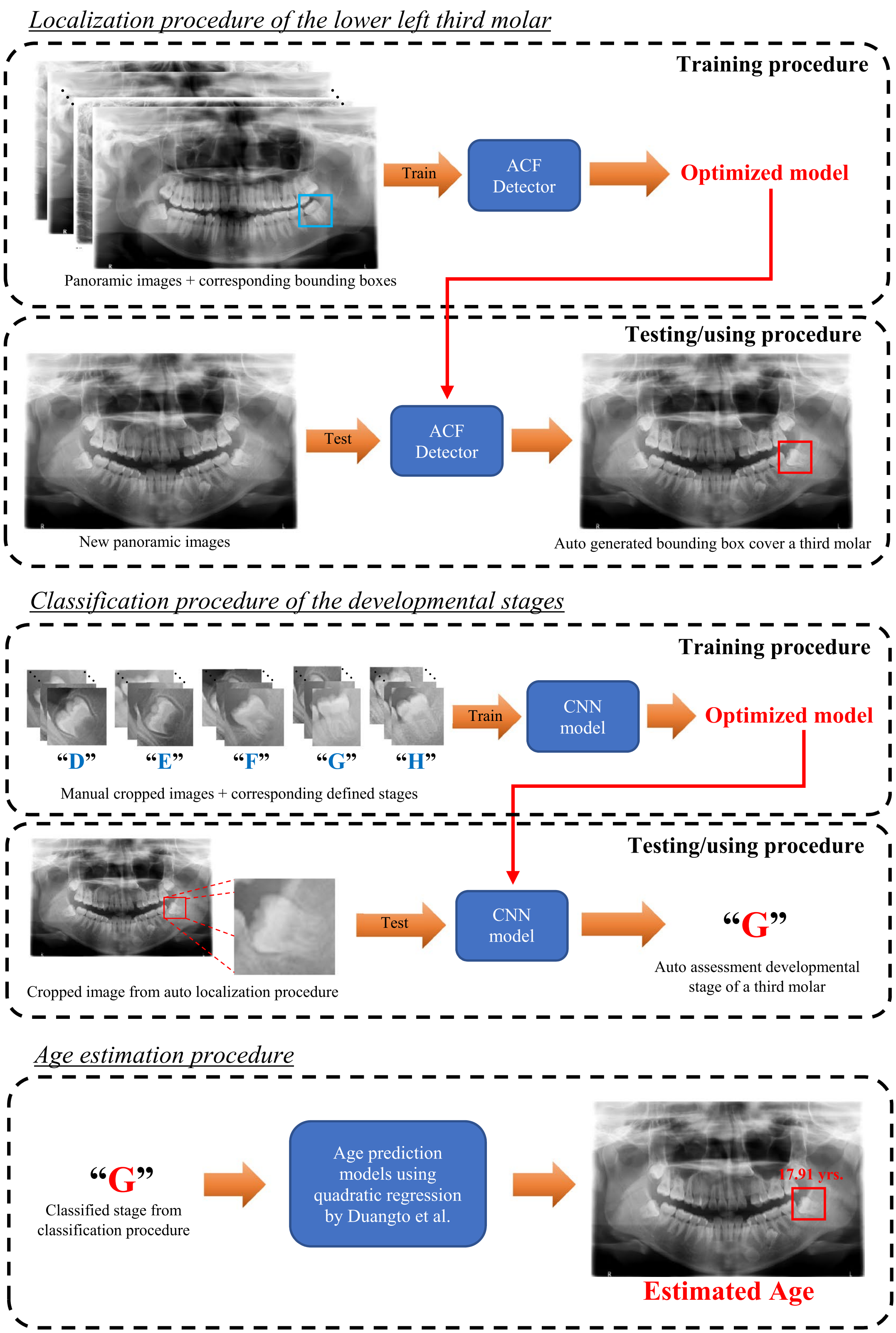


**Fig. 2** Schematic overview of the proposed dental age estimation system including three procedures: localization, classification, and age estimation

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{5}$$

where TP, TN, FP, and FN refer to images of true positive (images from the stage under consideration were classified correctly), true negative (images from other stages were classified correctly), false positive (images from other stages were classified as the stage under consideration), and false negative (images from the stage under consideration were classified into other stages), respectively.

