Design and Implementation of Differentiated Analytics Workflow for Imaging Diagnostics on the Intelligent Integrated Digital Platform InSilicoKDD

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Abstract. In this paper we have proposed a conceptual model of differential analytical scientific workflow for imaging diagnostics of abnormal pneumonias. The model is based on the method of deep convolutional neural networks (CNN) and the approach of Gradient-weighted Class Activation Mapping (Grad-CAM), which uses specific for the class information from the gradient, incoming in the last convolutional layer of CNN, in order to create rough map of localization of important region within the medical image. The proposed conceptual model is implement in Python with Google's open source framework Tensorflow and Keras. In the development process, we have used customized Jupiter Notebook – Colab. For the creation and visualization plots we used Matplotlib. Neural Networks are pre-trained with ImageNet dataset, which consist of large amount of non-medical images. The experimental results for the 5 types of convolutional neural networks show accuracy more than 95%. The models for image diagnostics are integrated within the machine learning section of the intelligent platform for big biomedical data analytics InSilicoKDD.

INTRODUCTION

Nowadays personalized and precision medicine are innovative and hot trends worldwide [1]. The idea behind them is to prescribe personalized treatment for every patient according to his/her individual characteristics like genetics, environment, family history and individual risk factors. As far as precision medicine is concerned the enormous amount of information that has to be analyzed and interpreted has involved advanced IT in support of precision medicine as a crucial factor for its efficiency and applicability. Actually, Big Data analytics and Internet of medical Things make precision medicine a reality [3]. The fourth paradigm for Data-Intensive-Scientific-Discovery [2] and the digital platforms based on this innovative paradigm and scientific workflows have given great stimulus for scientific investigation in all areas of scientific study.

In our previous work we have proposed conceptual model of integrated approach for in silico knowledge biomedical data discovery for breast cancer diagnostics and precision therapy [4] on the basis of which we have implemented and deployed intelligent integrated digital platform InSilicoKDD in support of precision medicine for scientific research that has been verified and validated for the breast cancer issue [5].

Following our conceptual model of integrated approach for in silico knowledge biomedical data discovery, in this paper we present the model, design and implementation of differentiated analytics workflow for image diagnostics which we have built up and integrated within the scientific analytics workflow of the machine learning section of our InSilicoKDD prototype.

CONCEPTUAL MODEL OF DIFFERENTIAL ANALYTICAL SCIENTIFIC WORKFLOW FOR IMAGING DIAGNOSTICS OF PNEUMONIAS

Pneumonia is one of the most often occurring infection of lungs worldwide. The most common symptoms of pneumonia include cough, fever, and trouble breathing. Worldwide pneumonia kills more the 1 million children, which is around 16% of all deaths of children who are under 5 years old. The pneumonia affects people of all ages and nations, but most affected are people from South Asia and sub-Saharan Africa. In USA every year more then 250 000 people are admitted to hospital due to pneumonia and around 50 000 cases of them have lethal outcome [6,7].

For the purpose of diagnostics, the medical doctor first of all checks for symptoms of the disease. Furthermore, the doctor subjects to analysis X-Ray images for sights of the lungs, caused by pneumonia. X-ray images are created by using very small dose of ionizing radiation. Pneumonia causes white spots in lungs, called infiltrates [8].

Nowadays, there exists a wide spectrum of digital platforms, cloud services, methods and algorithms in support of medical imaging and diagnostics [9,10]. Deep learning has proved to be a very successful method and technology for medical image diagnostics [11,12,13]. Deep learning models consists of multiple computation layers. This facilitates the analysis of very complex patterns in image recognition. Convolutional neural networks give opportunities to analyze multidimensional data like images, soundwaves, etc. The image is represented digitally as 2D arrays, where every element of the array represents the intensity of one of the base colors (red, green and blue). The analysis is conducted as series of stages, where each stage consists of two types of layers. Convolutional layers are organized in features maps. Each unit is connected to local batches through a set of weights. They also detect local conjunction of features from the previous layer. Pooling layer combines semantically similar features into one single feature [16,17.18]. The conceptual model of differentiated analytic workflow for image diagnostics based on deep learning is shown in Fig.1.

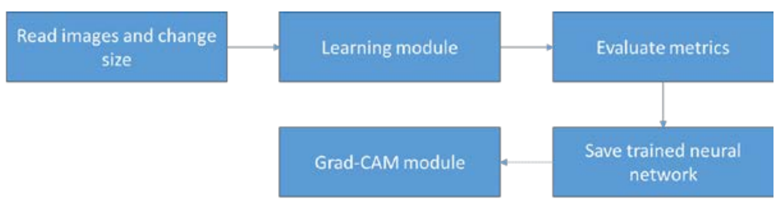

Figure 1: The conceptual model of differentiated analytic workflow for image diagnostics based on deep learning.

