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ОРИГИНАЛЬНАЯ СТАТЬЯ

AUTOMATIC DETECTION OF MANDIBULAR FRACTURES ON PANORAMIC RADIOGRAPHS USING THE CONVOLUTIONAL NEURAL NETWORK

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Purpose. Convolutional neural networks (CNNs) have extensive medical applications, such as the detection and diagnosis of diseases and clinical disorders. This study used CNN to detect mandibular fractures (MFs) on panoramic radiographs.

Methods. This study evaluates 275 panoramic radiographs retrieved from the archives of the Oral and Maxillofacial Radiology Department of Tabriz School of Dentistry. From all of the radiographs, 124 have MFs, and 151 have no fractures. In our methodology, first, the location of MFs was detected and marked on the radiographs by two oral and maxillofacial radiologists. Next, noise reduction was performed using the Chebyshev type II filter. To standardize the images, their primary resolution was modified and converted to 227 x 227. Next, the AlexNet CNN was used to train and classify images with and without MF. The images were randomly partitioned into training, validation, and test groups, where 60% were used for network training, 20% for validation, and 20% for final testing. The precision, recall, and F1 score were measured to assess this algorithm's efficacy for detecting MFs.

Results. The algorithm's precision, recall, and F1 score for detection of MFs are 0.968, 0.834, and 0.896, respectively.

Discussions. Mandibular fractures can be detected by panoramic radiographs and using CNN increase the accuracy of diagnoses, reach more definite diagnosis, and accelerate the reading and interpretation of radiographs.

Conclusion. The suggested algorithm successfully detects MFs on panoramic radiographs with high accuracy. Therefore, CNN-based models enhance the detection of MFs on panoramic radiographs.

Keywords: convolution neural network, mandibular fracture, panoramic radiography, image processing, deep learning.

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АВТОМАТИЧЕСКОЕ ОБНАРУЖЕНИЕ ПЕРЕЛОМОВ НИЖНЕЙ ЧЕЛЮСТИ НА ОРТОПАНТОМОГРАММАХ С ИСПОЛЬЗОВАНИЕМ СВЕРТОЧНОЙ НЕЙРОННОЙ СЕТИ

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Сверточные нейронные сети (CNN) имеют обширное медицинское применение такое, как обнаружение и диагностика заболеваний и клинических состояний. В этом исследовании CNN использовалась для обнаружения переломов нижней челюсти на ортопантомограммах.

Материалы и методы. В исследовании были проанализированы 275 ортопантомограмм, полученных из архивов отделения лучевой диагностики в челюстно-лицевой области Стоматологической школы Тебриза. Из всех ортопантомограмм на 124 были обнаружены переломы нижней челюсти, а на 151 – нет. В нашей методике два врача-рентгенолога выявляли переломы нижней челюсти. Далее осуществлялось шумоподавление с помощью фильтра Чебышева II типа (Chebyshev type II filter). Чтобы стандартизировать изображения, их первичное разрешение было изменено и преобразовано в формат 227 x 227. Затем AlexNet CNN использовался для обучения и классификации изображений с переломами нижней челюсти и без них. Изображения были случайным образом разделены на группы обучения, проверки и тестирования, из которых 60% использовались для обучения сети, 20% – для проверки и 20% – для окончательного тестирования. Точность, полнота и оценка F1 были измерены для оценки эффективности этого алгоритма для обнаружения переломов нижней челюсти.

Результаты. Точность алгоритма, полнота и оценка F1 для обнаружения переломов нижней челюсти составила 0,968, 0,834 и 0,896 соответственно.

Обсуждение. Переломы нижней челюсти можно обнаружить с помощью ортопантомограмм, а использование CNN повышает точность диагностики, позволяет получить более точный диагноз и ускорить анализ и интерпретацию изображений.

Заключение. Предложенный алгоритм с высокой точностью успешно обнаруживает переломы нижней челюсти на ортопантомограммах. Таким образом, модели на основе CNN улучшают выявление переломов нижней челюсти на ортопантомограммах.

Ключевые слова: сверточная нейронная сеть, перелом нижней челюсти, ортопантомограмма, анализ изображений, глубокое обучение.

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Mandibular fractures (MFs) are the most common (60%-70%) type of maxillofacial fractures that are frequently encountered in emergency departments [1]. The mean age of patients with MF is 38 years in males and 40 years in females. MFs are much more prevalent in males [2]. Motor vehicle accidents, street fights, and falls are the main causes of MF. Moreover, MFs occur more frequently in communities with lower socioeconomic classes [1, 2].

