Is Convolutional Neural Network Accurate for Automatic Detection of Zygomatic Fractures on Computed Tomography?

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Purpose: Zygomatic fractures involve complex anatomical structures of the mid-face and the diagnosis can be challenging and labor-consuming. This research aimed to evaluate the performance of an automatic algorithm for the detection of zygomatic fractures based on convolutional neural network (CNN) on spiral computed tomography (CT).

Materials and Methods: We designed a cross-sectional retrospective diagnostic trial study. Clinical records and CT scans of patients with zygomatic fractures were reviewed. The sample consisted of two types of patients with different zygomatic fractures statuses (positive or negative) in Peking University School of Stomatology from 2013 to 2019. All CT samples were randomly divided into three groups at a ratio of 6:2:2 as training set, validation set, and test set, respectively. All CT scans were viewed and annotated by three experienced maxillofacial surgeons, serving as the gold standard. The algorithm consisted of two modules as follows: (1) segmentation of the zygomatic region of CT based on U-Net, a type of CNN model; (2) detection of fractures based on Deep Residual Network 34(ResNet34). The region segmentation model was used first to detect and extract the zygomatic region, then the detection model was used to detect the fracture status. The Dice coefficient was used to evaluate the performance of the segmentation algorithm. The sensitivity and specificity were used to assess the performance of the detection model. The covariates included age, gender, duration of injury, and the etiology of fractures.

Results: A total of 379 patients with an average age of 35.43 ± 12.74 years were included in the study. There were 203 nonfracture patients and 176 fracture patients with 220 sites of zygomatic fractures (44 patients underwent bilateral fractures). The Dice coefficient of zygomatic region detection model and gold standard verified by manual labeling were 0.9337 (coronal plane) and 0.9269 (sagittal plane), respectively. The sensitivity and specificity of the fracture detection model were 100% ($p > .05$).

Conclusion: The performance of the algorithm based on CNNs was not statistically different from the gold standard (manual diagnosis) for zygomatic fracture detection in order for the algorithm to be applied clinically.

Published by Elsevier Inc. on behalf of the American Association of Oral and Maxillofacial Surgeons
J Oral Maxillofac Surg 81:1011-1020, 2023

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Disclosure: This work was supported by the National Key Research and Development Program of China (2019YFF0302401).

Conflict of Interest Disclosures: None of the authors have any relevant financial relationship(s) with a commercial interest.

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Received November 20 2022

Accepted April 23 2023

Published by Elsevier Inc. on behalf of the American Association of Oral and Maxillofacial Surgeons

0278-2391/23/00393-2

https://doi.org/10.1016/j.joms.2023.04.013

Zygomatic fracture is a common type of maxillofacial trauma,[1] which accounts for 33.3% of mid-facial fractures.[2] Zygomatic fractures involve complex and diverse anatomical structures of the mid-face, often combined with fractures in adjacent facial regions (ie, compound fractures).[3] Radiological examinations are often required for diagnosis. In contrast to conventional X-rays, computed tomography (CT) scans consist of a series of two-dimensional tomography images with isotropic voxels and show details of the position and the displacement direction of fractures. In recent years, maxillofacial CT has been regarded as the 'gold standard' for the diagnosis of maxillofacial fractures.[4] However, analyzing large numbers of radiographs manually is often time-consuming and laborious, which may lead to missed diagnoses with details such as bone structure and undetectable fracture lines.[5] Moreover, accurate manual diagnosis relies on maxillofacial doctors with professional training, which may have limited application and present difficulties in emergencies requiring accurate and efficient diagnosis with general doctors. It is necessary to develop computer-aided tools to aid the diagnosis of zygomatic fractures using CT scans.

Over recent years, deep learning has been gradually applied to various medical fields, with satisfying performances in medical image positioning, segmentation, and diagnosis.[6] Convolutional neural network (CNN) is a type of algorithm that is usually applied in medical image detection and diagnosis. Its accurate and stable performance make up for the drawbacks of manual film reading, which require specialists, equipment, and hospitals. So far, it has been proven to successfully reach the level of experts in classification of tuberculosis, pulmonary nodules,[7] breast cancer, brain lesion,[8] cataract grading,[9] and other diseases.

Among different applications of CNN, the region segmentation model can quickly and accurately lock the lesion area with high sensitivity to the imaging changes and location changes of the edge region.[10,11] As an advanced semantic segmentation model, U-Net has been applied to the segmentation of regions of interest in medical images, and achieved high accuracy and stability in segmentation regions, such as vertebrae and parietal bone.[12,13] As another part of the CNN algorithm, feature detection models are used in target image feature recognition. Among them, the ResNet model has a deeper network system structure and fits the changing sample better, which is widely used in the detection and diagnosis of lesion image.[14] In oral and maxillofacial surgery, ResNet was reported for the diagnosis and classification of mandibular fractures based on panoramic radiograph and CT scanning, with satisfactory results in the last 2 years.[15,16]

The purpose of the study was to evaluate sensitivity and specificity of an automatic algorithm for detection of zygomatic fractures on CT scans based on CNN. The investigators hypothesized that the performance of the algorithm based on U-Net and ResNet were consistent with the gold standard. The specific aims of the study included the following steps: 1) target samples of adults with and without zygomatic fractures were collected, 2) human experts reviewed CT images to determine fracture status (positive/negative), 3) developed a training dataset to create the model to determine fracture status and create a test dataset to test the performance of the model, 4) applied the model to the test set to determine fracture status, and 5) compared the fracture status detected by the algorithm to detection results by humans and evaluated the performance of the model by sensitivity and specificity.