Read images module inputs images from the hard drive. For images input we use OpenCV, free open source library for computer vision. It is designed for real-time image processing, but also can be used for reading and processing a single image [20]. After reading, we resize image to 224x224, because we need images to be of the same size on the input of the convolutional neural networks. The learning module creates CNNs with pre-trained weights and performs training with X-Ray image dataset. Learning module can use several convolutional neural networks (VGG-16, VGG-19, Resnet-50, InceptionV3 and Densenet-121). The evaluate metrics module computes precision, accuracy and sensitivity (PAS) parameters in order to evaluate the efficiency of the constructed machine learning models. Grad-CAM module reads the single image, performs Grad-CAM analysis and displays image on the screen with Grad-CAM heat map.

EXPRERIMENTAL TECHNOLOGICAL FRAMEWORK

For the purpose of our research we use python libraries and frameworks to create experimental framework. Python is chosen as being one of the most popular programing languages for implementing machine learning algorithms. Tensorflow [23] is a deep learning framework developed by Google. The framework is very flexible and it can be executed on various systems and can implement a wide range of algorithms. Tensorflow supports single-device execution and executions on multi-device environment, providing APIs on Pyhon, C++ and Java. Keras [24] is built on top of Tensorflow. It offers simple APIs on Python for deep leaning models building and training and minimizes the user efforts. Keras can be scaled up to large clusters. Google Colab [25] is customized Jupiter Notebook, one of the most opular web based development environment for data science. Colab unlike usual Jupiter Notebook, provides opportunities to use Graphical Processing Units (GPUs) free. Numpy is package for scientific numerical computation [26]. To conduct our research and achieve adaptability, we have applied several types of convolutional neural networks

(CNNs). CNNs are pre-trained with ImageNet, which does not have decal data, but have complex features in images. We get pre-trained networks and train them with Keras. For optimization, we use Adam algorithm for optimization of stochastic functions [27]. We have trained networks with 50 epochs, initial learning rate, 3e-4. The learning rate decay is calculated as follows:

$$\text{learning rate decay} = \frac{initial\ learning\ rate}{epochs} \qquad (1)$$

The VGG-16 and VGG-19 are some of the most commonly used convolutional neural networks. They have 16 and 19 layers, respectively. They have ability to recognize very complex features and have good ability to generalize. Inception-V3 is a deep convolutional neural network based on Google Inception Architecture. This neural network is very difficult to be trained, and therefore, we use pre-trained versions of the neural network. Residual networks reformulate layers as residual functions with reference inputs of the layer. Densenet-121 is a densely connected convolution neural network. The difference from other neural networks is that every layer is interconnected to other layers within the network. The number of the direct connections for each layer L is determined as follows:

$$\text{number of direct connections} = \frac{L(L+1)}{2} \qquad (2)$$

Grad-CAM (Gradient-weighted Class Activation Mapping) is applied to “visual-explain” the decision of large convolutional network. This method uses gradients to detect regions of interest within the image. Big advantage of this method is that you should not change the architecture or retrain CNN. The evaluation of gradient starts from the last convolution layer and ends at the first layer. The method creates colorful heat map, and we combine both the image input and the heat map. It is very useful in the case of X-Ray diagnosis because it gives the opportunity to identify the important regions with anomalies.

Network weights are saved in .h5 file format. This format is Hierarchical Data Format (HDF) and supports multidimensional arrays. It is used to save weights of trained neural network. For visualization of the image and the identification of abnormal region we have applied the visualization library Matplotlib in Python.

The requirement for the experimental dataset is that should be binary classified. The dataset comprises chest X-Ray images of chest (Pneumonia) from real patients from the clinical care in Children’s Medical Center, Guangzhou, China. The dataset is cut into train validation and test partitions. Figure 2 shows the number of images in the dataset and its distribution. The dataset consists of X-Ray images. The train partition includes 1341 normal images and 3875 images with detected pneumonia, while the validation set comprises 234 normal images and 390 images with detected pneumonia. Each image is classified into one of two categories:

1. Normal – images of normal chest and lungs without sign of pneumonia
2. Pneumonia – images with signs of pneumonia

EXPERIMENTAL RESULTS AND ANALYSIS

We have verified our differentiated diagnostic workflow with image dataset of X-Ray images of pneumonias. We have trained a few neural networks and have compared their results. Every images has been resized to 224 pixels because every image in the dataset is with different resolution and aspect ratio.

