Transfer training tools and methods for diagnostic tasks

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Abstract
The research about implementation transfer learning in medical diagnostics is important because it allows to evaluate how well already trained neural networks can adapt to specific medical data. This helps to understand which architectures work best, how to improve diagnostic accuracy, and reduce the risk of false positives. In addition, such research contributes to the development of more reliable and interpretable models, which is critical for physician confidence and the implementation of AI in real-world clinical practice.

Keywords
Machine learning, transfer training, medical diagnosis, artificial neural network, accuracy

1. Introduction

Transfer machine learning (TML) can be useful for training analytical diagnostic models as a basis for medical diagnostics, as it allows you to use already pre-trained models (models after the parametric synthesis stage) on new, similar tasks, reducing the need for large amounts of data. In medicine, even modern medicine, there is often a lack of large annotated data sets – usually, this applies to rare diseases, or viral (less often bacterial) infections that have passed the stage of seasonal or qualitative mutation, or diseases at the beginning of the epidemic (as was the case with COVID-19, for example) [1]–[3]. That is why the ability to adapt knowledge from other industries or similar tasks is very valuable. For example, models trained on a large general set of medical images can be further trained on smaller specific data sets for a specific diagnosis, which improves accuracy and reduces development time. This is especially important in radiology, where the analysis of CT, MRI, or X-ray images can be improved using models that have already learned to recognize common pathologies. It also reduces the risk of retraining, since the basic characteristics of images or signals (for example, tissue features or anomaly patterns) have already been studied by the model before. Unlike the neuroevolution approach, which usually requires a large data set to synthesize a more universal model, the principle of TML is to adapt an existing model to a specific, narrower task. In addition, it can contribute to better generalization of models, allowing them to work on different sets of patients, even if they differ in demographic or technical parameters [3].

TML shows good results precisely when using deep neural networks (DNNs) because of their ability to automatically extract and summarize complex multi-level data features. DNNs consist of many layers, where most layers are layers with hidden neurons, each of which learns to recognize certain patterns – from the simplest (edges, textures, normal indicators) on the lower layers to more complex (shapes, objects, splashes, pathologies) on the higher ones. This makes it possible to reuse already trained layers without the need for training from scratch, which is crucial for tasks where access to large amounts of annotated medical data is limited [2]. Moreover, retraining or complete re-synthesis of DNN can be extremely complex and resource-intensive for a computing system, which is not sufficiently optimized due to the receipt of a small amount of new data (2).

This is particularly effective in areas such as medical image analysis (CT, MRI, X-ray), where the first layers of DNN trained on large shared datasets (such as ImageNet) can be used to recognize basic visual patterns, while only the last few layers are adapted to a specific task. This significantly reduces the need for computing resources and training time. In addition, this strategy helps to avoid re-

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learning on small sets of medical data, since the initial layers already contain generalized characteristics that are well transferred between similar tasks, because the dataset can contain updated data of either individual patients or a specific pathology that requires confirmation or refutation.

Another reason for effectiveness is the ability of DNN to work with nonlinear and complex relationships in data, which is important in medical diagnostic tasks where pathologies can have complex and variable manifestations. With TLM, high accuracy can be achieved even with relatively small data sets, making this approach practical and effective in real-world medical applications [1]–[3].

However, which DNN topologies to choose, which methods can help better teach a structurally synthesized model, how to adjust the metaparameters of methods, and, ultimately, whether such an approach is really optimized for medical diagnostics should be considered in this paper [1]–[3].

2. Related Works

Automation of medical diagnostics is the use of technologies, in particular data processing algorithms, machine learning and artificial intelligence, to partially or completely perform the process of detecting diseases and making diagnoses. This may include analyzing medical images (MRI, CT, X-rays), interpreting laboratory tests, recognizing symptoms based on electronic medical records, and even predicting disease risks [4]–[8].