The algorithm may accomplish auxiliary diagnosis in primary hospitals and emergency treatments that lack experienced doctors and professional equipment, as well as alleviate the human and material consumption of fracture diagnosis in specialized hospitals.

Materials and Methods

STUDY DESIGN

To address the research purpose, we designed and implemented a cross-sectional retrospective diagnostic trial study. The study population was composed of patients in Peking University School of Stomatology from January 2013 to December 2019 (Fig 1). The zygomatic fracture was defined according to the classification by Audigé et al[17] including zygoma body, zygomaticomaxillary suture, zygomaticofrontal suture, zygomaticotemporal suture, and sphenozygomatic suture.

The inclusion criteria were, as follows: 1) Chinese, aged 18 - 80; 2) no history of maxillofacial tumor; 3) no systemic bone metabolic disease; 4) no maxillofacial deformity; and 5) no history of radiotherapy or chemotherapy. The exclusion criteria were, as follows: 1) congenital maxillofacial asymmetry, such as severe occlusal deviation, nasal septum deviation, and microtia; 2) history of maxillofacial hard tissue surgery; and 3) no previous history of maxillofacial fractures (more than 3 weeks).

All patients were informed of the research content and risks, and all patients signed the informed consent.

The study had been approved by the Ethics Committee of Peking University School and Hospital of Stomatology (PKUSSIRB-202054056).

STUDY VARIABLES

In this study, the predictor variable was the fracture status of patients (with or without fracture). The

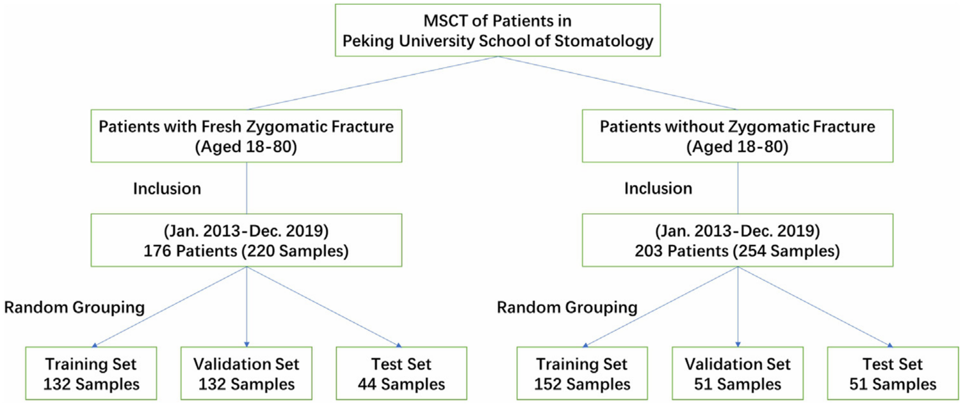

FIGURE 1. Overview of the datasets.

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outcome variable was the detection result of the fracture detection model. Each CT scan was evaluated by the model. Detection result was coded as positive (output '1') if a fracture was detected in the target area, and the result was coded as negative (output '0') if no fracture was identified. The covariates including age, gender, duration of injury, and etiology of fractures, which could be related to the outcome were collected and described carefully.

DATA COLLECTION

All patients' craniofacial CT images were obtained from the radiological department of Peking University School of Stomatology in Beijing, China. All CT scans were performed with a 16-slice CT scanner (Optima CT 520; GE Healthcare, Waukesha, WI), with 1.25-mm slice thickness and 512*512 resolution ratio. The data of all patients were exported as digital imaging and communications in medicine format. All CT samples were randomly divided into three groups at a ratio of 6:2:2 as training set, validation set, and test set, which were used for training model, tuning parameter, and evaluating performance.

ALGORITHM MODEL BUILDING

Zygomatic Region Labeling

Projection planes of these CT scans (referring to the following section of maximum intensity projection (MIP) image generation) were synthesized. The region of zygoma of each sample was drawn using Visual Geometry Group (VGG) Image Annotator 2.0.1 according to the zygomatic fracture classification by Audigé et al.[17] (Fig 2), which is considered the gold standard of image segmentation of the zygomatic region.

Region Detection Algorithm Training

As can be seen in Figure 3B, the CT scans cover a broad anatomical region and the zygoma only takes up a small space. The contrast of zygoma image generated from the original CT data was poor. Therefore, the zygoma region detection was a crucial step in achieving zygoma fracture detection. A multiphase approach was proposed in the present study to guarantee the contrast of region of zygomatic bone in the generated MIP images[18] (as shown in Fig 4 and Appendix).

