Using Deep Convolutional Neural Network to Create a DCNN Model for Brain Tumor Detection

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Abstract

Deep Convolutional Neural Networks (DCNN), are used in several areas of a medical image, making possible identification of an irrelevant object exactly where it appears in an image, its orientation or even its scaling. In this work we propose a DCNN model with detailed ontology of different types of the most common forms of cancer and integrate it with our PPIR module for simulation in medical imaging. Our focus is to train it separately for each particular form of cancer and each particular view. The DCNN model will have as input a sequence of images, known images obtained from TCIA (The Cancer Imaging Archive). We aim to use PyTorch to load the dataset and preprocess to prepare for training, specify activation functions, regularization, and other parameters. To train the DCNN we use the training dataset in Matlab and PyTorch's optimization module by specifying a loss function, such as cross-entropy loss, and an optimizer, such as stochastic gradient descent, the learning rate and number of epochs. Finally, we want to evaluate the performance of the trained DCNN using the validation dataset. In our study we used a dataset of MRI patients' examinations. Even though we are in the first steps of building up a model, we aim in the future to use the same DCNN model trained for different forms and levels of cancer.

Index Terms— Neural networks, ANN, Deep convolutional neural networks, (DCNN), medical imaging, prediction, training, cancer.

1. Introduction

A. An overview of artificial neural networks

ANN, Artificial Neural Network (it is a computational model that it is created by the human mind. It is a type of machine learning algorithm that aims to recognize patterns and make predictions by simulating the behavior of interconnected neurons.[1]. These neurons can be modeled using mathematical functions. An Artificial Neural Network is composed by interconnected neurons or nodes organized into layers. An ANN have an input layer, one or more hidden layers, and an output layer. The connections between these neurons, similar to synapses, have their weights that determine the strength of the connection. [2]

The flow of information in an ANN is forward, starting from the input layer, passing through the hidden layers, and finally producing an output in the output layer. Each neuron get inputs from the previous layer, applies a transformation (usually a weighted sum and an activation

4979

function), and passes the result to the next layer. The weights of the connections are adapted during the training process in order to optimize the performance of the network on a given task.
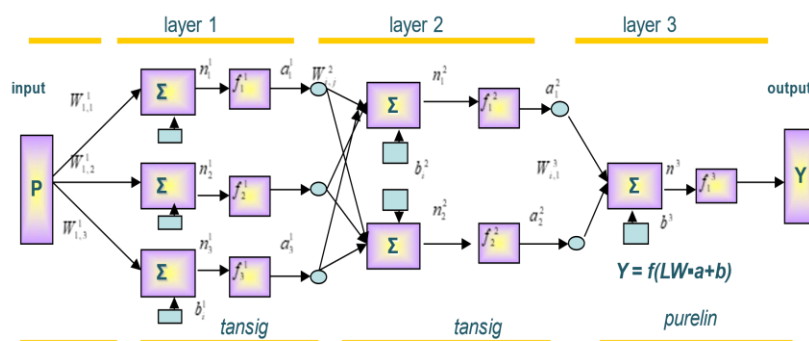

Fig. 1. ANN example

There are two important processes during training an ANN, such are: the forward propagation and the backpropagation. In the forward propagation, the data that serves as input are fed into the network, and the output is computed layer by layer. Then the output taken is compared to the optimum output, and the discrepancy between them it is measured by the error function. The role of the backpropagation is to update the weights in the network by propagating the error backward from the output layer to the input layer. In this way it adjusts the weights according to the gradient of the error function with respect to the weights. [3]. As we know, there are different Artificial Neural Networks such as: Feedforward Neural Network (FNN), Convolutional Neural Network (CNN), Deep Neural Network (DNN) etc. The last one is an ANN that has multiple layers which are hidden. These networks are able to learn complex representations of the data in a hierarchical way. DNN have been successful in different domains, including computer vision, speech recognition, processing of natural language, medical image processing etc.