It should be noted that work on automating decision-making in medical diagnostics has been underway for quite a long time, which is associated with a number of important current needs:

- speed up the diagnostic process-automatic systems can significantly speed up the analysis of a patient's set of clinical indicators, which is critical in acute conditions (for example, stroke, heart attack), especially if you correctly configure the online transmission of clinical indicators after, for example, the actual analysis to the general system [1]–[7];
- improved accuracy – artificial intelligence (AI) techniques can detect patterns and non-obvious connections that a person may miss, even in an ultra-large data stream, reducing the risk of false or missed diagnoses;
- reduce the burden on doctors – automation helps reduce the share of routine work of doctors, giving doctors more time for complex clinical cases and communication with patients;
- increased access to health care – in the event of a shortage of qualified specialists in the regions or problems with the departure of medical care to dangerous, restricted locations, automated systems can help compensate for this shortage by providing high-quality preliminary diagnostics, and signal the real need to attract qualified specialists to extraordinary cases [8];
- standardization of diagnostic solutions – reducing the influence of the human factor allows you to minimize the variability in diagnosis between different doctors.

Therefore, it is necessary to clearly distinguish between the role of AI in the processes of such automation – AI is a key component of automation, since it is able to:

- process and analyze large amounts of medical data – images, tests, medical histories;
- recognize complex patterns and correlations that are difficult to detect even for experienced doctors [6]-[8];
- learn from previous cases-constantly improving the accuracy of predictions and diagnoses;
- perform routine tasks, such as sorting cases by risk level or automatically collecting patient data.

In general, AI does not replace doctors, but acts as a tool that enhances their capabilities, helping them make informed decisions and improve the quality of medical services.

The TML approach has a number of key advantages over classical machine learning methods, which is especially important in medical diagnostics. Therefore, TML has less need for large data sets–classical ML models require a large amount of annotated medical data to learn from scratch. Since collecting and labeling such data in medicine is complex and resource-intensive, transfer training allows you to use already trained models, adapting them to a specific task.

On the other hand, faster adaptation to new tasks. Learning from scratch (especially in DNN) requires a lot of time and computing resources. TML allows you to shorten this process by reusing the basic characteristics you have already learned [8].

In addition, the resulting neuromodels are better generalizability – DNNs trained on large shared data sets already contain knowledge of common features of images or signals, which makes them more resistant to changes in data than models trained only on specific medical sets.

The derived advantage of using TML is to reduce the risk of retraining – in classical approaches, when training on small medical datasets, the model can remember the features of a specific set (whether it is a specific group of patients, a specific disease, or even a specific patient), rather than learn general patterns. Thanks to transfer training, the basic levels of the network already contain generalized knowledge, which makes the adapted model more resistant to various variations in medical data. As already noted, learning DNN from scratch requires powerful hardware. TML reduces the need for long-term training and allows you to achieve high accuracy even on less powerful systems, thereby increasing the efficiency of using computing resources. Also, the TML approach has a certain versatility: the same approach can be used for various medical tasks: analysis of X-rays, CT, MRI, diagnostics using electrocardiograms or histological images.

Thus, TML is significantly more efficient than classical methods, as it allows you to adapt existing models to medical diagnostic tasks faster, more accurately and with less resource costs.

To clearly demonstrate this, let's look at a comparison table of different ML approaches for our problem of automating medical diagnostics in the form of a Table 1.

Table 1
Comparison of classical ML approaches with TML

Criteria	Transfer machine learning	Transfer machine learning
Need for data	Smaller, uses already trained models	Smaller, uses already trained models
Training time	Shorter, because it adapts already trained models	Shorter, because it adapts already trained models
Requirements for computing resources	Less, because mostly only the last layers are taught	Less, because mostly only the last layers are taught
Generalization of knowledge	Better yet, the basic features are already learned on large sets	Better yet, the basic features are already learned on large sets
Risk of overfitting	Lower, because the model already has general knowledge	Lower, because the model already has general knowledge
Flexibility in use	High-can be adapted for various medical tasks	High-can be adapted for various medical tasks
Application examples	Analysis of X-rays, CT, MRI, histology, ECG, pathology recognition	Analysis of X-rays, CT, MRI, histology, ECG, pathology recognition
Accuracy	Higher, especially for small data sets	Higher, especially for small data sets
Practical effectiveness	High-faster implementation in clinical practice	High-faster implementation in clinical practice

Transfer training is more effective for medical diagnostics when access to large amounts of data is limited and deployment speed is critical. Classical machine learning is useful when it is possible to build a large, high-quality dataset and train the model for a specific task.