Panoramic radiography is a conventional imaging modality for assessing and detecting of MFs. However, panoramic radiography as two-dimensional imaging comes with the drawbacks such as patient positioning, anatomical noise, superimposition of structures, geometrical distortion, and contrast problems, which can all complicate the accurate detection of fracture location [3]. Artificial intelligence and deep learning methods are finding popularity in medical fields. Convolutional neural networks (CNNs) in particular, are one of the common methods of deep learning used in medicine due to their flexibility and high accuracy of prediction. This has led to the development of various models for the automatic prediction of the risk of diseases, detection of disorders and pathologies, disease diagnosis, and prediction/assessment of disease prognosis.

In the field of oral and maxillofacial radiology, several studies have assessed the efficacy of deep learning for the detection of oral and maxillofacial disorders and diseases; these include identification of anatomical and cephalometric landmarks, screening and detection of osteoporosis on panoramic radiographs, detection of vertical root fracture on panoramic radiographs, assessment and detection of maxillary sinus lesions/diseases on panoramic radiographs, detection and classification of alveolar bone defects on panoramic radiographs, detection and classification of unerupted supernumeraries on panoramic radiographs, and detection and counting of teeth on panoramic radiographs [4-14]. CNNs are powerful methods for the detection and classification of images; hence it makes CNNs a straightforward tool for radiology applications [15].

In recent years, demand for radiographic services in emergency departments has greatly increased, which puts a considerable burden on the workforce [16]. As mentioned earlier, MFs have a high prevalence, and panoramic radiography is currently the most common radiographic modality requested for their detection. As a result, the emergence of the studied method can significantly reduce the burden. Thus, this study aimed to assess the efficacy of a CNN for the automatic detection of MF location on panoramic radiographs. The results of this study can greatly help radiologists in the detection of MF location on panoramic radiographs and can also reassure them about the accuracy of their diagnosis.

Materials and Methods.

Collection of datasets.

A total of 275 panoramic radiographs of 96 females and 179 males were retrieved from the archives of the Oral and Maxillofacial Radiology Department of School of Dentistry of Tabriz University of Medical Sciences (PACS system) from May 2020 to May 2022. Among the retrieved radiographs, 124 have MFs, and 151 have no fractures. Panoramic images have been obtained by the RAYSCAN X-ray unit (Samsung, South Korea) at the Oral and Maxillofacial Radiology Department of School of Dentistry of Tabriz University of Medical Sciences with 1500 x 3000 resolution and automatic exposure settings, which includes a 69-90 kV voltage, 7-17 mA amperage, and 14-16 seconds irradiation time. The PACS software conducts initial and final image reconstruction.

Panoramic images are categorized into groups with (group A) and without (group B) MF by two oral and maxillofacial radiologists, and the fracture location is annotated in group A. On images with MF, bounding boxes are drawn around each fracture line, and the respective image is assigned to the MF group. Figure 1 shows panoramic radiographs with and without MF, identifying the fracture location and its annotation.

Radiographic noise reduction.

Quantum mottle is one of the problems associated with radiographic images, which distorts the image and adversely affects image interpretation and diagnosis. Thus, the Chebyshev type II filter is used in this study for noise reduction, which is suitable for this purpose [17, 18]. Figure 2 shows a panoramic image after using the Chebyshev type II filter for noise reduction.

This study is conducted in two phases. The first phase includes classifying images and differentiating those with MF from those without MF in the CNN. The second phase includes detection of fracture location on images with MF in the CNN. MatlabR2021a software version 8.6.0.267246 is used for image analysis in a 64-bit system with a single CPU at Windows7.

First phase: Classification of models in the CNN.

