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DESIGNING CNN NEURAL NETWORK MODEL FOR DETECTING FRACTURES OF LOWER EXTREMITIES BY X-RAY IMAGES

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Bone fractures of the lower limbs are one of the most common injuries that can occur as a result of various mechanical impacts such as falls, blows, traffic accidents or injuries received during sports. These injuries can differ significantly in nature, location and degree of complexity. Classification of fractures is important for choosing the optimal treatment, which helps to reduce the risk of complications and accelerate the healing process.

Fractures of the lower extremities can be classified according to several criteria, including type of injury, location, complexity, and cause.

Determination of bone fractures of the lower extremities is carried out using clinical or radiological methods. Each of these methods has its own characteristics and is used to confirm the diagnosis, assess the degree of damage and choose the optimal treatment tactics.

Having analyzed the subject area, several main aspects can be emphasized:

– difficulties arise when diagnosing fractures of the lower extremities, because it is a rather unclear and complex structure of bones, which consists of many components;

– there are many types of fractures and they are not easy to detect, they vary in complexity and require special types of treatment;

– modern methods make it possible to obtain a detailed picture with damage with great accuracy, but incorrect interpretation can only worsen the quality of diagnosis and treatment.

The purpose of the work is using CNN neural network model for detecting fractures of lower extremities by X-ray images.

The neural network method for identifying bone fractures of the lower extremities on X-ray images is based on the application of deep learning technologies, in particular, convolutional neural networks (CNN). This approach allows you to automate the process of detecting damage, which helps speed up diagnosis and reduce the number of errors that can occur during manual image analysis [1, 2].

First, data collection is carried out, a sufficient number of x-rays of the lower extremities are accumulated, including images with and without fractures. These images should include different types of fractures (eg, transverse, oblique, helical) and different parts of the legs (femur, tibia, etc.). It is important to balance the data to avoid distortions (for example, if there are more images with fractures, the model may "get used" to find fractures more often than is really necessary).

It is necessary to mark each image: is there a fracture on it, where exactly is it located. This work is usually done by trained doctors or radiologists who manually select areas on the images.

The finished images are normalized, brought to the same size and scale to ensure the correct operation of the neural network and improve the quality using methods to increase contrast and remove noise, which makes the bones clearer. To increase the number of images, various changes are applied to them, such as rotation, mirroring, scaling. This helps to make the model more resistant to different variations of shots. The images are divided into training, validation and test sets (usually in a ratio of 70-20-10) to correctly evaluate the model and avoid the problem of overtraining.

The next stage is the selection and adjustment of the neural network model, for our purposes it is convolutional neural networks (CNN), which are suitable for working with images [3, 4]. Use ready-made models, such as ResNet, VGG, or create special ones, for example, U-Net, which can be adjusted for the task of fracture detection. The quality of the network depends on the number of layers, the size of the filters and other parameters.

The model is trained on the training data set, using the annotations as "correct" answers. During training, she learns to recognize features that indicate a fracture. Adam or Stochastic Gradient Descent (SGD), adjust the weights in the neural network for a better result. The model is tested after each training epoch on the validation set to see how much it has improved and if there are any errors.

The model is evaluated on characteristics such as how well it finds fractures and how well it excludes cases without fractures. If the performance is not good enough, the settings can be changed and the model is supplemented with new layers to improve performance. Sometimes an additional setting is used to achieve better results.

Test set that has not been used before is used for verification. This helps evaluate how well it performs on new data and whether it can handle real images. During testing, the accuracy and correctness of the model's work are evaluated in order to be sure of its effectiveness.

Upon successful testing, the model is integrated into a program or system that automatically analyzes X-ray images. A simple interface is created for it, so that doctors can upload images and receive a result about the presence or absence of a fracture and its location. In addition, the system can show the probability of a fracture or the severity of the damage.

If the program is successful, it is tested in real conditions and improved. In real practice, the model can be used together with the doctor to ensure the most accurate diagnosis.