Case study VGG16: Convolutional Network for Classification and Detection. VGG-16 has 138,357,544 parameters and depth 23. The network is pre-trained with ImageNet dataset. The results from GRAD-CAM are shown in table 1. The visualization of the identified region including the heat map in a medical image is shown in Fig.2. The training loss and accuracy versus the number of the epochs for the case study of VGG-19 is shown in Fig.3.

Table 1. Case study VGG16: Convolutional Network for Classification and Detection.

	Confusion matrix	
	Predicted NO	***Predicted YES***
Actual NO	True negative 285	False positive 16
Actual Yes	False negative 3	True positive 450

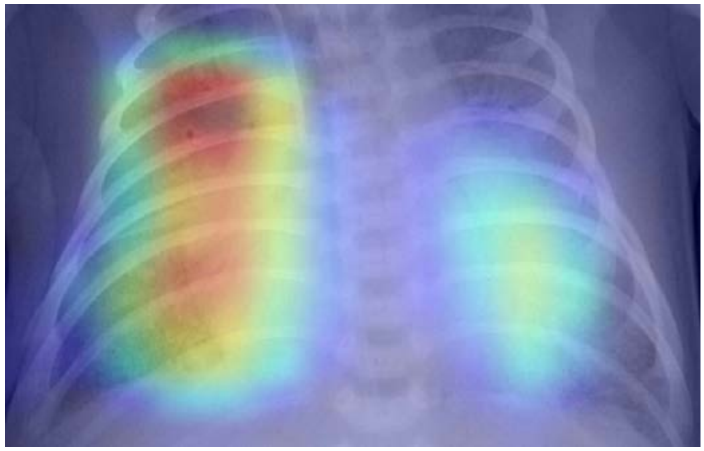

Figure 2: Visualization of the identified region including the heat map in a medical image for the case study VGG16: Convolutional Network for Classification and Detection.

Case study InceptionV3. In this case study CNN has 23,851,784 parameters and the depth is 159. The network is pre-trained with ImageNet dataset. The results from GRAD-CAM are shown in table 2. The training loss and accuracy versus the number of the epochs for the case study of InceptionV3 is shown in Fig.4.

Table 2. Case study InceptionV3.

	Confusion matrix	
	Predicted NO	***Predicted YES***
Actual NO	True negative 276	False positive 19
Actual Yes	False negative 9	True positive 492

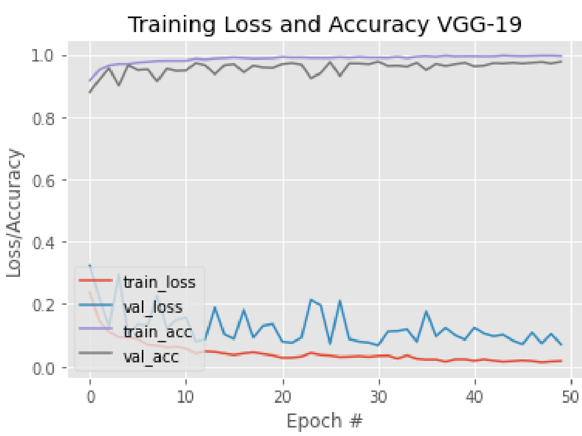

Figure 3: The training loss and accuracy versus the number of the epochs for the case study of VGG-19

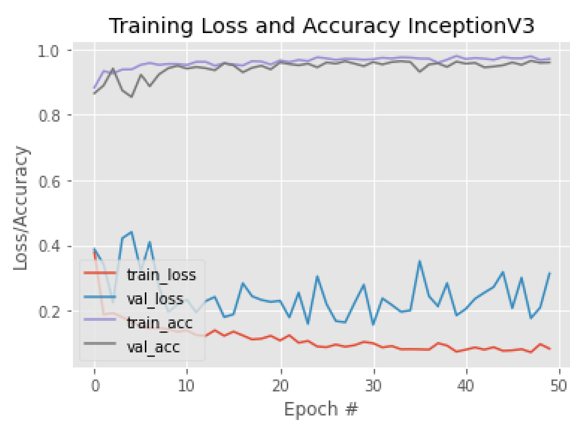

Figure 4: The training loss and accuracy versus the number of the epochs for the case study of InceptionV3

Case study RESNET 50. In this case study the CNN has 25,636,712 parameters. The network is pre-trained with ImageNet dataset. The results from GRAD-CAM are shown in table 3. The training loss and accuracy versus the number of the epochs for the case study of RESNET 50 are shown in Fig.5.The visualization of the identified abnormal region including the heat map in a medical image is shown in Fig.6.

Table 3. Case study RESNET 50.