To date, a number of independent and professional researches [9]-[14] have already been conducted on the introduction of TML technologies in medical diagnostics. TML involves using the knowledge gained by the model when solving one problem to improve results on another, often similar problem. This approach is particularly useful in medicine, where there is a limited amount of data to train models [7].

After analyzing a set of studies, we can conclude the general advantages of using TML in medicine, among which the researchers identified:

- resource savings: models pre-trained on large shared data sets can be adapted to specific medical tasks with less time and data.;

- improved accuracy: adapting models to medical data can lead to higher diagnostic accuracy, even with a limited amount of specific medical data.
- However, it should also be noted the general disadvantages and risks associated with the implementation of TML in medical diagnostics:
- risk of transferring inappropriate characteristics: if the baseline model was trained on data that is significantly different from medical data, this may lead to the transfer of inappropriate or undesirable characteristics, which will worsen the quality of diagnosis;
- interpretation problems: machine learning models, including those that use TML, can be black boxes, making it difficult to understand the reasons for making certain decisions that are crucial in medical practice;
- need for thorough validation: it is necessary to carefully test adapted models on medical data to ensure their reliability and accuracy before implementing them in clinical practice.

Overall, while TML offers significant benefits for medical diagnosis, it is important to consider potential risks and limitations while ensuring that models are thoroughly validated and adapted to the specifics of medical data.

As already noted, within the framework of this work, it is extremely important for us to deal with a number of issues related to the implementation of transfer training in medical diagnostics, namely: which DNN topologies to choose; which methods can help to better teach the structurally synthesized model; how to configure the metaparameters of methods. A similar research structure should be argued [.

Choosing a deep neural network (DNN) topology for transfer learning, configuring metaparameters, and learning methods are critical aspects when it comes to applying machine learning technologies to medical diagnostics. Here are some important points that explain why this is so important and how you can improve your results.

2.1.1. Selecting the DNN topology for transfer training.

The network topology (or architecture or structural structure) is crucial because it determines how the neuromodel will process data. For medical tasks, such as image diagnostics or analysis of medical records, architectures that are well-suited for image processing are most commonly used [15]:

- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)
- Transformer-based models (most often for sequential data).

The choice of topology affects:

- model performance: an incorrect topology may cause the model to fail to learn or process data efficiently;
- generalization capability and quality: it is important that the network can transfer the acquired knowledge to new medical tasks without losing accuracy;
- model complexity: for small medical data sets, simpler models can be more efficient than complex ones that require huge amounts of data [16].

2.1.2. Methods for improving the training of a structurally synthesized model

In order to train the model more effectively, the following methods are used:

- Fine-tuning: this is the process in which a network pre-trained on a large amount of shared data adapts to a specific medical task. This method allows you to preserve the knowledge gained at the previous stage of training, and only partially retrain the model on new data [11];
- Data augmentation: in cases where medical data is limited, you can use data augmentation techniques to artificially enlarge the data set, creating new examples from the original ones through transformations (rotation, shifting, image scaling, etc.);
- Regularization: regularization techniques such as Dropout or L2 regularization help prevent overfitting, which is especially important when there is not enough data for training [12].

2.1.3. Configuring metaparameters

Among the metaparameters (or hyperparameters for some methods) of methods for training structurally synthesized models, there are [5]:

- learning rate: it is important to adjust the learning rate correctly so that the model does not get stuck in local lows or learn too slowly [15];
- batch size: the batch size determines how many examples will be processed before updating the scale. This can affect the stability and speed of learning;
- number of epochs: the number of iterations (epochs) of training in which the network adapts to data is an important factor for achieving optimal results.