### Age estimation procedure

The next step was estimating age based on the classified stage of the lower left third molar. The regression equations proposed by Duangto et al. for males and females are given in Eqs. (6) and (7), respectively (Duangto et.al., 2017):

$$y = 7.648 + 0.753\text{x} + 0.093\text{x}^2 \tag{6}$$

$$y = 6.421 + 1.256\text{x} + 0.055\text{x}^2 \tag{7}$$

where $y$ is the estimated age and $x$ is the development score, which ranges from 5 to 9, according to the lower left third stage classification of the molar (D to H).

To evaluate the preciseness of age estimation, Pearson's linear correlation coefficient was calculated.

## Results

### Lower left third molar localization

In 200 panoramic images of the test set, the lower left third molar positions were located automatically. To achieve the best results, the ACF parameters of the detector were fine-tuned. The number of stages was set to 3, and the negative samples factor to 3 throughout the experiments. According to the experiments, the detector could identify the location of the lower left third molar accurately with 99.50% accuracy (199 of 200 images). The location of the lower left third molar could not be detected in only one case.

### Developmental stages of the classification

The CNN model was trained using the transfer learning technique, based on the pre-trained network, ResNet50, and used to classify the 199 detected and cropped images. The optimal parameters were a maximum epoch of 30, an initial learning rate of 0.001, a number of epochs for dropping the learning rate of 15, and a factor for dropping the learning rate of 0.1. The network was fed with 32 images for one batch size (mini batch size = 32). The performance for each developmental stage is shown in Table 1. The average sensitivity, specificity, PPV, NPV, and accuracy were 83.41%, 96.11%, 84.02%, 96.08%, and 93.66%, respectively. The confusion matrix of the classification results for all stages is shown in Table 2. The classification results showed that the percentage of accuracy ranged from 67.50 to 97.50%, with 83.25% on average.

### Age estimation

The classified developmental stages were used to estimate age using the equation proposed by Duangto (Duangto et.al., 2017). Table 3 displays the percentage of accuracy for each difference in estimated age using the proposed method and chronological age ranging from ±0.5 to ±5.5 years. The results showed that in more than 90% of the data, the proposed technique could estimate age with a difference of no more than ±4.0 years from chronological age. The result achieved an overall mean absolute error of 1.94 years and median

**Table 2** Evaluation metrics in each classified stage

| Classified stages | Sensitivity | Specificity | PPV | NPV | Accuracy |
|---|---|---|---|---|---|
| D | 87.50% | 100.00% | 100.00% | 96.97% | 97.50% |
| E | 97.50% | 95.23% | 82.97% | 99.37% | 95.67% |
| F | 82.50% | 98.16% | 91.67% | 95.80% | 95.07% |
| G | 67.50% | 93.57% | 71.05% | 92.48% | 88.62% |
| H | 82.05% | 93.57% | 74.42% | 95.80% | 91.42% |
| Average | 83.41% | 96.11% | 84.02% | 96.08% | 93.66% |

**Table 1** Confusion matrix between the developmental stages being assessed by the expert and classified by the proposed method

| | | Developmental stages classified by the proposed method | | | | |
|---|---|---|---|---|---|---|
| | | **D** | **E** | **F** | **G** | **H** |
| Developmental stages assessed by the expert | D | **35 (87.50%)** | 5 (22.50%) | 0 | 0 | 0 |
| | E | 0 | **39 (97.50%)** | 1 (2.50%) | 0 | 0 |
| | F | 0 | 3 (7.50%) | **33 (82.50%)** | 4 (10.00%) | 0 |
| | G | 0 | 0 | 2 (5.00%) | **27 (67.50%)** | 11 (27.50%) |
| | H | 0 | 0 | 0 | 7 (17.95%) | **32 (82.05%)** |

**Table 3** Percentage of accuracy in age estimation of lower third molars in males and females within different values between estimated dental age in the proposed method and chronological age from ±0.50 to ±5.50 years

| Difference in value (years) | Number of cases | % Accuracy |
|---|---|---|
| ±0.5 | 20 | 10.05 |
| ±1.0 | 53 | 26.63 |
| ±1.5 | 84 | 42.21 |
| ±2.0 | 116 | 58.29 |
| ±2.5 | 149 | 74.87 |
| ±3.0 | 169 | 84.92 |
| ±3.5 | 173 | 86.93 |
| ±4.0 | 181 | 90.95 |
| ±4.5 | 192 | 96.48 |
| ±5.0 | 197 | 98.99 |
| ±5.5 | 199 | 100.00 |

absolute error of 1.72 years. Finally, the correlation coefficient between estimated and chronological age was calculated. It demonstrated an excellent correlation with $\rho = 0.91$ ($p < 0.05$).

