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Diagnosis of Tuberculosis Using Medical Images by Convolutional Neural Networks

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Abstract

Background: One of the best ways to reduce the spread of tuberculosis (TB) is to diagnose the disease using chest X-ray (CXR) images as a low-cost and affordable method. However, there are two problems: the lack of adequate radiologists and the possibility of misdiagnosis. This is why it is necessary to use an accessible and accurate diagnostic system. This research aimed to design an accurate and accessible automatic diagnosis system that can solve diagnosis problems using deep learning.

Methods: Six convolutional neural networks (CNNs), InceptionV3, ResNet50, DenseNet201, MnasNet, MobileNetV3, and EfficientNet-B4, were trained by transfer learning, the Adam optimizer, and 20 training epochs using the new, large, and accurate TBX11K dataset. The network was designed to categorize images into three groups: patients diagnosed with TB, patients exhibiting lung abnormalities unrelated to TB, and healthy individuals with no evidence of TB or other pulmonary anomalies within the lung imagery.

Results: In the testing step, the networks achieved very high performance. The EfficientNet-B4 network outperformed the other networks with a sensitivity of 97.1%, specificity of 99.9%, and accuracy of 99.5%. It also performed better than previous studies in TB diagnosis using CXR images by CNNs.

Conclusion: This research showed that with access to large high-quality datasets and standard training, it is possible to entrust the diagnosis of TB using medical images to computers and artificial neural networks with high confidence as they achieved accuracies higher than 99%.

Keywords: Convolutional neural network, Medical images, Deep learning, Chest X-ray, Tuberculosis

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Introduction

Tuberculosis (TB) is an infectious disease. It is one of the top ten causes of death in the world and the most important cause of death by infectious agents. Due to the deadly nature of TB and its high prevalence, the World Health Organization (WHO) has emphasized preventive measures to reduce the disease, planning to eradicate the TB epidemic by 2035 (1,2). One of the most important ways to reduce TB mortality is early detection, considering that between 2000 and 2018, more than 58 million people were rescued through early diagnosis and timely treatment (3). TB often attacks the respiratory system and lungs (4). As a result, one of the most important ways to diagnose TB is to use chest X-rays (CXRs) as a cheap, accessible, and fast method (5).

The most critical problems of this method are incorrect diagnoses and the scarcity of radiologists. Firstly, the specificity of this method is low due to the similarity of lung diseases, the variety of interpretations by radiologists; the inexperience or fatigue of specialists may cause between 10 and 30% error in their diagnoses (6). Secondly, more than 95% of TB patients live in developing countries. They do not have sufficient radiologists and medical infrastructures (3). Therefore, it is necessary to develop a tool that increases the accuracy of radiologists' diagnoses and can make the diagnosis in the absence of radiologists.

Using computer-aided diagnosis (CAD) systems can improve diagnostic accuracy, optimize time spent, and reduce the workload of radiologists. Recently, methods based on convolutional neural networks (CNNs) have attracted more attention in image analysis and have achieved promising results in this area (6). Due to the power of automatic feature learning, deep neural networks can extract their input features automatically with minimal human intervention. CNNs are used for deep learning in images as they are able to receive an image, extract its important features, and make decisions about the image based on the purpose for which they were made. Local feature detection, arrangement of nodes in several dimensions (i.e., width, height, and depth), and sharing weights are the essential features of CNNs for image processing (7-11).

The TBX11K dataset is a new collection of CXR images that is larger than other TB datasets and has more than two TB classes. This large dataset has not yet been used in CXR image classification for TB diagnosis.

Objectives

The main motivation of this research was to use the new and accurate TBX11K dataset to enhance the performance of CNNs in the diagnosis of TB using medical images because they can be used as a low-cost, accessible, fast, and accurate method in less developed areas that lack infrastructures and radiologists.

Methods

Motivating data

The images used in this research were taken from the TBX11K dataset. This Dataset was published in 2020 and includes hospital patients with CXR imaging and TB Micro bacterium tests to diagnose TB. The TBX11K dataset comprises 11 200 CXR images, each measuring 512 by 512 pixels, and categorized into six distinct label types. This research used images 256×256 in size with three labels: healthy, sick but non-TB, and TB (Figure 1). However, as the test set was not released, only 8400 training, evaluation, and testing images have been used (Table 1) (12).

