[1] Zobeda Hatif Naji Al-Azzwi1

[2] Alexey N. Nazarov

Medical image Classification using Transfer Learning: Convolutional Neural Network Models approach

Abstract: A relatively low life expectancy in their greatest grade is caused by more debilitating diseases in the medical sector. Any kind of misdiagnosis may lead to improper medical intervention and lower the likelihood that a patient will survive. Making an appropriate treatment plan to cure and enhance the quality of life for patients suffering from any kind of illness starts with an accurate diagnosis. Convolutional neural networks and computer-aided disease detection systems have produced success stories and advanced the science of machine learning significantly. Compared to more conventional neural network layers, the deep convolutional layers automatically extract significant and reliable characteristics from the input space. Within the suggested structure, we use two convolutional neural network architectures (VGG16 and VGG19) to perform two types of medical imaging (x-ray and MRI) investigations in order to categorize brain tumors as normal and up normal as well as classify x-ray pneumonia or normal. The transfer learning strategies by VGG16 and vgg19 models that is, using MRI and x-ray to fine-tune and freeze are then examined in each investigation. In order to increase dataset samples and decrease the likelihood of over-fitting, data augmentation techniques are performed to MRI slices and x-rays for results that can be more broadly utilized. In the proposed studies, the fine-tune VGG19, VGG16 architecture attained highest accuracy up to 0.95with x-ray and 0.80 respectively. The accuracy0.98 used MRI in terms of classification and detection with VGG19.

Keywords: Transfer learning, deep learning, X-ray, MRI

I. INTRODUCTION

Transfer learning(TL) is a machine learning technique where a model learned on one task is modified to perform a related but distinct task. The process of improving a neural network model that has previously been trained on a new dataset or task is known as transfer learning in deep learning. TL is one of approach of Deep learning DL and DL is a subset of machine learning.

Deep learning has showed promise in a variety of sectors, most notably medicine. This method does still have certain limitations, though, such as the small number of classified medical photos needed to train deep learning models. Transfer learning, which applies the knowledge from previously trained models on ImageNet to the current job, has emerged as a solution to this problem. That leaves open, nevertheless, the fact that the features taken from ImageNet are not medical.[1]. The process of Computer Assisted Diagnostics (CAD) and medical image interpreting is largely driven by machine learning.

Rather than employing features that have been analytically retrieved, convolutional neural networks (CNNs) have the potential to learn features directly from the visual data, enabling computer-aided diagnosis (CAD). However, because tumor appearances differ and sample sizes are tiny, CNNs for medical imaging are challenging to train from scratch. Alternatively, the need for huge datasets can be eliminated by using transfer learning to extract tumor information from medical images using CNNs that were pretrained for non-medical tasks.[2]

[1] Moscow Institute of Physics and Technology (MIPT)/Phystech School of Radio Engineering and Computer Technologies (FRKT) Department of Intelligent Information Systems and Technologies.

ORCID: https://orcid.org/0000-0002-8504-4170

Moscow, Russia

Email: al-azzavi.z@phystech.edu

[2] Federal Research Center Computer Science and Control of Russian Academy of Sciences Moscow, Russia/SPIN РИНЦ: 6032-5302

ORCID: 0000-0002-0497-0296

ResearcherID: G-3154-2013

Scopus AuthorID: 7201780424/

Email: a.nazarov06@bk.ru

Medical image classification (MIC) uses transfer learning (TL) from pretrained deep models as usual procedure. It depends on the specific situation at hand as to which feature levels should be reused, and evenly fine-tuning every layer of pretrained models may not be the best approach. Recent differential training procedures, including layer-wise finetuning (LWFT) and transfusion (TF), which treat the layers in the pretrained models differently, are partially inspired by this realization[3].

The contribution of this paper is to give a comprehensive understanding of transfer learning, give details about the most common state of the art in deep learning, and improve learning in the target domain by leveraging knowledge from the source domain and learning tasks. This study helps the health industry, because responding rapidly to an emergency is essential.