Transfer training can be a good (if not the best) approach to implementing ML in medical diagnostics in general, given the frequent problem of data limitations, because the medical field often lacks large data sets to train models from scratch. TML allows you to use already trained models, which significantly reduces the need for data and time. Moreover, since decisions often need to be made quickly in medicine, the use of models pre-trained on large sets of General Data allows you to achieve results faster, and therefore solutions based on the use of the TML approach differ in speed and efficiency. It is also worth paying attention to the fact that transfer training allows you to effectively adapt General models to specific tasks related, for example, to rare diseases or specific medical images. Thus, TML will help increase the adaptability of neuromodels. [16]

However, this approach also has its own risks, especially if the adaptation of the model to new medical data has not been properly performed. It is important that the validation performed is thorough and takes into account the specifics of specific medical data, otherwise there is a risk of incorrect diagnoses.

Transfer training has great potential for medical diagnostics due to its ability to effectively use limited data and reduce training time. However, it is important to carefully choose the network architecture, configure metaparameters, and take into account the specifics of medical data to achieve optimal results [17].

3. Materials and the methods

As noted earlier, DNN networks are most often used for the TML approach. Quite often, among medical clinical data, you can find visualized test results, for example: X-rays, or MRI or CT. Then the diagnostic task is a more complex task of computer vision – image recognition. That is why among all possible topologies of DNN networks, we will choose those topologies that best demonstrate themselves in working with images, namely: CNN, DenseNet, VGG16, ResNet and InceptionNet [18]-[20]. For clarity, we will compare all the considered topologies in the form of a table: Table.2.

The CNN architecture is one of the most common architectures for image processing. It consists of several layers:

- convolutional layers: key components for identifying image features such as contours, textures, etc.;
- pooling layers: reduce image size while maintaining important features;
- fully connected layers: exit at the last stage for classification or regression.

Overall, CNNs are highly efficient in image recognition due to their ability to process spatial structures.

DenseNet or Densely Connected Convolutional Networks): this is an improved version of CNN, where each layer has direct connections to all previous layer [18]s. This allows the model to have more context and make better use of information from previous stages. Compared to conventional CNNs, increased learning efficiency is most often noted due to the reduction of the problem of gradient attenuation and improved accuracy due to the stronger exchange of information between layers.

VGG16 or Visual Geometry group 16: this is a deep CNN with 16 layers. It uses small filters (3x3) and large layers for more accurate feature detection. Of course, this architecture is easy to implement and learn thanks to the use of the same filters (3x3) in all layers [19].

The ResNet architecture uses the concept of skip connections, which allows you to skip certain layers and avoid the problem of fading gradients when training deep networks. It can work effectively with very deep networks (up to several hundred layers). And the structural feature improves learning ability by using redundant links that allow you to skip multiple layers without losing important information [20].

Table 2
Comparison of DNN topologies

Characteristics	CNN	DenseNet	VGG 16	ResNet	InceptionNet
Architecture	Base layers with convolution and pooling	Tightly connected layers	Deep CNN with 16 layers	Skip connections	Inception blocks with different filters
Network depth	Usually 10-30 layers	Usually 100-200 layers	16 layers	High (can reach hundreds of layers)	Many depth options depending on the configuration
Main advantage	Easy and efficient image processing	Improved learning thanks to thick connections	Simplicity, works well with small data	Skip layers (skip connections) for deep networks	Higher efficiency thanks to the use of various filters
Disadvantages	May have problems with deep networks	It can be difficult to calculate due to the large number of parameters	Large volumes of parameters, which can be a problem for memory	It can be difficult to train with a lot of parameters	Optimization is required to reduce parameters
Learning speed	Moderate	Slower due to the large number of parameters	Fast training thanks to the simplicity of the architecture	The right setup for an effective workout	High thanks to the combination of different filters
Application in medicine	Diagnostics of medical images, pathology analysis	High-precision image classification	Diagnostics of images with small details	Analysis of complex medical images	Wide real-time application for image analysis

InceptionNet (GoogleNet): this is an architecture that includes the concept of Inception blocks, where filters of different sizes (1x1, 3x3, 5x5) are used for each layer in order to preserve a variety of functions. It differs in that it increases efficiency and reduces the number of parameters by combining filters of different sizes. Well adapted for real-time use [19].

