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Application of Deep Convolutional Neural Networks in the Diagnosis of Osteoporosis

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Introduction

Osteoporosis has emerged as a serious health issue all over the world as a result of our aging society. Osteoporosis, as defined by the World Health Organization (WHO), is a systemic skeletal disease characterized by decreased bone mass, altered bone tissue microarchitecture, and, as a result, increased fragility and susceptibility to fractures. In 2019, there were 32 million cases in Europe, or 5.6% of the European population over 50.Lifestyle factors, particularly diet and physical activity, influence the progression of this disease. As a result, it is reasonable to anticipate that the pandemic will exacerbate the situation and significantly impact patient disease progression. The incidence rate is expected to rise significantly in the near future, according to reports. It is important to keep in mind that patients were referred to osteoporosis-dedicated follow-up examinations much less frequently in the past two years and as a result, many patients are still unaware of their condition. When osteoporotic fractures occur, osteoporosis is usually diagnosed at an advanced stage. The spine is particularly vulnerable to this. As a result, ongoing research is required to develop the most effective diagnostic approach that would enable early detection of osteoporosis. The general trend of research in this field indicates that the analysis of bone tissue microarchitecture yields the best results.

Description

Lately, a fast improvement of AI calculations has occurred, particularly profound learning techniques. An idea in machine learning called deep learning is based on artificial neural networks. They typically employ multiple interconnected layers of neural networks. Deep belief networks, convolutional networks, recursive networks, long short-term memories, deep Boltzmann machines and deep coding networks are just a few of the many architectures of these kinds of networks. In the process of recognizing images, many of them perform exceptionally well, including biomedical ones. Artificial neural networks have been used to diagnose intramucosal gastric cancer, early diagnose and predict chronic kidney disease, major depressive and bipolar disorders, COVID-19 pneumonia and other conditions. Additionally, there are publications on novel deep learning-based osteoporosis diagnosis methods. The estimation of uncertainty as a measure of confidence in the model's predictions is one of the important issues when building machine learning models, including deep models. This issue, among others in the space of PC vision, is effectively tended to by utilizing Bayesian convolutional brain organizations (BCNNs). Uncertainty estimation is incorporated into these kinds of networks to prevent over fitting. In situations where CNNs are an appropriate learning model, but there is insufficient data, BCNNs are preferred because they are less likely to become over trained. The problem of uncertainty estimation can be extended using BCNNs and experimental results, among other things [1].

Interpretability is a significant issue that hinders the wider application of machine learning models, particularly in healthcare. When the decisions it makes can be fully comprehended, a model is interpretable. Sadly, machine learning models, particularly deep models, resemble black boxes to common users. As a result, gaining a deeper comprehension of the models mechanisms becomes essential if we are to expand the use of AI solutions in healthcare. Thusly, endeavours are being made to work on the interpretability and straightforwardness of AI models. This is because practical implementation applications necessitate establishing trust between users and decision-making models. The main issue with machine learning is balancing optimisation and generalization. Tuning the model to provide the best performance for the learning data is the goal of optimization. On the other hand, the model's performance when processing new data is determined by its granularity. Generalization for validation data reaches a constant level after a certain number of iterations (epochs) of the learning algorithm and then (mostly) begins to deteriorate. This indicates that the model is over-fitting the learning data (overtraining). Over-fitting can be stopped in a number of ways, all of which are referred to as regularization methods. When it comes to learning deep convolutional neural networks, popular regularization techniques include: transfer learning, dropping out, adding data, stopping early, regularizing weights (L1, L2, max-norm) and other things Included is a summary and comparison of these and other methods of regularization. New efficient algorithms, such as the two-stage training strategy, are constantly being proposed as a result of the ongoing research into the regularization issue [2].

Deep convolutional neural networks (DCNN) can be used to analyse and classify spinal CT images to reveal the porosity of L1 spongy tissue due to the results of the research. In the field of osteoporosis diagnosis research, this is a novel strategy. To the best of the authors knowledge, there is no research that employs deep learning algorithms to address this issue. Before using images to build the classifier model, the stage of image pre-processing and analysis can be significantly simplified using the proposed method. Based on the raw data from images, the convolutional neural network is able to reveal the internal features of individual observations while maintaining high classification efficiency. The article talks about the materials that were used in the research, how images were chosen, how classification models were built and the architecture of the network models that were used and the results of the network operation. The article concludes with a summary of the accomplishments and a plan for future work. The research results are discussed and compared to those of other works. The level of 90% was exceeded by the vast majority of all quality indicators for the aforementioned models. Considering the extremely limited number of observations used to train the models, this is an excellent result [3].

There were 200 observations in each class, of which 50 came from the test set, 50 from the validation set and 100 from the training set. These are very small datasets for deep neural networks because sets of thousands of observations are typically used for training. The method of using pre-trained classifiers on a very large Image Net dataset allowed for very good results. Adding two layers of a custom classifier at the model's conclusion and fine-tuning the top layers of the convolutional basis proved to be extremely successful. According to the findings, this strategy may be useful for smaller datasets. It should also be emphasized that the models with the smallest topological depth produced the best results. There were 19 layers in the VGG16 model's convolution base,

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while there were 22 layers in the VGG19 model. For a very small portion of the training set, the models with the lowest complexity proved to be the most effective. This could imply that the MobileNetV2, Xception and ResNet50 models could not account for the sufficient number of observations. However, despite having the most layers (780), the InceptionResNetV2 model achieved very high quality indicators (ACC=94%, TPR=90% and TNR= 98%).The fact that the areas of interest were manually extracted is one of the discussed methods shortcomings [4].

However, this issue necessitates distinct research and will, as a result, become an area of interest in subsequent work.

As it tends to be seen, the outcomes got are at a level practically identical with the consequences of different creators, accomplished in tackling comparative grouping issues. Because they involved the same kind of images those obtained through computed tomography the findings in this article are easiest to compare to those in the studies. The spine, one of the parts of the human skeleton that is most susceptible to osteoporosis, is the anatomical subject of both of these studies. The spine is the subject of numerous experiments aimed at preventing the final stage of the disease due to its crucial role in the structure of the human body and complications following vertebral fractures that sometimes result in death or immobilization of the patient. The results of the study, which are presented in Table 4, show that classifiers with the AlexNET model had sensitivity values ranging from 78.83% to 98.56%. The used classifiers sensitivity and specificity, TPR=83.9% and TNR=93.8%, were also stated in the work [5].

Conclusion

In contrast, the study uses artificial neural networks and takes a slightly different approach to diagnosing osteoporosis. Rather than pictures, the exploration material comprised of information on the age, weight, level and T-file of the femoral neck. The osteoporosis risk prediction algorithm would make use of the displayed parameters as input data. The outcomes were as follows: TNR is 90.12%, ACC is 78.83%, AUC is 0.829 and TPR is 51%. The classifier's low sensitivity value may indicate that the theory about how important it is to study the microarchitecture of bone tissue is true.

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