A semantic segmentation network based on U-Net was trained to automatically extract the region of the zygoma. Combo loss (a weighted sum of soft DICE loss and crossentropy loss) was applied as the loss function to control the trade-off between the false negatives and positives, while enforcing a smooth training at the same time. The bounding box coordinates were obtained from the segmentation results. Furthermore, these coordinates were used to crop zygoma slices from original CT slices (as shown in Fig 5).

Zygomatic Fractures Diagnostic Labeling

DICOM files of samples were imported into Mimics Research 19.0 software (1996-2016 Materialise n.v.), displayed as axial, coronal, and sagittal sectional images and three-dimensional reconstruction images. The presence of zygomatic fracture based on the images of each section was determined by a professional maxillofacial surgeon. Samples with positive results were labeled '1', and the negative results were labeled '0' as the diagnostic label of zygomatic fracture for each case.

The number of layers, including fracture lines in the axial images, were labeled and recorded to the table as

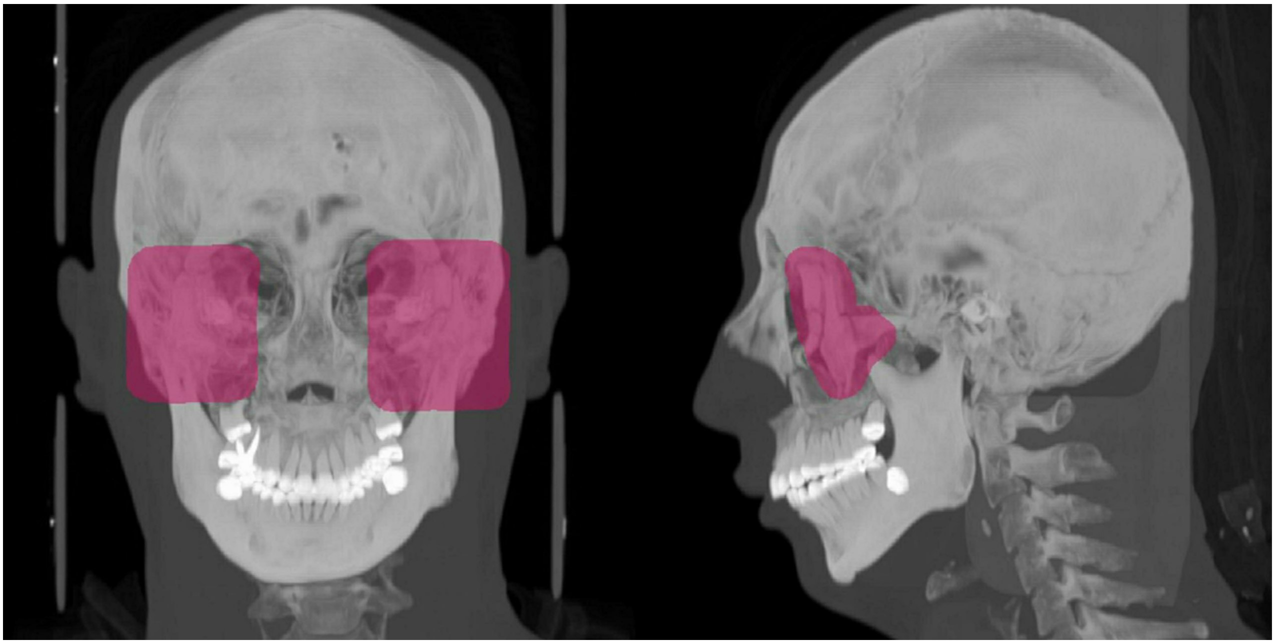

FIGURE 2. Projection planes of the zygoma region.