## Discussion

Applications of artificial intelligence (AI) are now used widely across many areas. In forensic science, it also is used to estimate age automatically, which might reduce operator variability and operation time. Automated age estimation using bones of the hand (Thodberg et.al., 2009; Thodberg et.al., 2017; Pan et.al., 2020; Remy et.al., 2021), pelvis (Li et.al., 2019), knee (Demircioğlu et.al., 2022), lumbar vertebrae (Malatong et.al., 2022), and trabecular bone (Sattarath et.al., 2021), as well as dental images, has been proposed in previous studies. Dental age estimation, by considering tooth development, showed less variability than other developmental factors and also indicated good relationship to chronological age (Chandramohan et.al., 2015). In a previous study (Upalananda et.al., 2021), the authors' proposed an accurate semiautomated approach based on Demirjian's method (Demirjian et.al., 1973) for assessing the developmental stage of the mandibular third molars in dental panoramic images (stages D to H). There are some processes that require manual interaction. The ACF detector, deep learning, and transfer learning techniques were therefore used in this study to develop a fully automated dental age evaluation technique.

In the localization procedure using the ACF detector, the location of the lower left third molar could not be detected in only one case, which was in stage H. As seen in Fig. 3a, the lower left third molar in this case aligned vertically. There were no cases with the same alignment as this case in the training set. Most of the examples in the training set were not vertically aligned, as shown in Fig. 3b.

This study only focused on stages D to H because they covered the age of 18 years or thereabouts, which is the age at which people are legally classified from children to adults. If the proposed method is reliable, it might be able to help in accurately estimating the age of young adults, which is unknown in situations requiring legal discretion. According to the classification results, the early stages (D and E) had higher accuracy than the later ones (F to H), and every misclassification differed by one stage from the developmental stage determined by the observer, which is consistent with the authors' previous study (Upalananda et.al., 2021) and that by Dhanjal (Dhanjal et.al., 2006). Since the roots in the early stages (D and E) were significantly distinct from other stages, they were easy to classify. On the other hand, it was difficult to distinguish between the later stages (F to H), as their root structures were similar. In particular, only the distal roots for stages G and H had differences, which were very difficult to consider. They corresponded to the human assessment according to Demirjian's method, which considers root transformation of the lower left third molar. This situation was represented by heat maps using gradient-weighted class activation mapping (Grad-CAM) (Selvaraju et.al., 2017), which was used to confirm where the network is visually, and its focus on specific patterns in the image. The most specific positions focused on by Grad-CAM were in most cases close to the root of the lower third molars, as shown in Fig. 4a. Another possibility for classification error was the network focusing on the wrong positions (not near the roots), as shown in Fig. 4b.

It was advisable to apply population-specific standards to enhance the accuracy of forensic age estimations, based on wisdom teeth mineralization (Olze et.al., 2004). Three previous works studied dental age estimation in the Thai population using the third molar (Duangto et.al., 2017; Thevissen et.al., 2009; Verochana et.al., 2016). Thevissen used maxillary and mandibular third molars, while Verochana and Duangto used only the mandibular third molar to estimate age. According to a report on dental panoramic images from de Oliveira (de Oliveira et.al., 2012), relevant anatomical structures were superimposed over the maxillary third molar tooth. Mandibular third molar teeth were therefore more suitable for age estimation than maxillary ones because they were clearer on panoramic images. This study applied equations from Duangto et al. to determine the age in developing stages of the third molars because their participants ranged in age from 8 to 23 years, which was comprehensive and applicable