We will use dropout as the basis of transfer training. Dropout is a regularization technique used in DNN to prevent overfitting. It randomly shuts down a certain percentage of neurons during training, which forces the model not to depend on individual neurons and process information more universally. In the context of transfer training, dropout can be used to improve the efficiency and stability of the model [18].

In TML, we often have a model pre-trained on a large set of General Data, and then adapt it to specific data (for example, medical images). Enabling dropout during adaptation reduces the risk of retraining on new data, especially if the amount of data is limited [18].

During fine-tuning, when we adapt an already trained model to a specific task (for example, classification of medical images), dropout helps to avoid over-training on a small data set. This ensures that the model does not remember specific features of training data, but can summarize new examples [20].

TML often involves using models that have been trained on large shared data sets and then adapted to a narrow, specific task (such as detecting specific diseases in medical images). Because new data may be less representative or have fewer examples, dropout helps reduce the likelihood that the model will remember insignificant or noisy data that can cause diagnostic errors [19].

TML often experiments with different dropout values (for example, 0.3-0.5), depending on the task and data availability. Too high a dropout can make learning more difficult, while too low a dropout will not give the desired regularization effect.

4. Experiment

A sample of data on patients with Pneumonia from the Mayo Clinic's Article was selected for the experiment [21].

Images from the entire sample for the experiment will be redistributed as follows, as in Table.3.

Table 3
Data distribution between experiment stages

Train set	
Pneumonia	3875
Normal	1341
Test set	
Pneumonia	390
Normal	234
Validation set	
Pneumonia	8
Normal	8

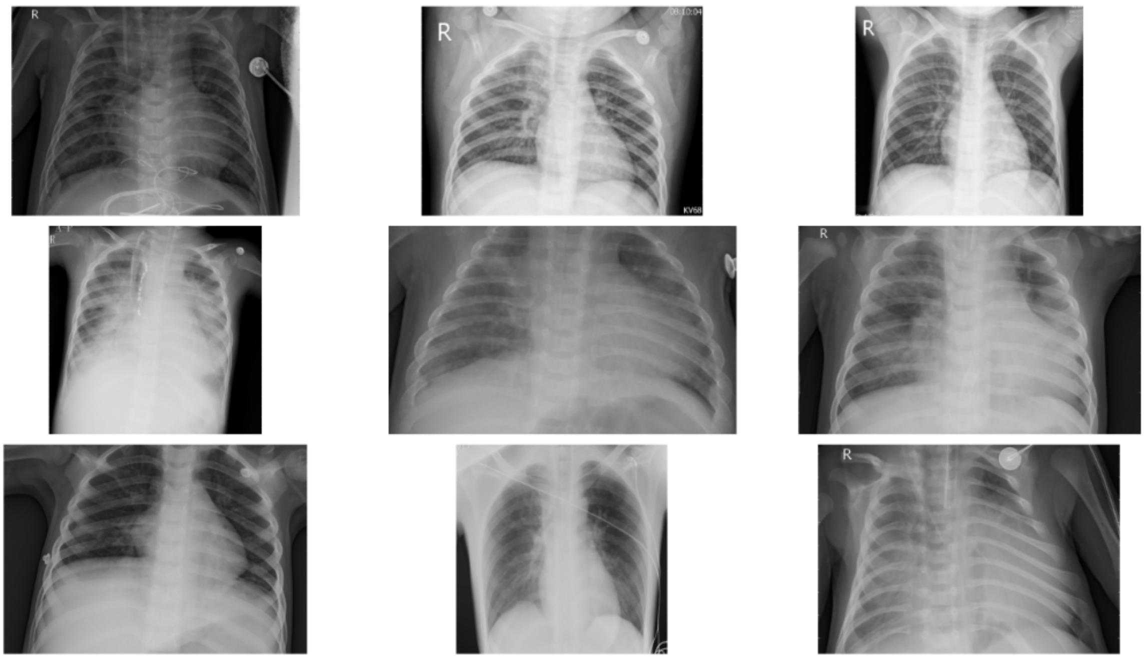

Figure 1: Example of images from a dataset

For all topologies, we define the following training metaparameters: Table. 4

Table 4
Table title

Metaparameter	Value
The number of epochs	10
Batch size	8+1+1
Detect that feature (activation function)	using the ReLU activation

The accuracy of all solutions demonstrates in the Table 5.