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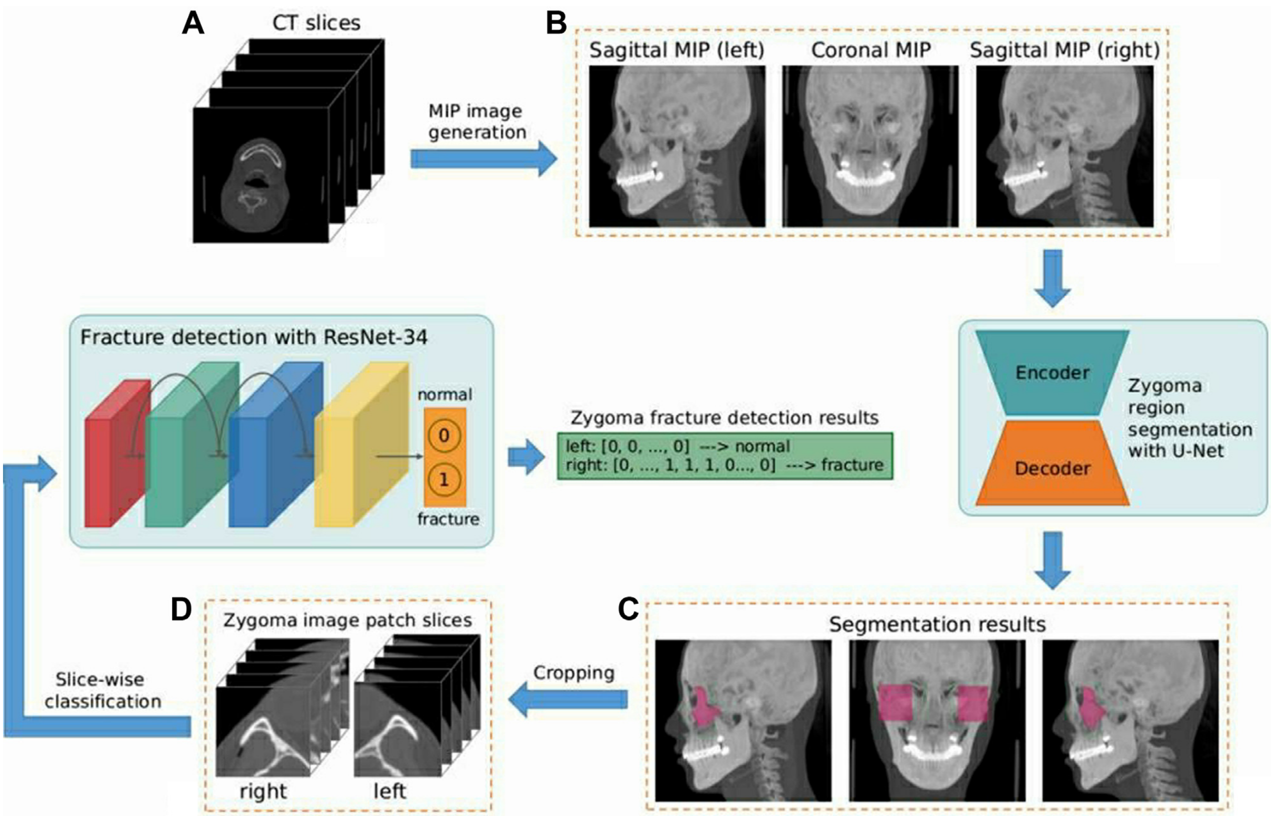

FIGURE 3. Workflow of the proposed method. As computed tomography (CT) slices of target sample were obtained (A) the workflow of the proposed method consisted of four steps. The first step was to generate the maximum intensity projection (MIP) images (B) from the input head CT data. The second step was to detect the regions of zygoma (C) on the generated MIP images by applying a U-Net model. Then, 3D bounding box coordinates were obtained according to the segmentation results, and they could be used to crop image patch slices of zygoma from original CT slices (D). The last step was to detect zygoma fracture by applying a slice-wise-based classification model (ResNet-34).

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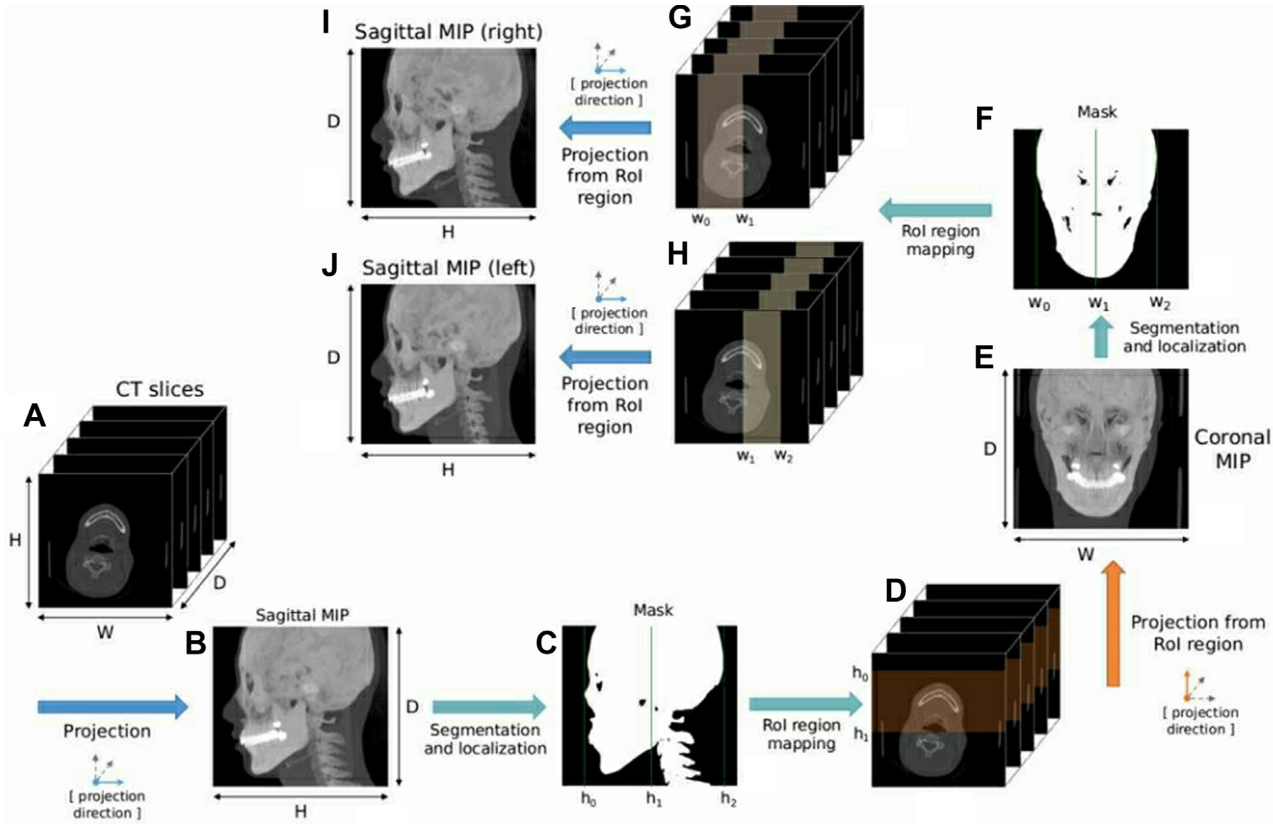