Deep Neural Networks (DNNs) are big neural network models, with many levels of neurons, that can automatically devise feature extractors from images and analyze visual imagery. Training such large neural networks became possible in the last years due to the evolution of the GPUs that are used to perform computations besides the CPU. [4]
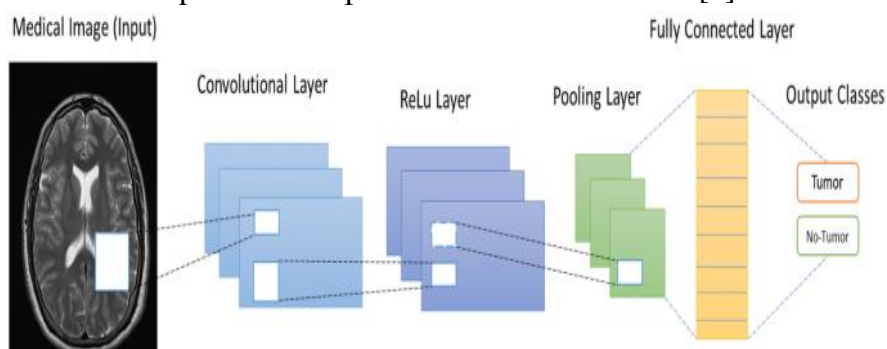

Fig. 2. CNN architecture

Deep Convolutional Neural Networks (DCNNs) are an architecture where all the automatically devised feature extractors are applied many times in several areas of an image, thus making it possible to identify an object irrelevant to where exactly in the image it appears, its orientation or even its scaling. [3]

4980

Eur. Chem. Bull. 2023,12(Special Issue 7), 4979-4989

DCNNs have shown great promise in analyzing and interpreting medical images due to their ability to learn complex visual patterns and features. DCNNs can be applied to medical images such are image classification, object detection, segmentation, image reconstruction, image generation etc., demonstrating great potential in assisting medical professionals in the analysis, interpretation, and diagnosis of medical images, contributing to improved patient care and outcomes.

The most well-known environment to use CNN and DCNN is Matlab [4]. Matlab's Deep Learning Toolbox provides detailed documentation, functions and examples to explore and review to gain a deeper understanding of implementing DCNNs in Matlab. Another way to use CNN and DCNNs is Python, with popular deep learning frameworks such as TensorFlow or PyTorch. Last year we had some applications of medical image processing and ANN use in Matlab. [1]. While Matlab provides a comprehensive environment for deep learning, there are some limitations to consider when using DCNNs in Matlab such as performance, GPU support, model portability, advanced features and flexibility and open-source availability. In the meantime, using DCNNs in Python, provides a powerful and flexible environment for deep learning research and development, with many functions, optimized performance, and extensive customization options. Due to the experience that our working group has in using numerical methods in biomedical images and ANNs in the Matlab environment. [5], [6], [7]. Working with the project "*Development of simulation and forecasting models and integration with the TCIA database of medical images*" [8], supported financially by the Albanian National Agency for Research and Innovation (AKKSHI/NASRI), , we are focusing on the development of our PPIR module segmentation and contouring models also in Python.

2. Methodology

A. Motivation

As mentioned, the main objective of this work is to create a CNN model to detect a tumor in its first stages. This plays an important role in the treatment of the patient until his complete recovery. Based on this importance, our working group is working on a project which aims first at creating a model for study purposes and familiarization by radiologists and oncologists with the capacities of artificial intelligence in determining the correct diagnosis in medical images. Our focus is creating a model for detection of brain tumors using segmentation with neural networks and deep learning methods.

In this topic, many studies have been carried out and the results are now known. [9], [13], [14].

The tumors are classified in two groups depending on, the type of tissue in which the cancer originates and the primary site, that is the location in the body where the tumor it is first developed. Based on the literature [10]. The main brain tumors are: Gliomas, Meningiomas, Pituitary Adenomas, Schwannomas, Medulloblastomas, Craniopharyngiomas. Also, there are some mixed types of cancer, where the type components may be from different categories. We are initially studying brain tumors with the contribution of a radio- surgeon with a long experience in neurosurgery and radiosurgery.

There are several common techniques used for brain tumor detection such are Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography

4981

Eur. Chem. Bull. 2023,12(Special Issue 7), 4979-4989

(PET), Magnetic Resonance Spectroscopy (MRS), Functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG).