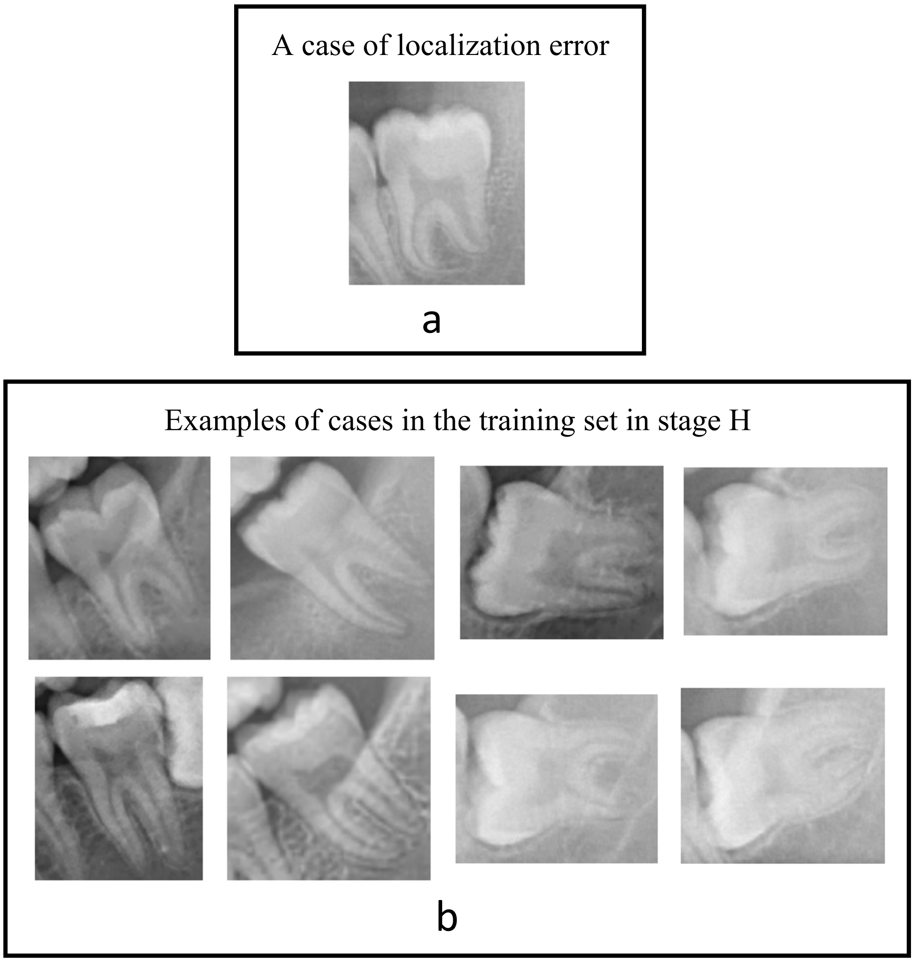


**Fig. 3** A case of localization error in which the lower left third molar aligned vertically (**a**) and difference from others in the training set that were not vertically aligned (**b**)

to this study. The difference between estimated and chronological age in their study ranged from ±0.5 to ±4.0 years, whereas it ranged from ±0.5 to ±5.5 years in this one. The misclassification in the developmental stage of the classification procedure might be the cause of increased errors.

Table 4 shows a comparison between proposed methods in recent studies on dental age estimation published within the last 5 years. Their outcomes could not be compared directly because they used different datasets, experimental settings, and evaluation metrics. Zaborowicz et al. employed the extracted tooth and bone parameters from panoramic images by using ImageJ software as the input features for the deep learning neural model to assess the age of children and adolescents (4–15 years) (Zaborowicz et.al., 2022). Their experimental results showed a mean absolute error of 4.61 months and correlation coefficient of 0.93. Vila-Blanco et al., Hou et al., and Atas et al. used pre-trained CNN models to train the full panoramic images for age estimation without the classification procedure (Atas et.al., 2022; Hou et.al., 2021; Vila-Blanco et.al., 2020). Vila-Blanco et al. developed two CNN models for dental age estimation called DANet (Dental Age Net) and DASNet (Dental Age and Sex Net). DANet used a sequential CNN path to estimate age, while DASNet included a second CNN path to predict sex and extract sex-specific features that were used to boost the accuracy of age estimation. According to results of the experiment, the median absolute error for DANet was 1.66 years, while it was 1.48 years for DASNet. Hou et al. investigated several neural network elements that are effective for age estimation. They used the well-known neural architecture search (NAS) method to further search models for dental age estimation based on characteristic exploration. According to the experiment's findings, their model achieved a mean absolute error of 1.64 years. Atas et al. modified the