This study's primary goal is to develop an effective deep learning model for medical image disease classification and present a comparative analysis of these models for two-class MRI and x-ray classification issues. Our research can shorten the time needed to diagnose a condition based on an MRI or X-ray image, which can also decrease the likelihood of human error. Additionally, it helps lower the patients' expenses. CNN models are constantly evolving; therefore, by identifying the most effective ones, we can enhance the services provided to the health sector.

The remainder of the document is structured as follows: We have examined the relevant paper materials and their research analogies in Section II. Section III covers a synopsis methods and dataset of a brain MRI and X-ray analysis, and a quick summary of public ally accessible brain MRI datasets. The many CNN models, pre-trained models, and transfer learning are explained by materials and models. Part IV. in the outcome and discussion.

II. RESEARCH METHOD

A. Related work

In this section illustration the contribution of Transfer learning TL with different approach of medical fields

In this paper focused on Breast cancer,[1] seeks to address this issue by reducing the impact of ImageNet by utilizing novel approaches for transfer learning and the availability of unlabeled medical photos of the same illness. In order to categorize the histological images of breast cancer in the ICIAR 2018 dataset into four classes invasive carcinoma, in situ carcinoma, benign, and normal the suggested method was applied to the modified Xception model. The suggested method received scores of 99.14%, 99.003%, 98.995%, 99%, 98.55%, and 99.14% for sensitivity, accuracy, precision, recall, and F1-score.

In this study focused on tumor brain included [4] Gliomas, meningiomas, and pituitary tumors were the three forms of brain tumors that they classified using the brain contrast-enhanced magnetic resonance imaging (CE-MRI) benchmark dataset. In order to investigate the effects of minimal pre-processing on classification performance and time consumption, the trained model architectures in this work were subjected to three distinct epoch numbers. Furthermore, the study offers respectable outcomes with a restricted number of epochs in a short amount of time. The suggested approach performs better than the most advanced techniques, with a classification accuracy of 98.71%.

In this study [5] used six deep learning algorithms on two brain tumor datasets (individually and manually combined) and one Alzheimer's dataset: InceptionV3, ResNet152V2, MobileNetV2, Resnet50, EfficientNetB0, and DenseNet201. With a total of 7,023 images 5,712 for training and 1,311 for testing the first brain tumor dataset exhibits testing accuracy of 98–99 percent and training accuracy of 99–100 percent. With a total of 3,264 images 2,870 for training and 394 for testing the second tumor dataset shows 100% training accuracy and 69–81 percent testing accuracy. With 10,000 images total 8,000 for training and 2,000 for testing the combined dataset yields 99–100% training accuracy and 98–99% testing accuracy. The Alzheimer's dataset, which consists of 6,400 images total 5,121 for training and 1,279 for testing has testing accuracy of 71–78 percent and training accuracy of 99–100 percent.

In this paper, [6] Through training from scratch and transfer learning, they investigate the most suitable technique for categorizing musculoskeletal pictures. Six cutting-edge architectures were used, and their performance was compared to that of a network trained from scratch and transfer learning. Based on the findings, transfer learning did improve the model's performance considerably and reduced its propensity for overfitting.

In this paper [7], presents a universal approach that is, an Internet of Medical Things (IoMT) proposal for the classification of medical images. It was designed in two steps: first, we use MobileNetV3 to perform a Transfer Learning (TL)-based method for feature extraction; second, we use Chaos Game Optimization (CGO) for feature selection, aiming to eliminate superfluous features and enhance performance a crucial aspect of IoMT. We assessed our methods with the Blood-Cell, PH2, and ISIC-2016 datasets. According to the experimental findings, the suggested method achieved accuracy of 97.52% on PH2, 88.79% on Blood-cell, and 88.39% on ISIC-2016. Furthermore, our strategy outperformed other current approaches in terms of the measures used.

B. CNN Architectures for Image Classification

One kind of deep learning technique that is frequently used for image recognition and classification applications is the convolutional neural network (CNN). CNNs are designed to recognize feature spatial hierarchies from input data in an automatic and flexible manner. Among the layers that comprise them are convolutional, pooling, and fully connected layers. Convolutional layers use filters or kernels to apply convolution operations on the input data and extract different features. Pooling layers serve to control overfitting and reduce computational complexity by reducing the spatial dimensions of the feature maps produced by the convolutional layers.