FIGURE 4. The pipeline of MIP image generation. (A): CT slices of samples. (B): Sagittal MIP image generated from the original CT slices. (C): Mask image of the bone obtained by OTSU threshold filter. (D): Location of RoI. (E): Final coronal MIP image generated by projecting the RoI region of CT slices. (I-J): Final sagittal MIP images.

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a sectional fracture label. All labels were then reviewed by another professional oral and maxillofacial surgeon. When there was a difference in opinion among the two surgeons, a third surgeon would break the tie. After proofreading, all annotated DICOM files and tables were exported.

Training of Zygoma Fracture Detection Algorithm

Once the zygoma slices were acquired, they were fed into CNN for fracture detection (fracture or normal) training. In this study, we used the pretrained ResNet-34 model on the ImageNet dataset[19] to accelerate the convergence of the model. The binary cross-entropy loss was adopted as the loss function to train the classification model. The F1 score was used to evaluate the performance.

At the inference phase, every generated slice image was sequentially fed into the trained ResNet-34 model to obtain two binary sequences (Fig 3). For each binary sequence, if the number of positive slices was greater than 2, the final result was positive (fracture), otherwise, the result was negative (nonfracture).

STATISTICAL ANALYSIS

For the zygoma region detection algorithm, the zygoma area segmented by the algorithm was validated with the corresponding gold standard. DICE similarity coefficient was used as the evaluation index of the segmentation algorithm. Dice coefficient (DICE),[20] also called the overlap index, is often used for validating performances of the image segmentation algorithm. It describes the degree of similarity between two contours by estimating the percentage of their overlapping areas and their total area. The DICE was calculated as follows:

$$Dice(P,T) = \frac{|P1^{T1}|}{\frac{|P1|+|T2|}{2}} = \frac{2TP}{FP + 2TP + FN}$$

P1 represent the region segmented by the algorithm, and T1 represent the actual target region. TP: true positive region, T1ˆP1, FP: false positive region, and FN: false negative region. The DICE ranges from 0 to 1. It is generally believed that DICE similarity coefficient >0.7 indicates high repeatability and has a good