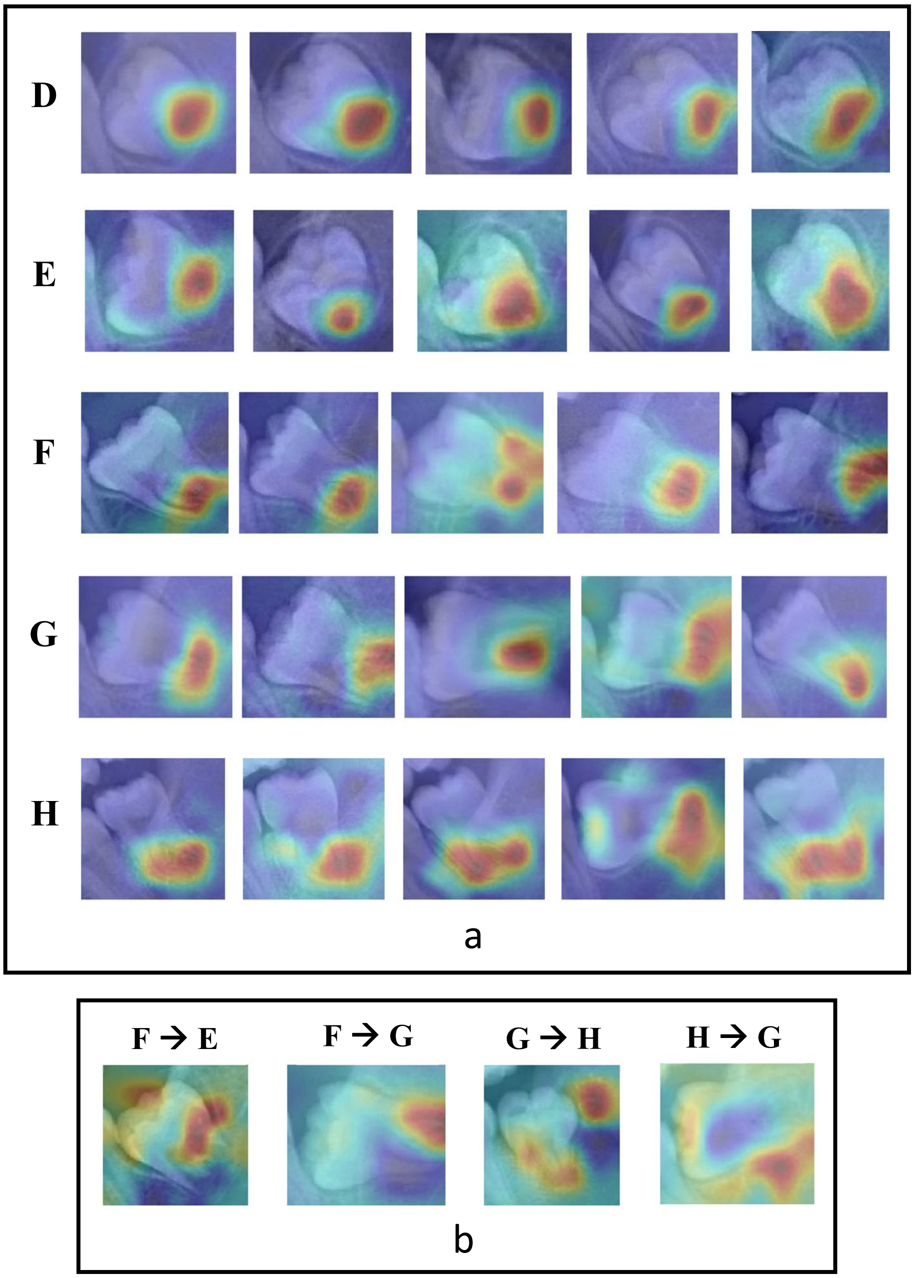


**Fig. 4** Heat maps implemented using Grad-CAM. **a** Most specific positions focused on close to the root of the lower third molars and **b** examples of misclassification where the network focused on incorrect positions

transfer learning-based model, InceptionV3, by reducing the number of parameters to speed up computation and improve the accuracy of dental age estimation. The experimental results showed a mean absolute error of 3.13 years, and correlation coefficient of 0.87. Grad-CAM was presented in their reports. They reported that teeth, gum tissue, and the upper jaw were distinct areas on the heat maps, while Vila-Blanco et al. and Hou et al. reported distinct areas only of the teeth. They were able to ascertain that trained networks for the task of estimating dental age mainly concentrated on the region of teeth in full panoramic images. Therefore, many works proposed the dental age estimation method that considered only specific teeth. Milošević proposed methods that considered only the region of teeth in full panoramic images (Milošević et.al., 2022).