B. Preparatory phase

In our study we used a dataset of MRI patients' examinations obtained in different diagnostics centers across Albania. We are in the process of developing the project which initially analyzes the level of use of artificial intelligence and new technologies in medical imaging. Through visits to diagnostic departments in 10 regional hospitals, 3 university hospitals and 7 private hospitals, we have evidenced a low level of use of new technologies, software and programs that enable automation, optimization or the use of artificial intelligence. according to the results of the questionnaire we developed. Regardless of the improvements in the last two years in the installation of some new equipment such as CT and MRI, again, the level of use of artificial intelligence in medical imaging is quite low. In recent years, AI has made significant advancements in the field of medical imaging, revolutionizing the way medical professionals interpret and analyze medical images.

As mentioned, the best environment is Python for ANN and DCNN use [11]. There are several methods to use Python for different purposes which we are testing. In our case we used Matlab to prepare the datasets.

C. Preparing the Dataset

We used MRI brain scans using The Cancer Imaging Archive (TCIA). TCIA is a publicly available, open-access repository that provides a comprehensive collection of cancer-related medical images, associated clinical data, and radiology reports. [12] It is a resource for researchers, clinicians, and educators who work with medical imaging data in the field of oncology. TCIA hosts a wide variety of imaging data, including radiographic images (such as X-rays), , magnetic resonance imaging (MRI), computed tomography (CT),, positron emission tomography (PET)and histopathology images scans. The repository covers various cancer types and stages, allowing us to access and analyze a diverse range of cases. We downloaded MRI brain image datasets from TCIA, along with associated clinical and demographic data, to use as inputs to the DCNN model. This dataset has brain MRI images together with manual fluid attenuated inversion recovery abnormality segmentation masks. In total we selected a set of 150 MRI images from the collection of the lower-grade glioma in the cancer genome atlas that have fluid-attenuated inversion recovery sequence and the genomic cluster data available.
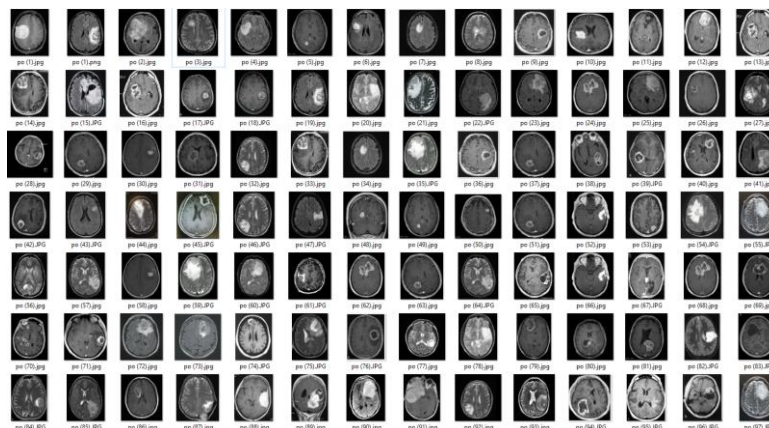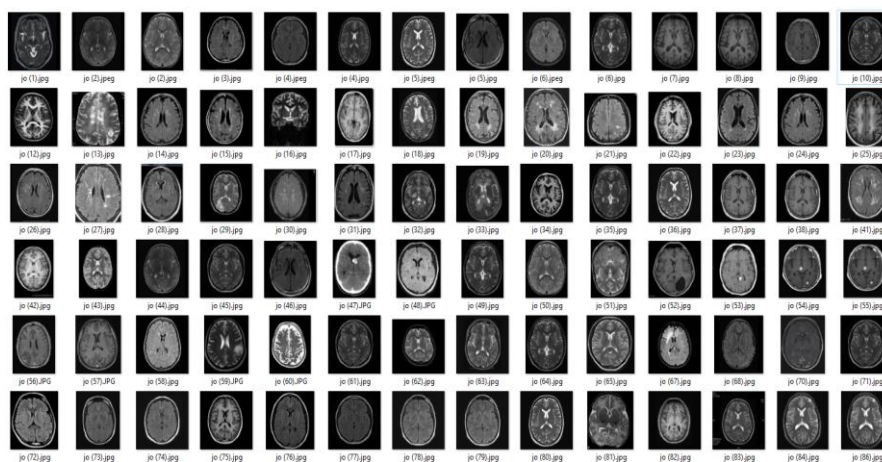