Patients with TB can include active TB, latent TB, or both, and patients without TB can have any type of lung disease except TB. Also, those categorized as healthy are people without TB or other lung diseases, and their CXR images do not show lung abnormalities.

Convolutional neural networks

CNNs generally have three layers: convolution, pooling, and fully connected. Like the specialist, the convolutional layer searches for patterns in the image, the pooling layer reduces information, and the fully connected layer, like the brain, makes decisions about the image. The CNN goes through two processes: forward and backward (13).

In the forward process, the input image passes through the convolutional, pooling, and fully connected layers, and classification is performed. The backward process optimizes the network parameters and weights using the backpropagation algorithm. Networks perform better when forward and backward processes are better and more efficient. Various networks have been designed to improve the forward process. This research used networks from six famous CNN families with different designs. These networks include InceptionV3 (14), ResNet50 (15), DenseNet201 (16), MnasNet (17), MobilNetV3 (18), and EfficientNet-B4 (19) (Table 2).

Among these, MnasNet and MobilNetV3 networks are lighter than other networks, run faster, and can be run on most types of processors and even mobile phones. In each network the version which had almost the same number of parameters was chosen.

Optimization

An Adam optimizer (20) with a learning rate of 0.001 and batch size of 16 was used to improve the backward process in this research. Transfer learning makes it possible to apply what has been learned in the past in another field (21). In this way, the time required for learning is reduced, and the network learns the patterns better using previous learning. Transfer learning with pretraining on ImageNet images and fine-tuning on TBX11K images were used for all networks in this research.

Due to difference in the patterns of ImageNet and

Table 1. Data based on label and step

Label	Healthy	Sick but non-TB	TB	Total
Training	2280	2280	396	4956
Evaluation	608	608	128	1344
Testing	912	912	276	2100
Total	3800	3800	800	8400

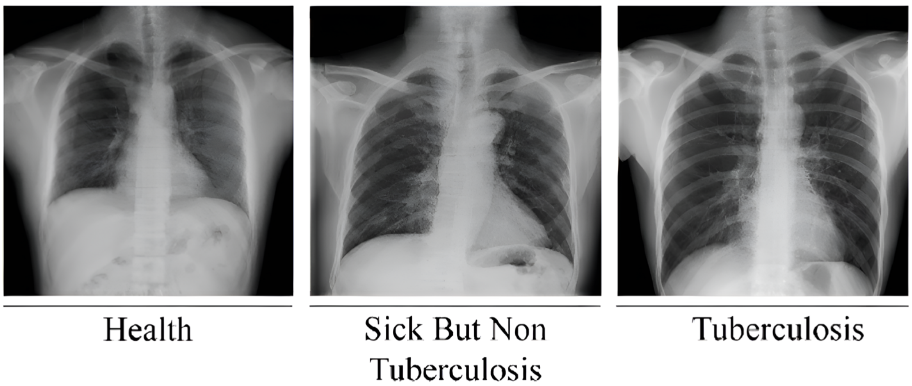

Figure 1. Sample image of TBX11K collection

Table 2. Networks and number of parameters

CNN	InceptionV3	ResNet50	DenseNet201	MnasNet	MobileNetV3	EfficientNet-B4
Parameters	21 791 715	23 514 179	20 013 928	4 383 312	4 205 875	17 553 995

CXR, all networks were allowed to be completely trained. Therefore, we let their layers and parameters be changed on the data set.

Train, evaluation, and test

In the training step, the network receives a batch of 16 images and identifies the class of images based on the amount of loss function received. The network starts to modify its parameters and weights using the backpropagations algorithm. This process continues until the amount of loss function is minimized in order to reduce the amount of loss function. Each training session uses all training images, which is called an epoch.

After each training epoch, the network is evaluated on a validation set based on accuracy to select the most accurate epochs to prevent underfitting and overfitting. Then, in the testing step, the network is compared with other networks on the testing set using positive predictive value, sensitivity, specificity, F1-score, kappa score, accuracy, and AUC indices.

Positive predictive value: A ratio of positive diagnoses labeled positive.

$$\text{Positive predictive value} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (1)$$

Sensitivity: The ratio of positive labels correctly identified as positive.