The resolution of images with (group A) and without (group B) MF is resized in 227 x 227 resolution before feeding to the CNN algo-

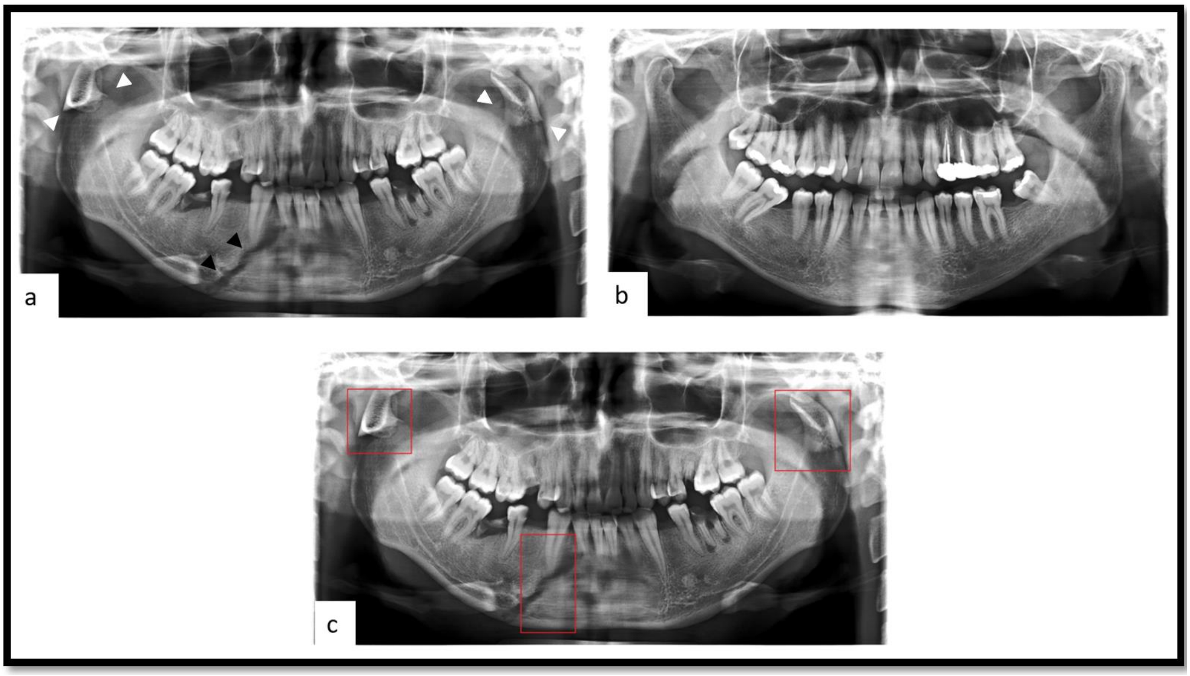

Fig. 1 (Рис. 1)

Fig. 1. Panoramic images.

a – patient with MF in right chin (black arrows) and both condylar necks (white arrows),

b – patient without MF

c – Identification and annotation of the fracture line (red boxes).

Рис. 1. Ортопантомограммы.

а – пациент с переломом нижней челюсти в области правого подбородочного выступа (черные стрелки) и в области шейки мыщелкового отростка с обеих сторон (белые стрелки),

b – пациент без перелома нижней челюсти,

с – обозначение и аннотация линии перелома (красные прямоугольники).

Fig. 2 (Рис. 2)

Fig. 2. A panoramic image after using the Chebyshev type II filter for noise reduction.

White arrow shows the fracture line in the right angle of mandible.

Рис. 2. Панорамное изображение с использованием фильтра Чебышева II типа (Chebyshev type II) для шумоподавления.

Белой стрелкой показана линия перелома угла нижней челюсти справа.

rithm. In the first phase of the CNN algorithm, AlexNet network is used for training and image classification. This network uses 32 layers for the training and classification of panoramic images. Among the images, 60% are randomly used for training, 20% for validation, and 20% for final testing. The epoch (maximum frequency of repetitions) is set to 100 for 0-100 training. Moreover, validation and final testing are performed at each training step. Also, the accuracy of training is set to 0.0001 for each step. The block diagram of the CNN for differentiation of images with and without MF is shown in Figure 3

tection+ misdetection

Recall=TP/(TP+FN) = Detection / detection + undetection

F1 Score= 2× (precision × recall)/ (precision +recall)

Where TP refers to true positive, FP refers to false positive, and FN refers to false negative. Detection is referred to correct detection of MF. Misdetection refers to mistaking MF with some other condition (detecting something else), and undetection refers to not detecting the MF (no detecting) [3].

Results.