Fig. 3. MRI images that have brain tumor

Fig. 4. MRI images that don't have brain tumor

D. DCNN model

A DCNNs network can be used for a detailed ontology of various types of most common forms of brain cancers. Usually, for each particular form of cancer and each particular view, is a separate trained DCNN. In this way, the DCNN will have as input a sequence of images, as well as various basic metadata, and will produce a set of candidate types of tumors (if any), as well as other potential non-cancer explanations, and either probabilities for each alternative diagnosis or just a ranking between them. It is important to have a large number of studies for all most common forms of brain cancer, including their variations, as well as non-cancer similar findings. [13]

The main objective is to use the same trained DCNN for different forms of cancer or/and for different views of the same form of cancer. (At this phase of our study, it was not possible). After the evaluation of the AI predictive models in a typical medical procedure, a radiologist makes a diagnosis over the taken sequence of images. However, a more accurate diagnosis results after considering further data from subsequent medical tests, e.g., a biopsy. Several metrics to assess the performance of the learned models will be employed, including accuracy, precision, recall, specificity and area under the curve. Explain ability Giving a single or even a differential diagnosis to a patient needs some explanation, in order to convince him to follow an associated treatment.

The number of layers in a DCNN can vary depending on the specific architecture and task requirements. In general, a DCNN typically has a deeper architecture compared to a CNN, with a larger number of layers. In Matlab, with command "*nnstart*", we can open the Neural Network Start GUI, which is a graphical user interface for designing, training, and simulating neural networks. [4] The number of convolutional and pooling layers varies based on the complexity of the input data and the desired level of feature extraction. The specific number of layers in a DCNN depends on factors such as the problem domain, dataset complexity, available computational resources, and the depth at which optimal performance is achieved. In our case due to high performance computing limitations, we started the CNN with a few layers from 10-20. It's important to note that the term "*deep*" in DCNN refers to the depth of the network in terms of the number of layers, rather than a fixed or specific number of layers. We are in the training phase to define the exact number and configuration of layers in our DCNN to finalize the architectural design for our specific model.

We started with a 10-layers CNN framework to perform segmentation and with our colleagues at Department of Radiology, American Hospital 3 in Tirana, we are testing the dataset of MRI brain images from different patients, after the training process of the network. The dataset was splinted into batches with size of 16 images for the training of the model due to limitation of memory capacity.

Some specifications that we try to adapt in our CNN is that the neurons have 3 dimensions: width, height and depth. Usually, a CNNs, each filter is repeated throughout the entire visual field. These repeated units share the same characterization regarding the weight vector and the bias forming in this way a typical map. Thus, all the neurons in a given convolutional layer respond to the same typical feature that is within their specific response field. Repeating units in this manner allows for the resulting typical map to be unchangeable under changes in the locations of input characteristics in the visual field.

In hidden layers, the characteristics maps are divided into rectangular sub-regions, and the characteristics in each rectangle are reduced independently to a single value, usually by taking their average or maximum value. To reduce the sizes of the characteristic's maps, the merging operation imparts a degree of the translational invariance to the characteristics contained within them, allowing the CNN to be more robust to changes in their positions. [6]. All these features allow CNNs to take better generalization for the vision problems. Weight partitioning reduces the number of free parameters that are learned, thereby reducing the memory requests for running the network and to have possibilities to train larger and the more powerful networks. Editing is a process of adding additional information to solve an ill-posed problem or to prevent overlap. [4].

With these specifications in mind, we are currently testing different mesh models in Matlab. At the same time, we are improving the computer computing capacities to later switch to python, pytorch. The DCNN model with the best results will be integrated with PPIR 2023.