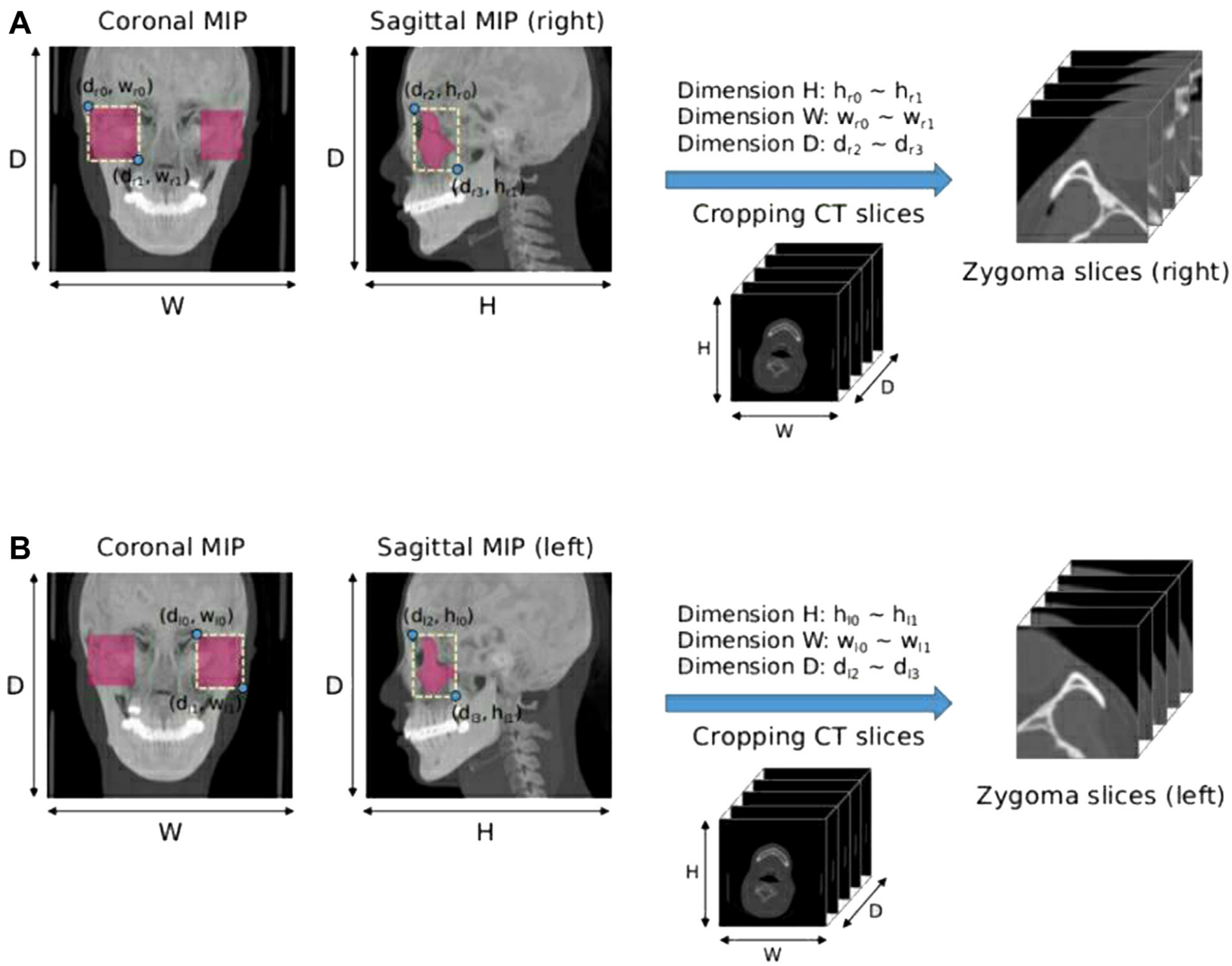

FIGURE 5. Illustration of zygoma slices cropping.

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effect between automatic segmentation and manual segmentation.

Manual labels were used as the gold standard for fracture diagnosis in the fracture detection algorithm. The sensitivity and specificity of the fracture diagnosis were calculated by comparing the output results of the test set data with the corresponding gold standard.

Results

CLINICAL FINDINGS

The study ultimately included the data of 379 patients, including 265 males and 114 females, with an average age of 35.96 ± 12.57 years. There were 203 nonfracture patients and 51 cases of bilateral zygoma selected as samples, so that there were 254 negative samples in total. There were 176 fracture patients with 220 samples of zygomatic fractures, including 132 unilateral fractures and 44 bilateral fractures (as shown in Table 1). Examples of samples with positive fracture status are shown in Figure 6.

Other variables included age, gender, duration of injury, and etiology of fractures. As shown in Table 1, there was no significant difference in test results between different age groups and genders in different status of patients.

The average duration of injury in fracture patients was 9.71 ± 5.84 days. Among them, 75 cases (42.61%) were injured within 1 week, 59 cases (33.52%) were injured between 1 and 2 weeks, and 42 cases (23.86%) were injured between 2 and 3 weeks. The sensitivity and specificity of the test results in each group were 100%, indicating no statistical difference. Factors resulting in fractures included traffic accidents (90, 51.14%), falls (51, 28.98%), fights and assaults (14, 7.95%), sport related injuries (7, 3.98%), industrial accidents (6, 3.41%), and falling objects (6, 3.41%). The number of training set, validation set, and test set were shown in Table 2.

Table 1. DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF THE STUDY PATIENTS

Characteristics	Positive Sample (n = 176)	Negative Sample (n = 203)	*P* Value
Average age, y	35.94(±13.63)	35.97(±12.02)	.1723(Mann-Whitney U test))
Sex, n (%)			.811 (Pearson χ^2test)
Male	54(30.68)	60(29.56)	
Female	122(69.32)	143(70.44)	
Duration (d)			
1-7	75 (42.61)	0	/
8-14	59 (33.52)	0	/
15-21	42 (23.86)	0	/
Etiology			
Traffic accidents	90 (51.14)	0	/
Falls	51 (28.98)	0	/
Fights and assaults	14 (7.95)	0	/
Sports	7 (3.98)	0	/
Industrial accidents	6 (3.41)	0	/
Falling objects	6 (3.41)	0	/
Others	1 (0.57)	0	/

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RESULTS OF REGION DETECTION ALGORITHM

A total of 474 cases' fracture labels and sectional labels were manually obtained. The U-Net model was trained using 379 generated MIP images. The performance of the zygomatic region detection model was verified with the gold standard of manual labeling. The DICE were 0.9337 (coronal plane) and 0.9269 (sagittal plane).