The development of a neural network architecture for the identification of bone fractures of the lower extremities on X-ray images involves several steps and requires the creation of a model structure that can effectively process medical images and recognize bone damage. Below is a detailed description of this process and the key elements of the architecture.

Most often, convolutional neural networks are used to process medical images, as they specialize in recognizing objects and features in images. CNNs allow models to learn different levels of image features: from simple (lines, edges) to complex (bone shapes, anomalies) [5].

The architecture consists of several layers, each of which performs its function, the main components of which make up:

– Convolutional layers using feature filters from an image. The first layers highlight simple elements (edges, corners), and the next layers extract more complex structures (parts of bones, possible fractures).

– Summarization layers reduce the dimensionality of an image, highlighting the main features and reducing the number of parameters the model has to process. This makes the network faster and less sensitive to drift or noise.

– Activation layers with ReLU activation function to study non-linear dependencies.

– Normalization layers: normalize the data to avoid overtraining and stabilize the learning process.

– Fully connected layers collect all features extracted by previous layers and form the original result (is there a fracture and where exactly).

The input layer receives an X-ray image that is normalized to a size of 224x224 pixels to simplify processing. Multiple Convolutional Blocks: Each block consists of a convolutional layer, an activation layer, and a summation layer. The first block can use 3x3 filters and have 32 channels to extract the base contours. Subsequent blocks can have a larger number of filters up to 128 to study more complex features. Also, apply summation blocks after each block to reduce the size of the data and prepare it for the next stage. At the end, the data is transferred to several fully connected layers, which combine the received information and perform classification, that is, determine the presence of a fracture.

From the optimizers, the choice falls on Adam or SGD. Depending on the classification, we choose cross-entropy as a loss function.

Some attention mechanisms can be used to make the model focus on specific areas of the image where fractures are most likely to occur. Residual blocks help to avoid loss of information when the signal passes through the layers, they are often used in ResNet.

The Dense Convolutional Network architecture is one of the advanced convolutional neural networks that is well-suited to the task of bone fracture identification in X-ray images due to its efficiency and ability to store information at all levels of the network. It differs from traditional CNNs in that each layer is connected to all previous layers, which allows storing information and facilitates the transfer of gradients during training.

To solve the problem of detecting fractures of lower extremities by X-ray images, it was using CNN neural network model for detecting fractures of lower extremities by X-ray images, which is shown in Figure 1.