In the first phase of the CNN algorithm,

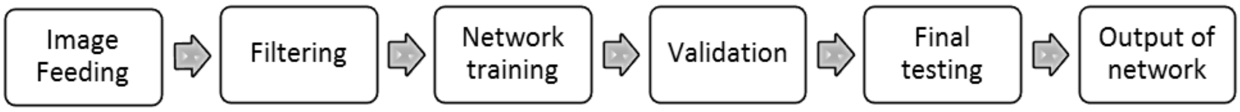

Fig. 3 (Рис. 3)

Fig. 3. The Block diagram of the CNN for the differentiation of images with and without MF.

Рис. 3. Блок-схема CNN для дифференциации изображений с переломами нижней челюсти и без них.

Fig. 4 (Рис. 4)

Fig. 4. Block diagram of the second phase of the CNN.

Рис. 4. Блок-схема второй фазы CNN.

Second phase: Fracture detection by the CNN.

In the second phase of the CNN algorithm, the AlexNet network is used for the training and image classification. It uses 53 layers for training and classification of panoramic images. Among the images with MF in the second phase, 60% are randomly used for training, 20% for validation, and 20% for final testing. Similar to the first phase, the epoch is set to 100 and the training accuracy is set at 0.00001 for each step. The block diagram of the CNN for detecting fracture location on images with MF is shown in Figure 4.

Evaluation matrices.

In this study, the precision, recall, and F1 score of the CNN are calculated using the following equations:

Precision= TP/(TP+FP) = Detection/ de-

the AlexNet model is used to detect and differentiate panoramic images with MF from those without MF. In figure 5 the graph shows the training and validation of the CNN in the first phase, and our result shows that the precision, recall and F1 score are 0.999, 0.859, and 0.924, respectively. Table 1 presents the precision and error values for three different epochs (frequency of training), validation, and final testing.

In the second phase of the CNN algorithm, AlexNet model is used for training and detection of fracture location on panoramic images with MF. In figure 6 the Graph shows the training and validation of the CNN in the second phase. The precision, recall, and F1 scores are 0.968, 0.834, and 0.896, respectively. Table 2 presents the results, and figure 7 shows some representative images of MF detection by

Table №1. Precision and Recall and F1 score of the CNN in the first phase.

Epoch	Precision	Recall	F1 Score
1	0.945	0.729	0.823
50	0.934	0.701	0.801
100	0.999	0.859	0.924

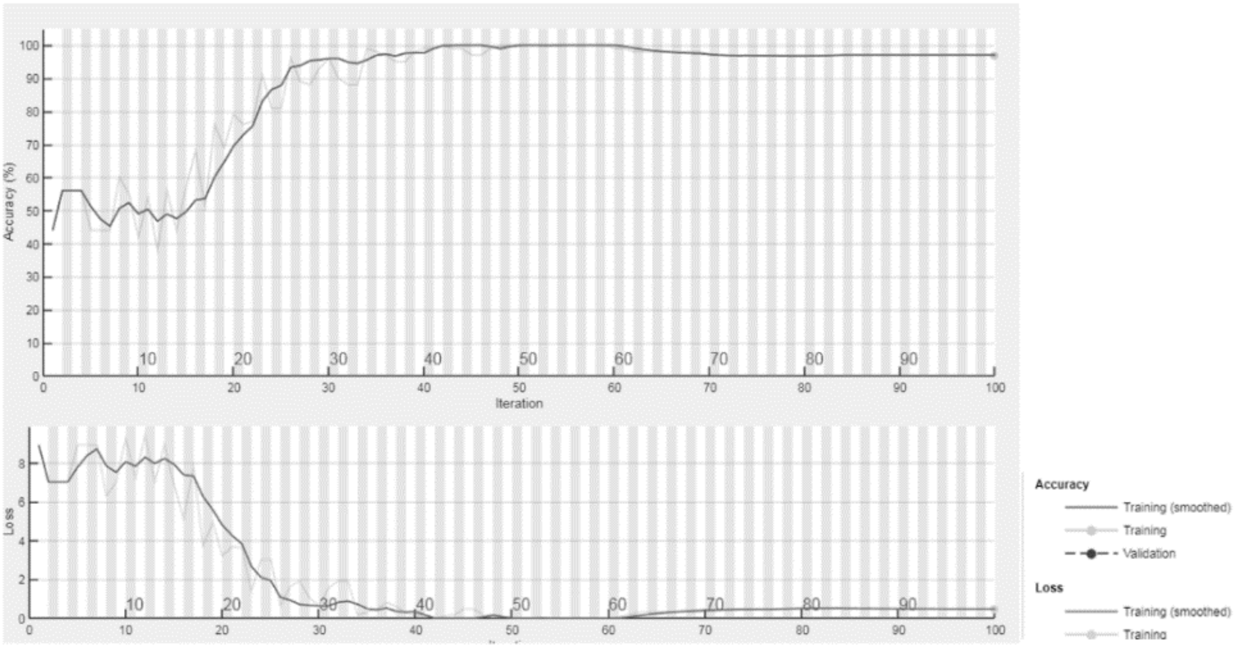

Fig. 5 (Рис. 5)

Fig. 5. Graph.