RESULTS OF ZYGOMATIC FRACTURE DETECTION ALGORITHM

The ResNet-34 model was trained on 9,917 (generated from 379 training CT scans) zygoma CT slice images. After training, an F1 of 0.9317 was achieved on 1,406 validation slice images (generated from validation 95 CT scans). The results showed that the sensitivity and specificity of all the samples were 100% (95% [CI]) in validation sets, which indicated that the results of all the samples were consistent with evaluations made by professional doctors (Table 3).

There was no statistical significance found between the factors and test results.

Discussion

Accurate diagnosis and classification of fractures by CT are crucial to treating facial fractures, especially for zygomatic fractures with complex anatomic structures. However, manual diagnosis of zygomatic fractures on CT scans is time-consuming and laborious, and fatigue and attention loss can lead to misdiagnosis and missed diagnosis. On the other hand, fracture diagnosis on CT scans relies on professional doctors, equipment, and venues, which increases the difficulty in

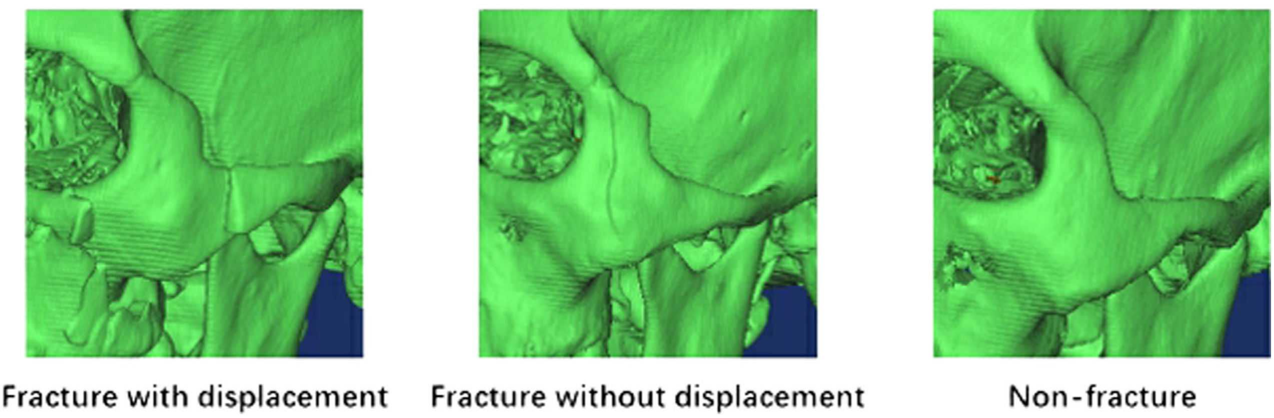

FIGURE 6. Examples of sample with positive fracture status.

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Table 2. DISTRIBUTION OF TRAINING SET, VALIDATION SET AND TEST SET

Fracture Status	Training set	Validation set	Test set	Total
Positive	132	44	44	220
Negative	152	51	51	254
Total	274	95	95	474

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primary hospitals. Deep learning was proposed by Geoffrey in 2006 as an emerging artificial intelligence technology. After AlexNet, an improved model born in 2012, deep learning attracted world-wide attention in various fields due to its great applicability in many industries.[21] CNN is a type of technology that produces the most satisfying results in medical image diagnosis. Its high accuracy and stability make up for the disadvantages of missed diagnosis depending on professional manpower and equipment.[22,23] CNN has been demonstrated to be a reliable technology in medical image diagnosis. The purpose of this study was to establish an intelligent algorithm model that can achieve automatic detection of zygomatic fractures. Our results showed a high performance in the model for fracture detection, and it may be beneficial for the primary diagnosis of patients with zygomatic fractures.

To detect the region of zygoma effectively from a broad anatomical region of CT scans, we used the U-Net as the region segmentation model. The model reduced the interest space of CT samples and achieved the automatic segmentation of zygoma region in the research. Based on the region of interest obtained by the region segmentation model, we used an image detection model based on ResNet34 to train the fracture detection. The gradient descent algorithm was used to optimize training efficiency. The diagnosis was consistent with the gold standard, thus, deeming it qualifiable to be recognized and diagnosed as zygomatic fractures.[24]

Over recent years, researchers have reported on the fracture diagnosis algorithm of CNN based on CT scans. In 2018, Sasank et al used NLP algorithm to diagnose craniofacial injury and parietal fracture based on CT scans, with a sensitivity of 94.9% and a specificity of 90.3%.[24] In 2019, Pranata et al selected VGG and ResNet models for classification and diagnosis of calcaneal fracture, respectively, with the accuracy of both models being 98% without statistical significance between the two models.[25] In 2020, Zhou et al carried out a multicenter CNN algorithm training on CT of rib fractures, with an improved accuracy of 91.1%.[26] In oral and maxillofacial surgery, our research center established a mandibular detection and classification diagnosis model based on ResNet51 in 2022. The overall accuracy was 96.4%, with an average area under the curve of 0.956.[16] However, the above algorithms are only suited for single bone fractures. As zygomatic fractures often occur with compound fractures and the anatomical structures are more complex, there are few reports on the application in relevant fields at present. Li et al trained the algorithm for the diagnosis of orbital blow-out fractures through Inception V3 CNN network in 2020, achieving an accuracy rate of 87%.[27] Warin et al realized the detection and diagnosis of frontal, midface, and mandible fractures by the algorithm based on DenseNet-169 and ResNet, achieving the overall accuracy of 0.70 and 0.61, respectively.[28] The performance of two studies was not enough to satisfy clinical requirements.