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (2)$$

Specificity: The ratio of negative labels correctly identified as negative.

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \quad (3)$$

F1-score: An indicator that shows the overall outcome of the positive predictive value and sensitivity and is defined as the harmonic mean of the positive predictive value and sensitivity. A high F1-score indicates high positive predictive value and sensitivity.

$$\text{F1 Score} = 2 \times \frac{\text{Positive predictive value} \times \text{Sensitivity}}{\text{Positive predictive value} + \text{Sensitivity}} \quad (4)$$

Kappa score: This index shows the agreement between the label and the network's prediction. Its proximity to 1 indicates better agreement, and its proximity to 0 indicates weaker agreement. In formulas 5–7, the kappa score is shown for the three classes (22).

$$\text{Kappa Score} = \frac{\text{P (Observed) - P (Expected)}}{\text{1 - P (Expected)}} \quad (5)$$

$$\text{P (Observed)} = \frac{\text{True (A) + True (B)+ True (C)}}{\text{Total}} \quad (6)$$

$$\text{P (Expected)} = \frac{\sum_1^I P_i L_i}{\text{Total}^2} \quad (7)$$

Where True (A) in (6) means correct prediction class A, L_i in (7) represents the marginal value of the class I label, P_i represents the marginal value of the class I prediction, and I is the number of classes.

Accuracy: The ratio of correct diagnoses to total diagnoses.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \quad (8)$$

AUC: Area under the receiver operating characteristic (ROC) curve. It evaluates the performance of binary classification.

The confusion matrix was also reported for three labels and two labels.

First, the data is downloaded from the web (23), and after pre-processing the data, including grouping into training, evaluation, and testing (Table 1) and converting the images to 256 × 256, each network runs on the data under the same conditions, and the results are reported. Six networks were run for their performance to be compared for the diagnosis of TB using CXR images. Also, in the network training process, the conclusions of previous research in TB diagnosis using CNNs were used. According to this, pretraining by ImageNet (24), transfer learning (25), and the Adam optimizer (26,27) were used to increase network performance.

Python programming language and the Pytorch library were used to implement the networks, and Google Colab was used as the programming environment.

This research was implemented in 2022 and has been approved by the Medical Ethics Committee of the Ministry of Health under the number of IR.IUMS.REC.1400.273.

Results

All networks were trained with 20 epochs on the training set. After each epoch was evaluated with the validation set, the network parameters were saved based on the epoch that obtained the best result on the validation set to be used in the testing step. This prevents overfitting and underfitting. The order of entry of training images was fixed in all epochs and for all networks. Figure 2 shows the results of the evaluation of the networks in 20 epochs.

In the evaluation step, the EfficientNet-B4, MnasNet, and MobileNetV3 networks performed more consistently

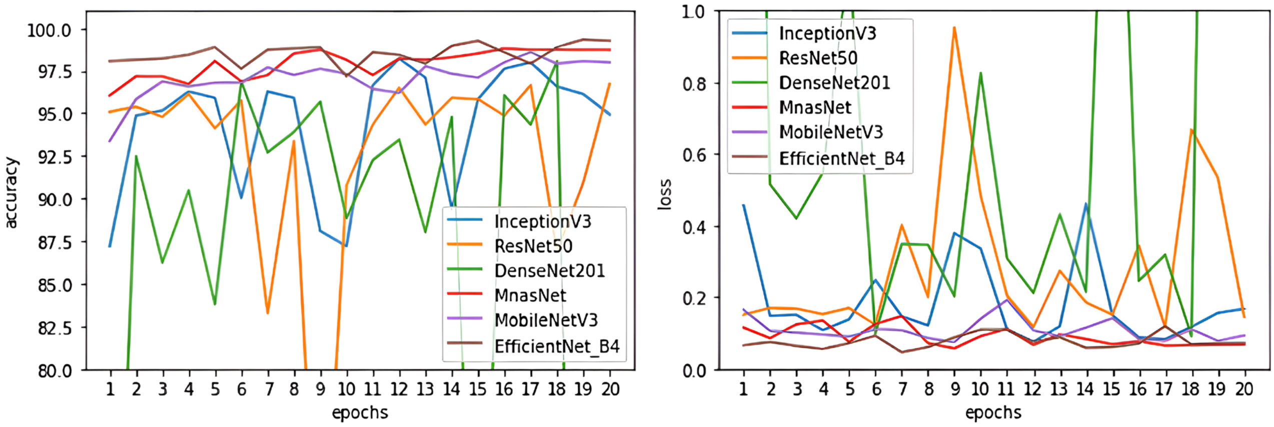

Figure 2. The results of the training and evaluation of the networks. The chart on the left shows the accuracy chart, and the chart on the right shows the loss chart