**Table 4** Comparison between the proposed method and previous studies on dental age assessment using dental panoramic images

| Authors | Input | Automated type | Data | | Stage assessment | | Age estimation performance (difference and correlation between estimated age and chronological age) |
|---|---|---|---|---|---|---|---|
| | | | Age range of samples (years) | No. of images | Demirjian's method | Accuracy | |
| Zaborowicz et.al., (2022) | Extracted tooth and bone parameters using ImageJ software | Semi | 4–15 | 619 | - | - | Difference: median absolute error = 1.48 years and mean absolute error = 4.61 months Correlation: $R^2$ = 0.93 |
| Vila-Blanco et.al., (2020) | Full image | Fully | 4.5–89.2 | 2289 | - | - | Difference: median absolute error = 1.48 years and mean absolute error = 2.84 years Correlation: $R^2$ = 0.90 |
| Hou et.al., (2021) | Full image | Fully | 0–90 | 27,957 | - | - | Difference: mean absolute error = 1.64 years |
| Atas et.al., (2022) | Full image | Fully | 8–68 | 1332 | - | - | Difference: mean absolute error = 3.13 years Correlation: $R^2$ = 0.87 |
| Milošević et.al., (2022) | Specific teeth image | Full images: fully Individual teeth: semi | 19–90 | 4035 | - | - | Difference: median absolute error = 2.95 years for full images, median absolute error = 4.68 years for individual teeth |
| De Tobel et.al., (2017) | Specific teeth image | Semi | 7–24 | 400 | 10 stages (modified) | 51.00% | - |
| Merdietio Boedi et.al., (2020) | Specific teeth image | Semi | 7–24 | 400 | 10 stages (modified) | 61.00% | - |
| Banar et.al., (2020) | Specific teeth image | Fully | 7–24 | 400 | 10 stages (modified) | 54.00% | - |
| Upalananda et.al., (2021) | Specific teeth image | Semi | 15–23 | 2235 | 5 stages (D to H) | 82.50% | Correlation: Spearman's rank correlation $r = 0.87$, $p < 0.001$ |
| Proposed method | Specific teeth image | Fully | 15–23 | 1000 | 5 stages (D to H) | 83.25% | Difference: median absolute error = 1.72 years and mean absolute error = 1.94 years Correlation: Pearson's linear correlation $\rho = 0.91$, $p < 0.05$ |

Four-thousand and thirty-five panoramic images were used in their study, which applied the CNN model with pretrained weights provided by base networks, also known as the transfer learning approach. It could estimate one floating-point number in the range of 0 to 100, which represented the estimated chronological age in years. They reported that the median absolute error between the estimated and chronological age was 4.68 years for individual teeth and 2.95 years for the region covering all teeth.

The same dataset was used for only individual teeth by De Tobel et al., Merdietio Boedi et al., and Banar et al., but the automated types were different (Banar et.al., 2020; De Tobel et.al., 2017; Merdietio Boedi et.al., 2020). Semiautomated techniques were proposed by De Tobel for classifying the stage of lower third molars from panoramic images, in which specific teeth were cropped manually. Next, the images of the cropped teeth were rotated vertically to an upright position. Then, deep learning techniques were applied to classify the developmental stage of the lower third molar, based on Demirjian's method. According to their study, automatic developmental stage assessment had an approximate accuracy rate of 51%. Merdietio Boedi et al. studied how the three different types of lower third molar segments — bounding box (BB), rough segmentation (RS), and full segmentation (FS) of the tooth — affected classification of the developmental stage in a manually drawn BB. The results demonstrated that a DenseNet201 CNN with full tooth segmentation provided the best accuracy at 61%. Banar et al. proposed a completely automated approach that produced classification accuracy. A method that can localize the third molar and subtract background before classifying its developmental stages, using 3 CNN models, has been proposed. The first CNN model was used for localizing the central coordinate of the tooth. The second one was utilized to segment the region of interest (ROI) of the tooth. Finally, the segmented ROI was classified by the last CNN model. Their study revealed that the proposed method could yield an accuracy of 54%, which is only moderate. An age estimation was not found in their reports. In a study by the authors (Upalananda et.al., 2021), a semiautomated approach based on deep learning technology was proposed for estimating age. The lower third molar was rotated manually to an upright position and cropped before being classified using Demirjian's approach in stages D to H. The experimental results demonstrated that the proposed technique could reach accuracy of 82.50%. However, it should be noted that only 5 developmental stages were included in the authors' study as opposed to 10 in theirs. This study presented the localization approach for the lower left third molar to fully automate the system while improving classification performance and proceeding to estimate the age. The classification result had an accuracy rate of 83.25%, and the median absolute error for age estimation was 1.72 years.