Training and validation of the CNN in the first phase.

Рис. 5. График.

Обучение и проверка CNN на первом этапе.

the CNN.

Discussion.

In the past decades, artificial intelligence and computer-aided detection (CAD) have been extensively studied in radiology. The main concept of CAD in radiology is to present a computer output as a second opinion to aid in interpretations by the radiologists aiming to increase the accuracy of diagnoses, reach a more definite diagnoses, and accelerate the reading and interpretation of radiographs. From the perspective of radiologists, they expect the CAD system to provide them with more precise information regarding the location of the problem/disorder; thus, they can save time and minimize misdiagnoses [19].

Several studies have assessed the detection of diseases and disorders on panoramic radiographs by using CNN with different algorithms or computed tomography scans [3, 8-12, 14, 20-22]. The results of these studies demonstrate a high efficacy for the CAD and CNN models in the detection of disorders.

In this study, we designed a CNN-based algorithm that is capable of differentiating images with MF from those without MF, and detecting the location of MF. The results show that this method is capable of correctly detecting the fracture location with no quantitative reduction and increasing the precision, recall, and F1 scores to 0.968, 0.834, and 0.896, respectively. In other words, the image quality remains constant after detection, indicating that the use of the AlexNet CNN increases the response precision, training, and classification.

Among related works, Son et al. use the

Table №2. Precision and recall and f1 score of CNN in the second phase.

Epoch	Precision	Recall	F1 Score
1	0.716	0.553	0.624
50	0.999	0.859	0.924
100	0.968	0.834	0.896

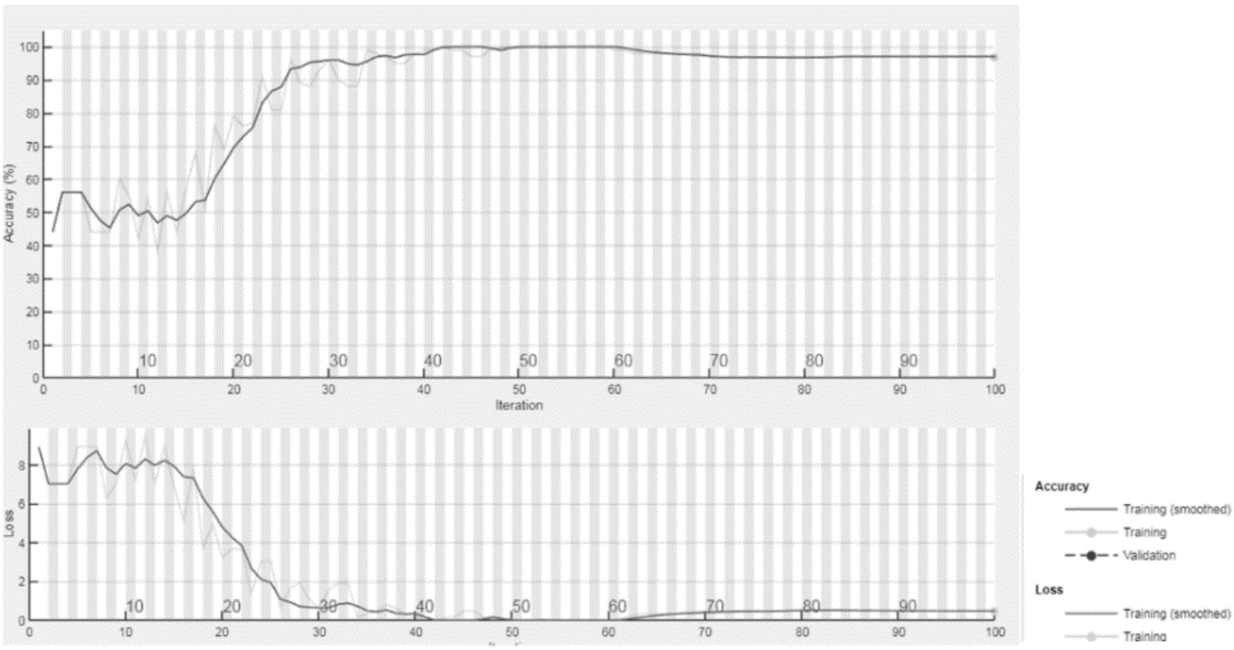

Fig. 6 (Рис. 6)

Fig. 6. Graph.