than the InceptionV3, ResNet50, and DenseNet201 networks and also experienced higher accuracy and less loss, which demonstrates the superiority of these three networks during the training and evaluation processes (Figure 2).

After the training and evaluation steps, the networks were tested using the testing set in the test step, based on the epoch with the best accuracy among the 20 epochs of the evaluation step.

It can be seen that in all networks, images of patients without TB, healthy people, and patients with TB are separated (Figure 3), which indicates the difference in the patterns of patients without TB from healthy people and people with TB and the separation of images of patients without TB as a separate group. Table 3 shows the results of implementing the networks based on three groups.

The results of Table 3 show that, in general, the networks showed high accuracy in identifying images of healthy people, patients without TB, and people with TB. The EfficientNet-B4 network recorded the highest accuracy and lowest loss, followed by the MnasNet and MobileNetV3 networks.

Based on the Kappa score in the third column of Table 3, the networks are divided into two groups in terms of performance. The EfficientNet-B4, MobileNetV3, and MnasNet networks showed close results and high performance, but the DenseNet201, ResNet50, and InceptionV3 networks were weaker in comparison. The EfficientNet-B4 network achieved a higher Kappa score and performed better than the other networks.

The results were recorded for comparison with other studies, based on two groups of people with TB and people without TB. Figure 4 and Table 4 show the results.

The network tests showed that the EfficientNet-B4 network performed as well as expected in the evaluation step. This network showed the best performance compared to other networks in terms of positive predictive value, specificity, F1-score, accuracy, and AUC. The MnasNet and MobileNetV3 networks also performed well, and the DenseNet201 network performed mediocrely compared to other networks. The InceptionV3 and ResNet50 networks could not compete with other networks (Table 4) but still performed better than most previous studies. Generally, the networks selected in this research achieved high performance on the TBX11K image set, which was more accurate than most previous studies. Among them, the EfficientNet-B4 network, which achieved the best performance in this research, showed higher accuracy compared to previous studies in TB classification for diagnosis using CXR images by CNNs listed in related works and Table 5.

Discussion

This research aimed to obtain a network that can diagnose TB with any level of severity and activity using CXR images with high confidence. For this, six networks were trained on the large TBX11K dataset with the three of labels of healthy people, patients without TB, and patients with TB, and the obtained results were reported and compared with the results of other studies in this field.

Compared to previous studies, the high accuracy obtained in this research showed that improving the training process and the data quality and quantity can increase networks' accuracy (31). The greatest difference from previous studies is the difference between the datasets used. In this research, the TBX11k dataset was used for the first time for classification. It achieved better results than previous studies on using CNNs to diagnose TB using CXR images.

One of the most important reasons for the positive impact of this dataset on the results is the separation of people without TB into healthy people and sick people without TB, which can help us in more accurate diagnosis (12) because patients without TB still have some kind of lung abnormality. Images of patients without TB contain patterns that are different from both healthy and TB patients. If we merge this group with the healthy group when running the network as patients without TB, the network is forced to assign these images to either the patients with TB or patients without TB groups. If we