### Limitations and future work

There are some limitations in this study that was unable to use more complex pre-trained networks such as ResNet-101, DenseNet-201, and EfficientNet-V2 B7, which could have improved classification performance. This was due to hardware restrictions. Although powerful deep learning algorithms, such as region-based convolutional neural networks (R-CNN) (Girshick et.al., 2014), Fast R-CNN (Girshick 2015), Faster R-CNN (Ren et.al., 2015), and many versions of Yolo (Redmon et.al., 2016; Redmon and Farhadi 2018; Redmon and Farhadi 2017), are now available for simultaneously detecting and classifying objects automatically in images, this study developed a fully automated technique that combines the ACF detector for localizing the CNN network for classification. This is because of the need to extend the authors' previous work in order to make it more effective. Therefore, the collection and use of more datasets are planned for future work in training deep learning of object detection in algorithms and improving the fully automatic system for dental age estimation. A useful tool was used to assess the legal adult age of 18 years old called Cameriere's cutoff values of the third molar maturity index (I3M). However, it was tested and applied to only Caucasian (Cameriere et.al., 2008) and French (Ribier et.al., 2020) populations. It would be fascinating to apply this technology to Thai data as part of a future study. On the other hand, the method in this study could be applied to different populations, if specific processes, such the age estimate equations, were created by modifying data from Thai populations to suit others.

## Conclusions

This study proposed an X-ray panoramic image-based approach for fully automated dental age estimation. The ACF detector and deep learning algorithms were applied to locate the lower left third molar and classify developmental stages using Demirjian's method. The classified stage was then utilized to estimate dental age automatically. According to experimental findings, the ACF detector and deep learning were able to detect and classify developmental stages automatically with an average accuracy of more than 83%. Finally, the fully automated system achieves a high correlation between the estimated dental and chronological age, $r = 0.91$ ($p < 0.05$). It was found that the proposed method could be applied in a clinical setting as a support tool in helping clinicians to evaluate the development of mandibular third molars more rapidly and objectively for dental age estimation.

#### Abbreviations

ACF: Aggregate channel features; AI: Artificial intelligence; BB: Bounding box; CNN: Convolutional neural network; DANet: Dental Age Net; DASNet: Dental Age and Sex Net; FN: False negative; FP: False positive; FS: Full segmentation; Grad-CAM: Gradient-weighted Class Activation Mapping; I3M: Third molar maturity index; NPV: Negative predictive value; PPV: Positive predictive value; ROI: Region of interest; RS: Rough segmentation; R-CNN: Region-based convolutional neural networks; TN: True negative; TP: True positive.

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**Authors' contributions**
PP, SS, UY, and KW conceived of the idea presented. WU collected the data. PP and KW developed the methodologies. PP and KW performed the experiments and analysis and wrote the main manuscript. All authors discussed the results and contributed to the final manuscript. The authors read and approved the final manuscript.

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Not applicable

**Availability of data and materials**
The data sets analyzed in this study are available from the corresponding author on reasonable request.

## Declarations

**Ethics approval and consent to participate**
This study was approved by the review board of the Faculty's Human Experimentation Committee, Faculty of Dentistry, Chiang Mai University, Chiang Mai, Thailand (document no. 50/2019). Informed consent was waived due to the retrospective nature of the study according to the board policy.

**Consent for publication**
Not applicable

**Competing interests**
The authors declare that they have no competing interests.

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