Training and validation of the CNN in the second phase.

Рис. 6. График.

Обучение и проверка CNN на втором этапе.

YOLO v4 for the automatic detection of MFs, and employ different preprocessing methods such as gamma modulation, multi-bounding, MLAT, and SLAT [3]. To assess the fractures, they use two classification types. The first classification is based on the anatomical location (six classes), while the second one is based on the fracture pattern (two classes). Their results indicate that the precision, recall, and F1 score values obtained in classification based on anatomical site are higher than the corresponding values in classification based on the fracture patterns. In other words, the former classification can detect a higher number of MFs compared to the classification based on the fracture pattern. In the study by Son et al., the precision, recall, and F1 score are 0.975, 0.794 and 0.875, respectively, indicating higher precision but lower recall and F1 score compared to our results.

Similar to our study, Warin et al. evaluate the detection of MFs on panoramic radiographs [21]. They assessed 1,710 panoramic images and two algorithms of Faster R-CNN and YOLO v5 to detect the location of fracture. The results show that the precision, recall and F1 score are 0.879, 0.935, and 0.906, respectively, for the Faster R-CNN algorithm, and 0.861, 0.932, and 0.890, respectively, for the YOLO v5 algorithm. Compared to our study results, the reported precision value in their study was higher, and the recall and F1 score values were lower than the corresponding values in our study.

Fig. 7 a (Рис. 7 а)

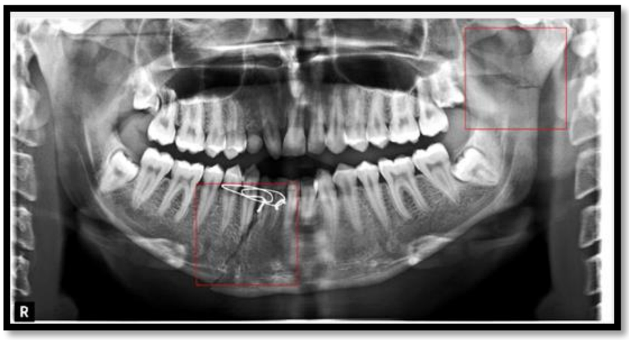

Fig. 7 b (Рис. 7 б)

Fig. 7. Detection of MF location on panoramic images by using CNN (red boxes).

a – a fracture line is detected in the right body of the mandible.

b – fracture lines are detected in the right chin and left condylar neck.

Рис. 7. Обнаружение местоположения переломов нижней челюсти на ортопантомограммах с помощью CNN (красные прямоугольники).

а – линия перелома в теле нижней челюсти справа.

б – линии перелома в области подбородка справа и шейке левого мыщелкового отростка.

In contrast to our study, Nishiyama et al., only assess the mandibular condyle fractures but similarly use the AlexNet algorithm to detect condylar fractures [20]. Nishiyama et al. use data collected from two different hospitals, although the same model of panoramic X-ray unit is used for image acquisition [20]. They assess the precision, sensitivity, and specificity of this algorithm in each hospital. They reported a precision of 84.5%, which is lower than the value obtained in our model (97%).

This study has some limitations, such as a small sample size. A CNN requires hundreds, thousands, or even millions of samples to obtain the best results and maximize its efficacy and reliability [20]. Thus, future studies are required on a higher sample to get more accurate results. Moreover, the present study uses panoramic images taken with specific exposure settings. More accurate and comprehensive models and algorithms can be obtained in the case of using different panoramic devices and assessing algorithms and network training by using different images captured by different panoramic units.

Conclusion.

After noise reduction, the properties extracted from the CNN algorithm with AlexNet model in the first phase enable MF detection. Next, the CNN with AlexNet model enables the detection of MF location on panoramic images in the second phase. The present results show that the proposed CNN model increases the precision, recall, and F1 score and successfully reveals MFs with high accuracy.

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