To create predictions, fully linked layers, which are usually found at the network's end, incorporate the retrieved characteristics. In a variety of computer vision applications, including object identification, image segmentation, and facial recognition, CNNs have demonstrated remarkable effectiveness. Convolutional Neural Networks (CNNs) have seen significant advancements from 2012 to 2020, with various architectures and improvements contributing to their development.

Here's a brief overview of some notable CNN models during this period: **AlexNet**[8] (2012): presented by Geoffrey Hinton, Ilya Sutskever, and Alex Krizhevsky. The 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) champion. first used deep CNNs—which have three fully connected layers after five convolutional layers—for image classification tasks. **ZFNet** [9](2013):Developed by Matthew D. Zeiler and Rob Fergus. A modified version of AlexNet with enhanced visualization techniques. **GoogLeNet/Inception**[10] (2014): Developed by researchers at Google (Szegedy et al.). Introduced the inception module, aimed at improving computational efficiency. Winner of the ILSVRC 2014. **VGGNet**[11] (2014): Developed by the Visual Graphics Group (VGG) at the University of Oxford. Known for its simplicity and depth, consisting of 16-19 layers. Performed excellent performance on ImageNet classification tasks. **ResNet** [12](2015): Proposed by Kaiming He et al. from Microsoft Research. vanishing gradient issue was addressed by the introduction of residual connections, which allowed for the training of extremely deep networks (50–152 layers). Winner of the ILSVRC 2015. **DenseNet** [13] (2016): given by Kilian Q. Weinberger, Laurens van der Maaten, Gao Huang, and Zhuang Liu. makes use of extensive connections between layers, such that all inputs from previous layers are received by each layer. enhances the propagation of features and solves the vanishing-gradient issue. **MobileNet** [14] (2017): Created by Andrew G. Howard and colleagues at Google. Designed with speed and efficiency in mind, for mobile and embedded vision applications. makes use of depthwise separable convolutions to minimize computation without sacrificing efficiency. EfficientNet [15](2019): suggested by Google's Mingxing Tan and Quoc V. Le. uses a complex scaling technique to optimize efficiency by balancing network depth, width, and resolution.

Vision Transformer[16] (ViT) (2020): presented by Google Research's Alexey Dosovitskiy and colleagues. uses the transformer architecture for picture classification tasks, which was first created for natural language processing. Competitor performance was attained by considering images as collections of patches. ResNeSt (2020)[17]proposed by Microsoft Research Asia's Hang Zhang et al. improves feature representation by introducing the Split-Attention technique. surpasses ResNet in accuracy across a range of metrics. These are a few of the most notable CNN structure from 2012 to 2021, each of which made a distinct contribution to the advancement of computer vision and deep learning. The use of deep learning in many fields, particularly the medical field, has shown promise. This method does still have certain limitations, though, such as the small number of classified medical photos needed to train deep learning models. Transfer learning, which applies the knowledge from previously trained models on ImageNet to the current job, has emerged as a solution to this problem. The fact that the features taken from ImageNet are not medical features is still a problem, though.

III. MATAILEAS AND METHODS

A. PREPROCESSING DATA SET

Preprocessing, as used in deep learning, describes the actions done to get raw data ready for feeding into a neural network model for training or inference. Preprocessing is crucial because it ensures that the data is in a format that the network can use to train from, which enhances the model's robustness, performance, and efficiency.

Examples of varied medical images from the two distinct medical image acquisition modalities—MRI and X-ray—are shown in Figures 1 and 2, respectively. Images of the inside of the body are created using radiation, similar to that used in x-rays. The way that various body structures, such as soft tissues and bones, absorb x-ray radiation as it passes through your body creates an image. Radiography is another term for X-ray imaging.