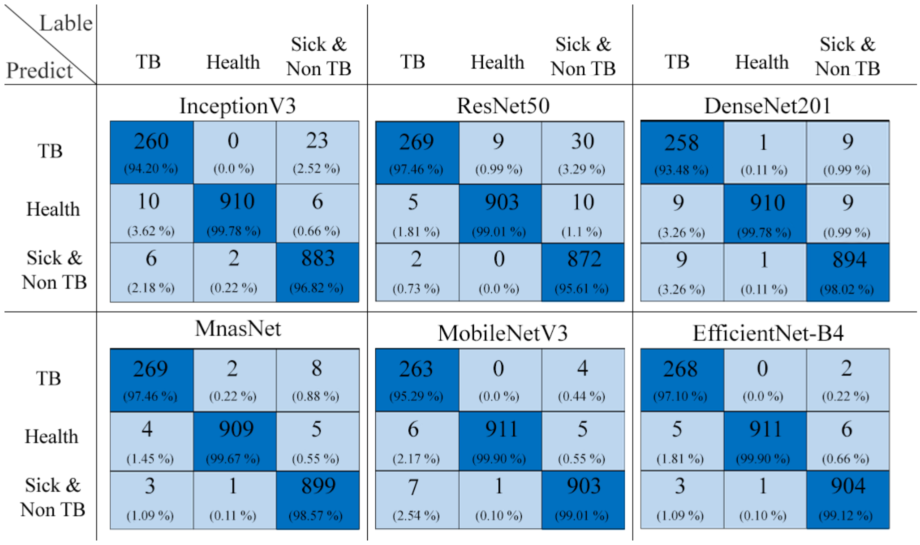

Figure 3. Confusion matrix of network test results on the test set. The columns represent labels, and the rows represent network predictions

Table 3. Network test results based on three labels

CNN	Corrects diagnosis	Kappa score	Loss	Accuracy
InceptionV3	2053	0.9631	0.0852	97.76 %
ResNet50	2044	0.9562	0.1405	97.33 %
DenseNet201	2062	0.9699	0.0949	98.19 %
MnasNet	2077	0.9818	0.0590	98.90 %
MobileNetV3	2077	0.9818	0.0540	98.90 %
EfficientNet-B4	2083	0.9866	0.0525	99.19 %

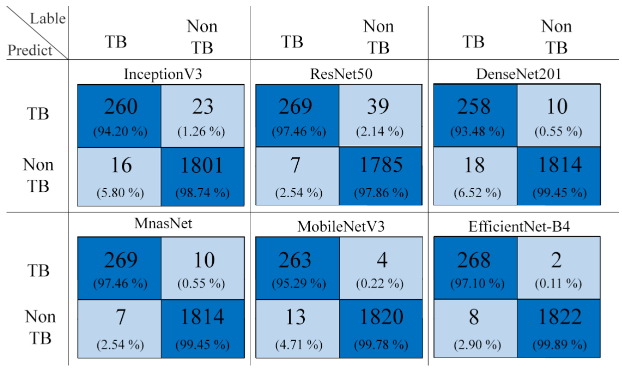

Figure 4. Confusion matrix test results of networks on the test set. The columns represent labels, and the rows represent network predictions

assign a patient without TB to either the healthy group or the TB group, due to the differences between the patterns of these two new groups, the accuracy of the network will decrease. Therefore, through the separation of patients without TB, the network accuracy considerably increased due to closeness of the patterns. Therefore, the network cannot converge well to its optimal state, and the number of network errors increases, and the accuracy of the network's classification decreases. For this, considering sick people without TB as a separate group can reduce the number of network errors and increase network accuracy. The high accuracy of this research using the above dataset also showed the effect of this separation.

In order to choose the best network among the implemented networks, their results were compared, and EfficientNet-B4, MnasNet, MobileNetV3, DenseNet201, InceptionV3, and ResNet50 showed more successful performances. Based on previous studies, the DenseNet201 network was expected to perform better than the InceptionV3 and ResNet50 networks, and the expected results were confirmed. The better performance of MnasNet and MobileNetV3 networks compared to DenseNet201 was surprising (32,33).

The EfficientNetB_4 network showed that it is superior to other networks in diagnosing CXR images like ImageNet images (19) and was able to perform better than other networks with an error rate of less than 0.5% and reach the highest level of accuracy in studies conducted on CNNs for TB diagnosis using CXR images so far (25,30,33).

On the other hand, the lightweight and fast networks MobileNetV3 and MnasNet, which had very low parameters, performed excellently and accurately. They were competitive with the EfficientNet-B4 network, which, despite the higher accuracy of the EfficientNet-B4 network, can be preferred over the EfficientNet-B4 in some cases. This research aimed to achieve low-cost, fast, and accessible methods. Therefore, these two networks, which can be implemented on weaker processors and even mobile phones, can be an excellent choice for developing areas for TB screening because they are very accurate, light, and fast.