3. Results

We have initially divided the images into two categories, images that contain a tumor structure that have different tumor sizes, locations, shapes, and diverse image intensities in order to train the model better and those that are theoretically clean. First, we converted the images into arrays. So, if each image is 256x256 the array shape should then be 150x256x256. These data sets are used for the training process. Also, we performed for each image the detection of brain tumor using "*BrainMRI_GUI*" function in Matlab. [14] Brain MRI tumor detection and classification function, helped us to classify the above images in two categories.
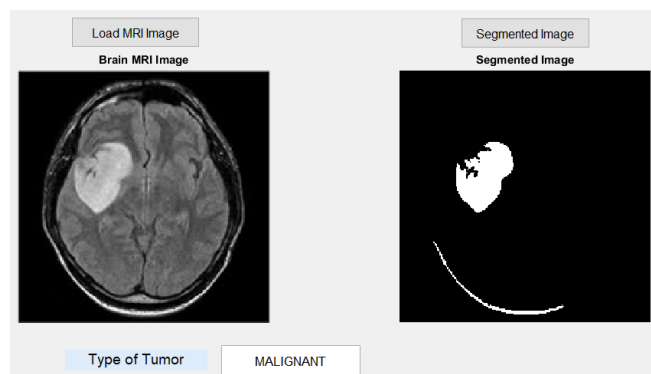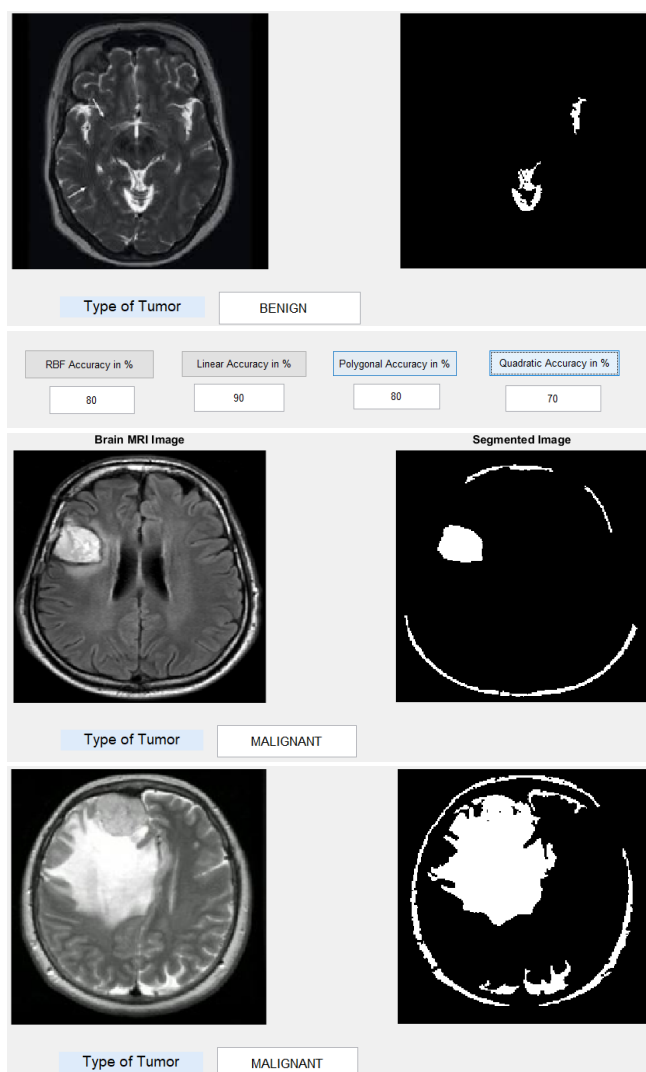
Fig. 5. Brain MRI tumor detection and classification