An MRI scan is a type of medical imaging that uses radio waves and a magnetic field to produce images of the inside of your body. It is used to investigate or diagnose brain cancers that affect soft tissue or disorders of the brain. A significant amount of images in the same medical image acquisition modalities are gathered from multisite sources for the classification task in the sparse labeled or small-scale target medical images. Both datasets download from Kaggle as shown in figuer1 and 2, MRI which is available online for free athttps://www. kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection. X-ray which is available https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

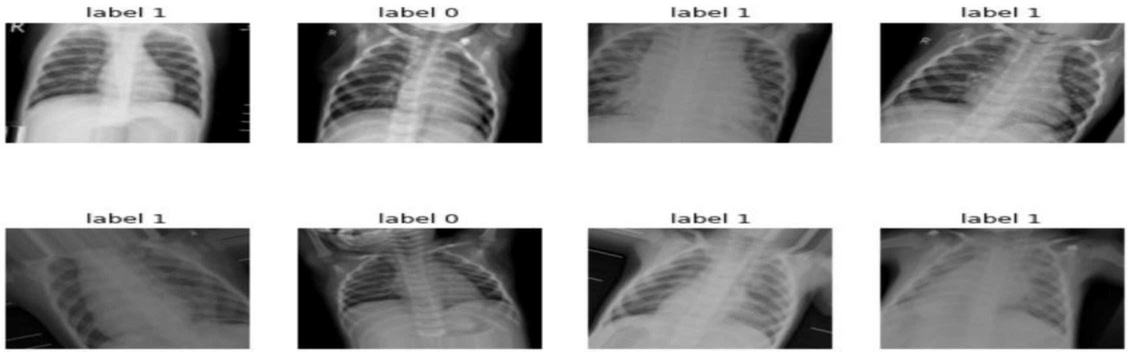


Figure 1: Sample of X-ray.

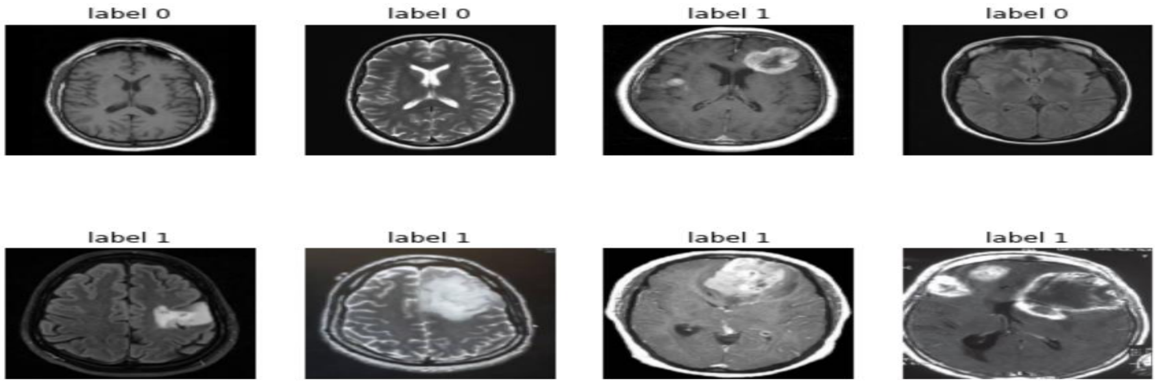


Figure 2 :Sample of MRI.

Image preprocessing is the process of transforming photos to standardize their appearance and size by cropping, resizing, or applying filters. To improve performance of transfer learning in this study we conducted Data augmentation and normalization are two further methods to image preparation. In order to ensure that the input data is properly conditioned and appropriate for training the neural network, preprocessing is essential to deep learning. We are taking in our consideration many step startedbyrescaling=1./255.width_shift_range=0.1,height_shift_range=0.1,shear_range=0.1,zoom_range=0.1,rotation_range=30brightness_range=(0.5, 1.0)

B. Pre-trained model and Transfer learning

A model that has already been trained to address a comparable problem is known as a pre-trained model[8-17]. To handle a similar problem, any one uses the model that was trained on another problem as a starting point rather than creating a new model from scratch. The suggested accessibility of hardware improvements, large data training, and computational resources encouraged innovation and renewal and helped the CNN's algorithms for a variety of tasks, including object identification, image segmentation, and classification [7-14]. The effectiveness of CNN in image categorization was attributed to a number of aspects besides the ones already mentioned[18]. The model's weights are preinitialized when a pretrained version is used, as opposed to randomly initialized while training from scratch[2].