The networks performed very well in terms of specificity. They differentiated TB from other lung diseases, which was important because misidentifying lung diseases is one of the most critical challenges of identifying the disease using CXR images, which results from the high similarity of the patterns of various lung diseases in the images (6).

Table 4. Table of network test results (%) based on two labels

CNN	Corrects diagnosis	Positive predictive value	Sensitivity	Specificity	F1-score	Accuracy	AUC
InceptionV3	2061	91.87	94.20	98.74	93.02	98.14	99.39
ResNet50	2054	87.34	**97.46**	97.86	92.12	97.81	99.14
DenseNet201	2072	96.27	93.48	99.45	94.85	98.67	99.64
MnasNet	2083	96.42	**97.46**	99.45	96.94	99.19	99.90
MobileNetV3	2083	98.50	95.29	99.78	96.87	99.19	99.88
EfficientNet-B4	**2090**	**99.26**	97.10	**99.89**	**98.17**	**99.52**	**99.98**

In each column the largest value becomes bold.

Table 5. Comparison of research results.

CNN	Accuracy	CNN	Accuracy
CNN ResNet18 (28)	75.4 %	Ensemble (AlexNet+GoogleNet) (29)	96 %
CNN manually (27)	80.6 %	Ensemble (Efficient Net B0-B4) (30)	97.4 %
CNN VGGNet (31)	81.6 %	ResNet50	97.8 %
CNN manually (26)	82.1 %	InceptionV3	98.1 %
DenseNet121 (32)	83.5 %	DenseNet201-Segmentation (33)	98.6 %
CNN AlexNet (24)	83.7 %	DenseNet201	98.7 %
CNN manually (34)	87.1 %	MnasNet	99.2 %
CNN GoogleNet (35)	91.7 %	MobileNetV3	99.2 %
Ensemble(VGG16+InceptionV3) (36)	92.1 %	InceptionResNetV2 (25)	99.4 %
VGGNet (37)	94.6 %	EfficientNet-B4	99.5 %

Note: The gray rows are the networks of this research, and the other rows are the networks with the highest accuracy obtained in other research.

Separating images related to different severities of TB can also help to increase the sensitivity, which requires collecting a sufficient collection of people with latent TB and active TB. A network that works successfully on such a set and recognizes weak patterns can effectively prevent TB because TB is not yet contagious in its latent stage. However, this research aimed to identify a network that can diagnose TB accurately in any severity.

Overall, this research achieved a very high performance in diagnosing TB with a high-quality and new TB dataset while using the experience of previous studies. On the other hand, it is even possible to enhance this performance in the future by using other techniques implemented in previous studies, such as segmentation (33), shuffle sampling (35,37), and data augmentation (28).

Conclusion

This research showed that with current networks, access to large and high-quality datasets, and appropriate training, TB diagnosis using medical images can be entrusted to computers with high confidence. This was confirmed by the current research results obtained using the new and large TBX11K dataset. The accuracy of a skilled radiologist with more than ten years of experience on this dataset was 84.8% (12), while the very small networks used in this research, such as Mobile Net, which can also be used on small processors such as mobile phones, achieved more than 99% accuracy. Therefore, these networks can be used right now in areas without medical infrastructures to eliminate the problems of TB diagnosis to some extent.

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Authors' Contribution

Conceptualization: Abolfazl Pordeli Shahreki, Masoud Roudbari.
Data curation: Abolfazl Pordeli Shahreki.
Formal analysis: Abolfazl Pordeli Shahreki, Fatemeh Sadat Hosseini-Baharanchi.
Funding acquisition: Masoud Roudbari.
Investigation: Abolfazl Pordeli Shahreki, Fatemeh Sadat Hosseini-Baharanchi.
Methodology: Abolfazl Pordeli Shahreki, Fatemeh Sadat Hosseini-Baharanchi.
Supervision: Masoud Roudbari.
Writing–original draft: Masoud Roudbari, Fatemeh Sadat Hosseini-Baharanchi.
Writing–review & editing: Masoud Roudbari, Fatemeh Sadat Hosseini-Baharanchi.

Competing Interests

None.

Ethical Approval

This research was approved by Iran National Committee for Ethics Biomedical Research under the code of IR. IUMS. REC.1399.543

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