	Confusion matrix	
	Predicted NO	***Predicted YES***
Actual NO	True negative 328	False positive 32
Actual Yes	False negative 8	True positive 471

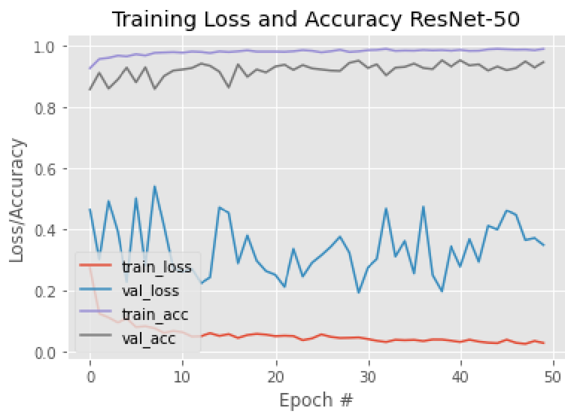

Figure 5: The training loss and accuracy versus the number of the epochs for the case study of RESNET-50

Figure 6: Visualization of the identified abnormal region including the heat map in a medical image for the case study of RESNET-50.

Case study DENSENET 121. It has 8,062,504 parameters and depth 121.The network is pre-trained with ImageNet dataset. The results from GRAD-CAM are shown in table 4. The training loss and accuracy versus the number of the epochs for the case study of DENSENET 121 are shown in Fig.7.

Table 4. Case study RESNET 50.

	Confusion matrix	
	Predicted NO	***Predicted YES***
Actual NO	True negative 328	False positive 32
Actual Yes	False negative 8	True positive 471

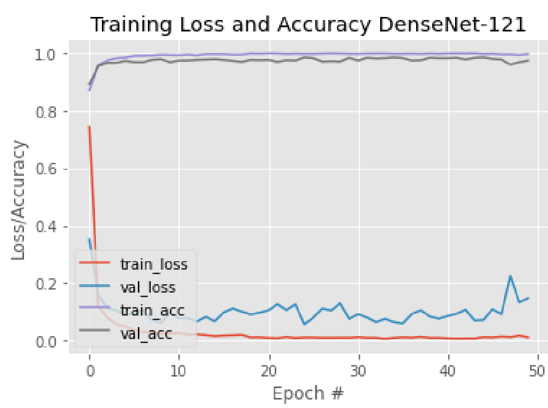

Figure 7: The training loss and accuracy versus the number of the epochs for the case study of DENSENET 121

The evaluation results of Precision, Accuracy and Sensitivity (PAS) for the 5 types of the experimental CNNs are summarized in Fig. 8. Obviously, all proposed models achieve more the 95% accuracy. The case study of DENSENET 121 shows the best results in respect to the PAS evaluation while VGG-16 shows the highest value of sensitivity.

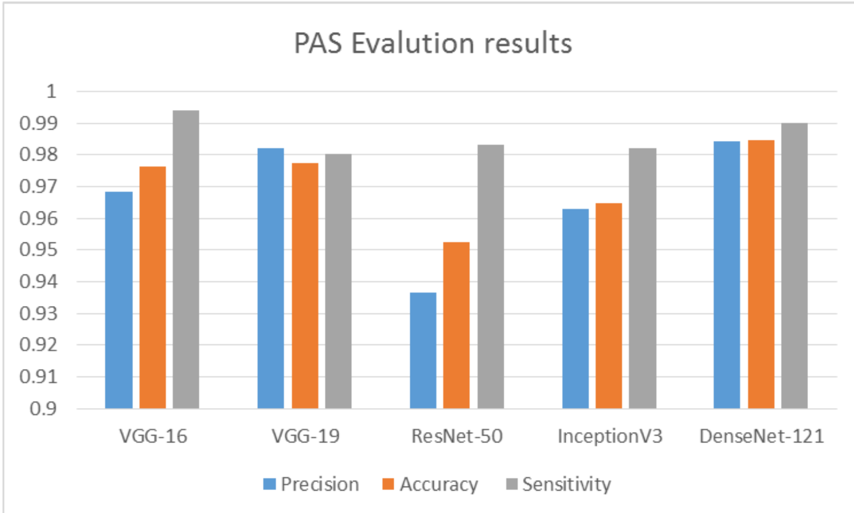

Figure 8. The evaluation results of Precision Accuracy and Sensitivity (PAS) for the 5 types of experimental CNN's

CONCLUSION AND FEATURE WORK

The experimental models preform with very high PAS metric results. Every model has more than 95% accuracy. The Grad-CAM method is preforming also very well. It marks out the zones in chest X-Ray image with infiltrates. In the future, we will create models that recognize different types of pneumonias including pneumonia caused by COVID-19. This field of study is very innovative and perspective, because in precision medicine it is essential to conduct personized diagnosis for every person and investigate the impact of specific factors such as individual life style, genetic inheritance and environmental influence.

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