Table 5
Data distribution between experiment stages

Neuromodel	Train Accuracy	Test Accuracy
CNN	89.69%	84.62%
DenseNet	92.45%	84.46%
VGG 16	61.81%	65.71%
ResNet	81.96%	81.73%
InceptionNet	69.04%	70.51%

The following Fig.5-6 show the dynamics of changes in diagnostic accuracy.

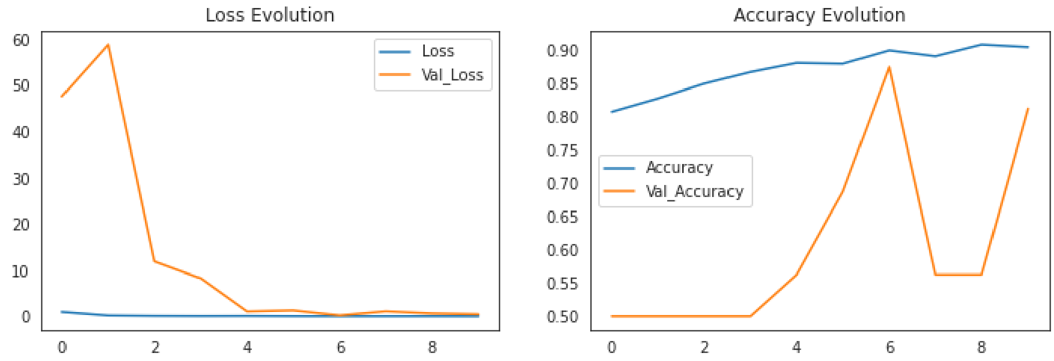

Figure 2: The dynamics of changes in diagnostic accuracy for CNN neuromodel

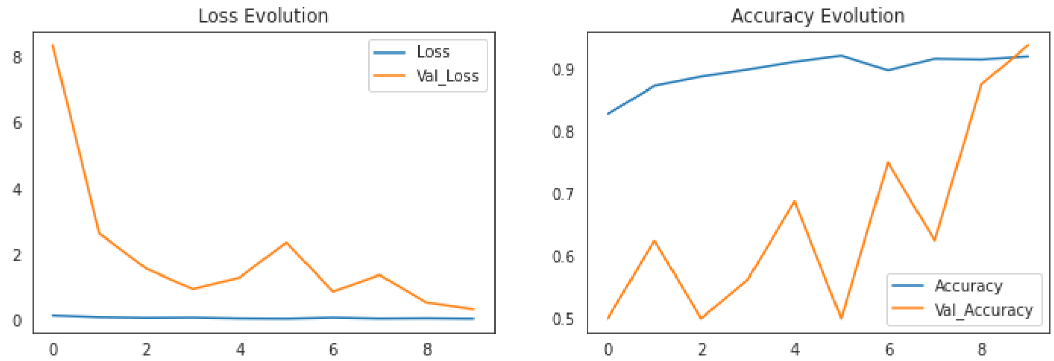

Figure 3: The dynamics of changes in diagnostic accuracy for DenseNet neuromodel

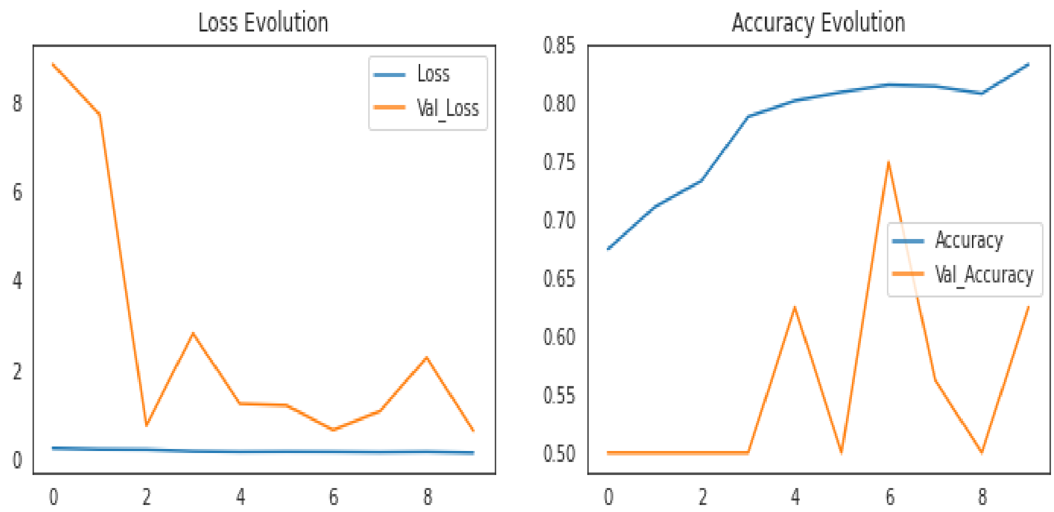

Figure 4: The dynamics of changes in diagnostic accuracy for VGG 16 neuromodel

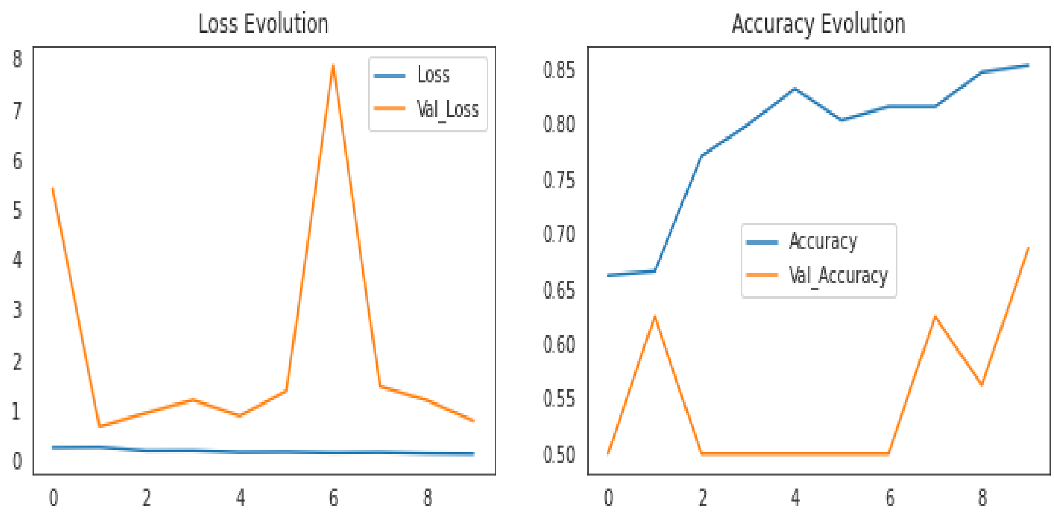

Figure 5: The dynamics of changes in diagnostic accuracy for ResNet neuromodel

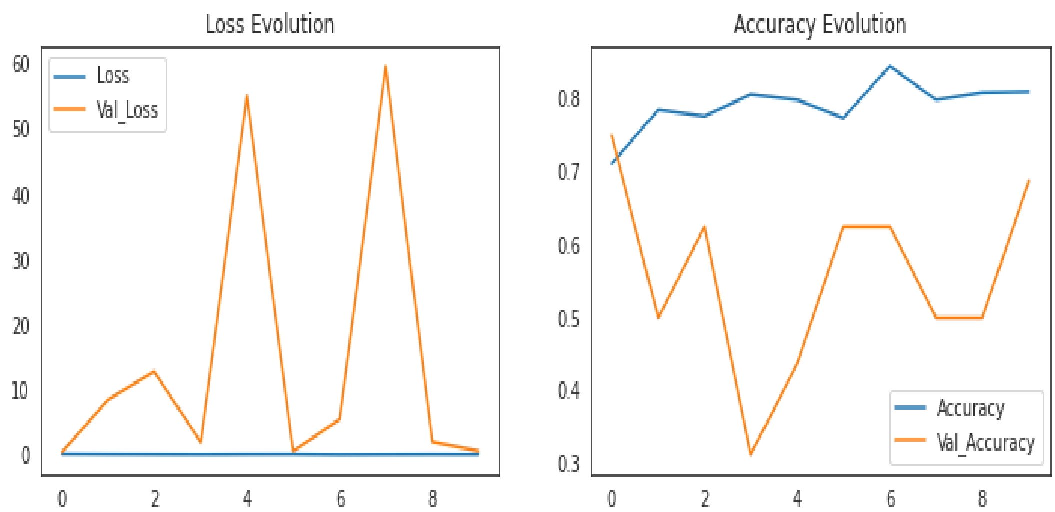

Figure 6: The dynamics of changes in diagnostic accuracy for InceptionNet neuromodel

5. Analysis of results

The analysis of the results should begin with noting the striking difference in accuracy between classical CNNs and all other types of DNNs. Most notably, the difference is not even 10-15%.

There are several possible explanations for why CNNs performed better in X-ray image classification compared to more advanced architectures such as DenseNet, VGG16, ResNet, and InceptionNet.

Firstly, it is simplicity of structure and lack of parameter overload. More modern architectures, such as ResNet or DenseNet, contain a large number of parameters and complex mechanisms that are optimized for processing very deep and complex images, such as ImageNet. X-ray images typically have fewer high-level texture features, so simpler CNNs can learn more efficiently without the risk of overfitting.