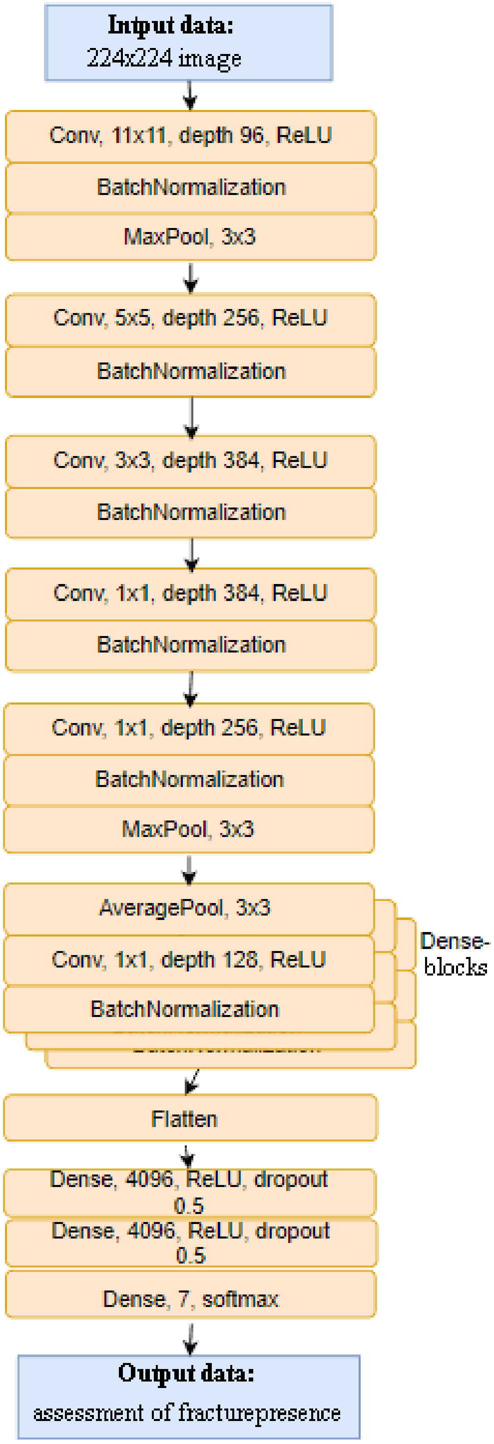

Figure 1. CNN neural network model for detecting fractures of lower extremities by X-ray images.

The input layer receives an X-ray image of 224x224 pixels and normalizes it for further processing.

The first Dense block extracts basic features such as contours and basic bone details. Subsequent blocks gradually extract more complex features, such as changes in bone shape, that may indicate a fracture.

Transition layers reduce the dimensionality of the image after each dense block, while preserving important information. With a deep architecture, in this case, the network remains computationally efficient.

After passing through all Dense Block and transition layers, the data enters the fully connected layer, which performs classification by determining whether the image contains a fracture. If the mesh is configured for segmentation, it can also highlight the exact fracture area. I use Adam for optimization. The loss function can be cross-entropy or IoU.

Thus, the problem of using CNN neural network model for detecting fractures of lower extremities by X-ray images was investigated. In particular, the Dense Convolutional Network architecture is used, which is one of the advanced convolutional neural networks, which is well suited for the task of identifying bone fractures in X-ray images due to its efficiency and ability to store information at all levels of the network. It differs from traditional CNNs in that each layer is connected to all previous layers, which allows storing information and facilitates the transfer of gradients during training. Regarding the advantages of DenseNet over other networks, it has fewer parameters compared to others, which reduces the need for computing resources. Also improved feature retention, where the model better remembers and uses features from earlier layers, improving its ability to recognize small details important for fracture detection. Thanks to tight connections and efficient gradient transfer, the model can be trained effectively even on relatively small data sets.

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УПРАВЛІННЯ ІНФРАСТРУКТУРОЮ ЗА ДОПОМОГОЮ DEVOPS ПРОЦЕСІВ

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Сучасні підприємства стикаються з викликами, такими як швидка зміна вимог, масштабованість і надійність інформаційних систем. DevOps дозволяє інтегрувати процеси розробки та операційного управління для більш ефективного впровадження програмного забезпечення та підтримки інфраструктури.

Метою даної роботи є дослідження ефективності застосування DevOps процесів для управління сучасною IT-інфраструктурою, а також вивчення їх впливу на швидкість впровадження програмного забезпечення, масштабованість та надійність систем.

DevOps пропонує принципово новий підхід до управління інфраструктурою, інтегруючи розробку та операційні процеси в єдиний цикл. Важливою складовою цього підходу є автоматизація, яка знижує потребу в ручній роботі. Автоматизація охоплює такі процеси, як тестування, розгортання та моніторинг систем, що дозволяє підприємствам швидко реагувати на зміни ринку.

Однією з ключових технологій, що використовується в DevOps, є Інфраструктура як код (IaC). Цей підхід дозволяє управляти інфраструктурою через код, а не вручну налаштовувати сервери, мережі та інші компоненти. Використання таких інструментів, як Terraform або Ansible, спрощує процес створення, налаштування та управління великими системами, роблячи їх більш гнучкими. Наприклад, за допомогою IaC компанії можуть миттєво розгортати нові сервери в хмарних середовищах, адаптуючи інфраструктуру до поточних потреб.