At present, artificial intelligence diagnosis of fractures can be divided into two steps, as follows: automatic segmentation of fractured areas, and recognition of fracture lines. The above steps need to be achieved by region segmentation and fracture detection models. The most traditional region segmentation model R-CNN requires lots of data and consistent imaging patterns for training, which is not competent for medical images segmentation. Fast R-CNN and faster R-CNN algorithm models are derived from R-CNN, accelerating training speed by adding (region of interest) pooling and neural network merging.[29] In this study, we selected the U-Net model as an advanced algorithm undergoing high-precision, modified and supplemented on the basis of the above

Table 3. SENSITIVITY AND SPECIFICITY OF FRACTURE DETECTION ALGORITHM

Test result	Positive	Negative	Total
Positive sample	44	0	44
Negative sample	0	51	51
Total	44	51	
Test parameter	Diagnostic performance	95% Confidence interval	
Sensitivity	100%	89.99-100%	
Specificity	100%	91.27-100%	

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algorithm.[30] The model is more suitable for medical images with a small sample size, multimodes, and high precision requirements.[31] The DICE reached 0.9337 (coronal plane), and 0.9269 (sagittal plane), both of which are considered as good accuracy (≥0.80).

Among recent reports, algorithms used in medical image detection and classification mainly include InceptionNet, VGGNet, ResNet, and vision transformer. InceptionNet reduces the input changes of network layers and training operations, but the accuracy still needs improvement in medical images.[32] VGGNet is a large-scale image recognition algorithm that applies maxpooling for image size reduction with a higher accuracy. However, there are many network parameters and great costs in operation of the algorithm.[33] Compared with the above algorithms, ResNet has the advantages of increasing the depth of network system structure, lower complexity, higher precision, and better effect in the processing of classification of crack images.[34] In the recent 2 years, vision transformer was reported to be applied for the diagnosis of femur fractures based on x-ray and showed superior performance over CNN as a new deep-learning technique.[35] However, there were no reports about its application in medical imaging diagnosis based on CT scans so far. In our study, the ResNet-34 was used as basic model of fracture diagnosis algorithm. The algorithm showed higher sensitivity and specificity when compared with previous reports on CT diagnostic algorithms for other fracture sites.

In this study, we used the image segmentation model and detection model, which were more consistent with the characteristics of images and samples, as the basic model, and the sensitivity and specificity of fracture detection were higher than the models reported in other studies. However, the study still has some limitations. Firstly, the number of positive cases in training samples was small. The incidence of midface fracture was lower than that of common systemic fractures such as femur and rib; therefore, the number of cases is relatively small and needs to be amplified. Secondly, the region extraction algorithm described in this study can only detect zygomatic fractures, including zygomatic body and adjacent suture of bones. Fractures of adjacent anatomical structures such as zygomatic process of temporal bone, maxillary and frontal bone were undetectable by the algorithm.

Based on the algorithm in the study, the artificial intelligence diagnosis of maxillofacial CT images was realized, and the fracture judgment results were automatically output. For primary hospitals, the model can help solve the limitations of insufficient expertise and equipment in fracture diagnosis. For specialized hospitals with a larger number of patients, the model may be helpful to reduce the consumption of human and material resources for manual diagnosis, improving hospital transfer and management abilities. Automatic detection model could also be an educational tool for nonspecialized staff, such as junior medical students and nonmedical volunteers, to train and validate the ability of fracture diagnosis. In future multicenter studies, the datasets and labels of each classification of complex zygomatic fracture should be amplified to meet training requirements of the algorithm. Zygomatic complex should be taken as a complete region for region labeling training so as to expand the range of algorithm recognition and clinical application. It can also be a part of further research to combine the fracture diagnosis model based on CT scans with the text information of patients' clinical characteristics to form multimodal data training samples and establish an artificial intelligence model to reflect the severity of fractures and make treatment decisions. After the above research, the algorithm may provide the basis for automatic diagnosis, classification, and treatment of zygomatic fracture, which will overcome the limitations of traditional manual diagnosis and treatment modes, achieving accurate and efficient diagnosis and treatment in possible emergency events.

In conclusion, the algorithm based on CNNs demonstrated satisfying performance for automatic detection of zygomatic fracture on CT scans. Both sensitivity and specificity were proved to be 100%. The algorithm proposed by this study can be used as a useful method for the automatic diagnosis of zygomatic fracture.

Acknowledgments

This work was supported by the National Key Research and Development Program of China (2019YFF0302401).

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