Secondly, it is limited variability in X-ray images. Unlike natural images (with huge variations in textures, colors, and objects), X-ray images have a similar structure and fewer unique features to extract. Conventional CNNs can quickly learn to extract the necessary medical features without the need for complex mechanisms like ResNet (residual connections) or DenseNet (dense layer connectivity).

Moreover, retraining and data requirements. Deep networks like ResNet or InceptionNet require very large amounts of data to train effectively. If your X-ray dataset is not large enough, then deeper architectures may not reach their maximum efficiency and may need to be retrained.

Further, artifacts and noise in medical images. Deeper architectures may be more sensitive to artifacts, noise, or contrast variations in X-ray images. Conventional CNNs, due to their simplicity, can learn to ignore unnecessary details and focus only on key patterns.

Finally, model optimization and adaptation. Some modern architectures are optimized for color or more variable images, while X-rays are usually black and white (grayscale). This can lead to inefficient use of many filters in large networks. Limitations in hardware resources

More complex networks require significantly more computing resources for inference. If the system used for training and testing had limited capabilities (e.g., weaker GPUs or limited memory), this could affect the performance of complex architectures.

6. Conclusion

For image-based medical diagnoses, each of these architectures has its advantages. CNN is a classic and efficient method, suitable for basic tasks. DenseNet and ResNet provide better deep network processing capability and reduce training problems, so they are suitable for more complex medical images. VGG16 is a great option for simple but accurate tasks. InceptionNet is optimal for reducing the number of parameters and improving efficiency, which is important for real-world medical applications.

Benefits of using transfer learning and dropout, in particular:

Reduced overfitting: The model becomes less prone to overfitting on new data, which is especially important when working with small medical datasets.

Improved generalization: Thanks to regularization, the model can better generalize knowledge and transfer it to new, previously unknown examples.

Improved learning stability: Combined with fine-tuning techniques, dropout helps the model consistently achieve optimal results without large fluctuations in performance on validation data.

Dropout is a useful technique for transfer learning, especially when adapting models to specific tasks with limited data, such as medical diagnosis. By using dropout during fine-tuning, you can effectively reduce the risks of overfitting and improve the model's ability to generalize to new examples.

Transfer learning has a great future in medical diagnostics, as it allows to effectively use knowledge from large datasets to analyze X-ray, CT, or MRI images, even when annotated medical data is limited. This significantly reduces training time and improves the quality of predictions, especially if the models are adapted to the specifics of medical images.

However, it is important to keep in mind that standard architectures trained on ImageNet are not always optimal for medical tasks, so they should be modified to take into account specific data features. In general, transfer learning is a promising approach that has already demonstrated success in clinical practice, but requires careful validation and adaptation to specific medical cases.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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