Transfer learning TL, by using weights from one dataset to another, a deep learning model can be trained using a machine learning approach called transfer learning. In the source domain, TL trains the forecast function in the target domain using data from numerous labeled data sets (like ImageNet).[7]. The idea behind this approach is to leverage the patterns discovered from a related work to get a head start, save a ton of computing effort, and achieve the best possible outcome for that model. The weights for the models utilized in this experiment were obtained from the ImageNet dataset, which was used for their prior training. Deep learning is a viable option for tiny datasets, but it takes a high number of samples to train a model for increasing accuracy. TL is frequently employed to overcome the shortcomings of a tiny DL dataset. Ther is difficulties to train a deep learning model from scratch with a tiny dataset.

Pre-trained models(vgg19,vgg16) have been employed for TL in this study, and the final three layers of the model have been fine-tuned to categorize ten different types of defects. When training a network, transfer learning is a simpler method than starting from scratch with a deep learning model[19]. In general, transfer learning is an effective deep learning technique that enables models to use information from datasets or prior tasks to enhance performance on new tasks. As such, it is a useful tool for a variety to solve different tasks [1][20].

Because it can significantly reduce the amount of labeled data and computer resources needed to train a model for a new job by starting with a pre-trained model, transfer learning is particularly useful in scenarios where labeled data is limited or computational power is sparse

C. FINE-TUNING MODELS:

The model's learnt features or parameters are applied as a foundation for training on a fresh, smaller dataset or an alternative task. Only specific layers of the model are adjusted or retrained on the new dataset as opposed to training the entire model from start, which can necessitate a significant quantity of labeled data and processing resources. This lets the model use the information from the pre-trained model and modify its learnt representations to fit the requirements of the current task or dataset. Because there not sufficient dataset, make fine-tuning models necessary. To tailor pre-trained networks to our classification objective, we changed their final three layers. Subsequently, we added another fully connected layer to the same pre-trained networks, replacing the one whose output size indicated the type of medical image. Reduced training time and data requirements.

We are using vgg16 is made up of sixteen completely connected convolutional layers. A stack of convolutional layers precedes the max-pooling layers in the design. It consists of three convolutional layer sets, each with two or three convolutional layers, and max-pooling comes after. The two hidden layers plus the output layer for classification make up the fully connected layers.

In order to maintain the same spatial resolution after convolution, it always pads the input and employs smaller 3x3 convolutional filters with a stride of 1. The network as a whole uses the ReLU activation function. On the ImageNet dataset, VGG16 performed admirably, proving its efficacy in image classification tasks.

And we are using VGG19 is an expansion of VGG16, with a total of 19 layers. Its design is comparable to that of VGG16, however it has more convolutional layers. VGG19's additional layers increase its feature extraction capability, which could lead to an improvement in performance for some jobs. The fundamental components and working concepts of VGG16 remain the same, with extra layers added to deepen the network in between. Similar to VGG16, VGG19 makes use of ReLU activation functions and smaller 3x3 convolutional filters with a stride of 1.

IV. SIMULATION RESULTS, ANALYSIS AND DISCUSSION

Using the colab for implementation VGG19 and VGG16. The purpose of the research was to analyze how well pre-trained transfer learning models performed in classifying the two different kinds of medical images. For every load scenario, we have chosen 2,800 MRI images and 5863 x-ray images for this investigation we have toke5861. For the training and testing samples, these photos have been split into ratios of 80% and 20%, respectively. With x-ray and MRI height, width = (224, 224), batch_size=64, two class (normal:0 and Pneumonia :1), 25 epoch with VGG 19 with Adam optimizer and learning rate 0,01. We are making preprocessing on dataset then training the models and calculate the loss and accuracy as shown in table1. Each data set have taken 5hours for training.

Table 1. vgg19 with x-ray

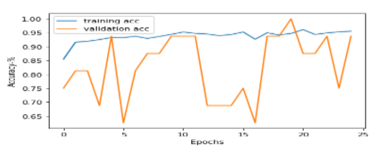
Train Vgg19 after preprocessing	train	validation
loss	0.2067	0.3179
Accuracy	0.954	0.937

To evaluate the pr-trained models different criteria calculated through training as shown Table 2.

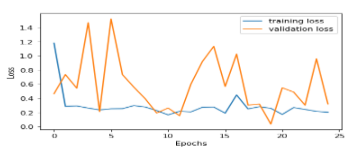
Table 2. Criteria to evaluate model

Binary classification	Precision	Recall	Fl-score
0	0.78	0.86	0.82
1	0.93	0.88	0.90

After make preprocessing on dataset to decrees the loss and try to increase accuracy. We are training the pretrained model. We kept the desired layers of the network while modifying the final layers to match the classes based on our dataset during the fine-tuning procedure. The computation of loss and accuracy is displayed below.



a. Show training and validation accuracy



b. Show training and validation loss

Fig3. display the VGG19 x-ray training and validation plot.

Using VGG16, we get the following results: recall is 0.38 f1-score = 0.53, case precision is 0.43, recall is 0.91 f1-score = 0.59 fo

a normal case. The value of Accuracy and loss as shown in Table3

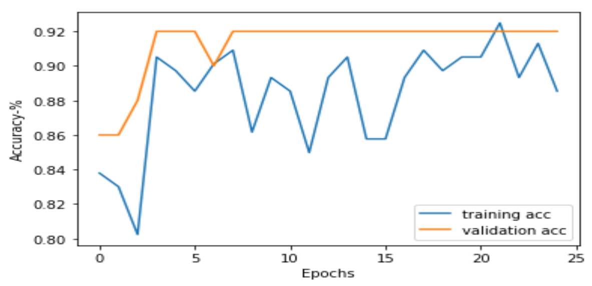
Table 3. Vgg16 with x-ray

VGG16	Training	validation
loss	0.648	0.50
Accuracy	0.801	2.00

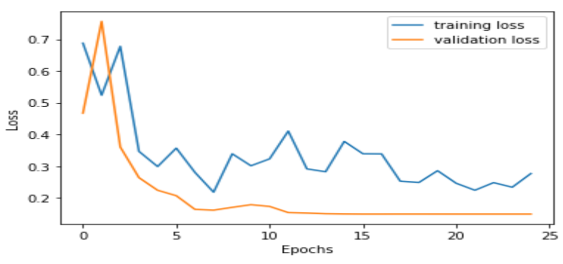
The second stage of our experiment fin-tuning VGG19 with MRI binary classification normal and up normal we l oad the data set to models. In order to help a model increase the precision and performance of its predictions, data augmentation is used in addition to the generation of data variants. In training, augmented data is essential. Then t raining the models With VGG19 size of image 224X224, batch size=64 and Adam optimizer with learning rate=0 .001. We calculate for normal case precision is 0.84, recall is 0.94 f1-score is 0.89, with up normal case precision is 0.97, recall is 0.91 f1-score is 0.94, we take in our consideration Adam optimizer with learning rate 0.01 and ti me training 5hours. The value of Accuracy and loss as shown in table 4.

Table 4. Vgg19 with MRI		
VGG19	training	validation
Loss	0.004	0.140
Accuracy	0.980	0.900

Transfer learning enables models to take advantage of information from datasets or tasks that are similar, whi ch can improve generalization and performance on the new task, particularly if there isn't as much training data available When fine-tuning on smaller datasets, pre-trained models can help avoid overfitting because they have previously acquired valuable features from large datasets.



a. Plot explain accuracy



b. Plot explain loss

Figure4.show the carve accuracy and loss of training VGG19 with MRI

Figure11: The simulation for all parameters in proposed design system.

V. CONCLUSION

Through training pre trained models we find Transfer learning makes greater performance and generalization feasible by enabling models to utilize data from similar datasets or tasks. This can help with performance and generalization on the new work, especially when training data is scarce. Pre-trained models can help prevent overfitting since they have already gained important features from big datasets. Robustness against overfitting can be achieved by fine-tuning on smaller datasets. This study stands as a significant stride towards advancing transfer learning framework systems, proposing an accelerated and more efficient pathway to diagnoses daises early.

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NOMENCLATURE

TL Transfer learning.

DL Deep learning.

CNN Convolution neural net work

CAD computer-aided diagnosis

MIC Medical Image classification

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