With "*nnstart*", we tested several models to find the best performance. To summarize the performance of our network, we showed the confusion matrix. As is shown, our classification model is getting right but there are types of errors it is making classification accuracy alone can be misleading if we have an unequal number of observations in each class or if we have more than two classes in our dataset.
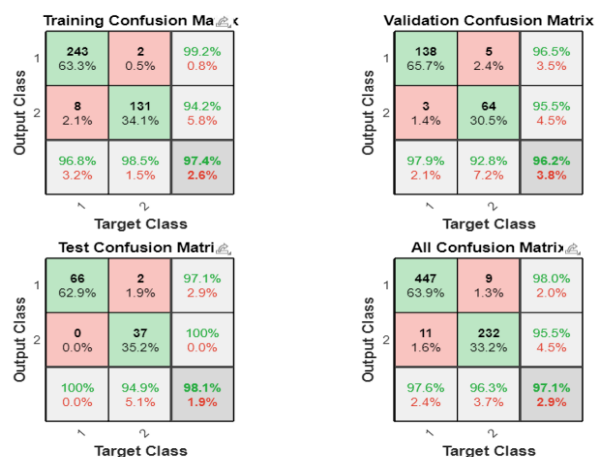

Fig. 6. Performance of network showed with confusion matrix

4985

The role of the confusion matrix it is to show the percentages of the correct and the incorrect divisions. The correct divisions are the green squares on the diagonal of the matrix and the red squares are the incorrect classifications. The percentages in the red squares are small when the network is correct, indicating thus small misclassifications. In several trainings, the network was not correct or accurate. We trained the network for a longer time and increased the number of hidden neurons.

The neural network is trained to work correctly with a randomly selected subset of its neurons. The best way it is to avoid training all nodes on all training data, in such a way that dropout diminish overfitting.

Having a convolutional network that has more training examples can diminish overfitting. This can be achieved by perturbing (e.g., rotating, scaling, moving) the data that we have to create new ones. Explicit methods of regularization include early stopping which is one of the best methods to avoid overfitting of a network is just to stop the process of training before overfitting can occur.

Another way to measure how good the neural network has fit the data is to plot the parameter that it is called the Receiver Operating Characteristic (ROC). This ROC plot serves to show the relation between false positive and true positive rates with the thresholding of outputs that is ranged from 0 to 1. The further to the left and up the line, the fewer false positives must be accepted to obtain a high true positive rate. The best classifiers show a line that start from the lower left corner, to the upper left corner, to the upper right corner. Class 1 identifies tumor patients and class 2 identifies patients without tumor.
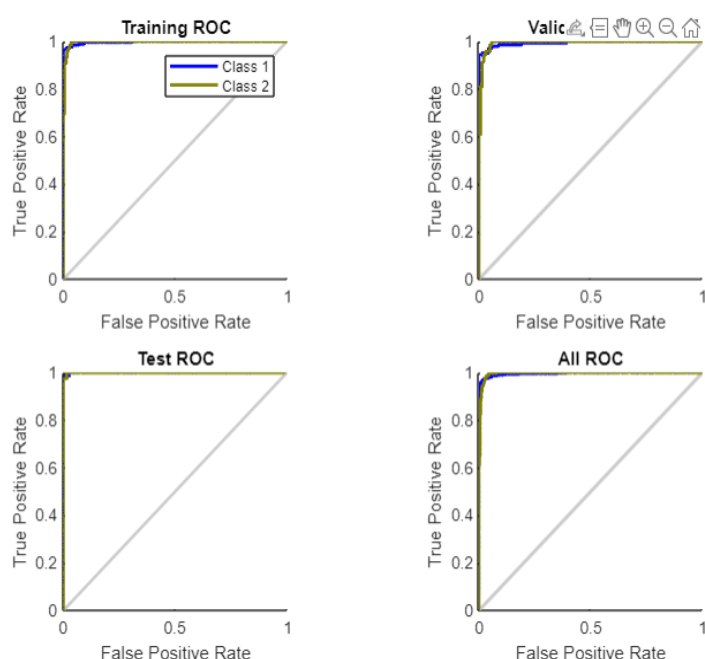

Fig. 7. Receiver operating characteristic curve

We indicated that AI tools can give a very important contribution helping clinicians to identify quickly characteristics in images, and more precisely.

The performance of the network is measured by calculating the mean squared error on a logarithmic scale. This error decreased rapidly as the network was trained during training period. This performance it is shown for each test set of the training and validation.
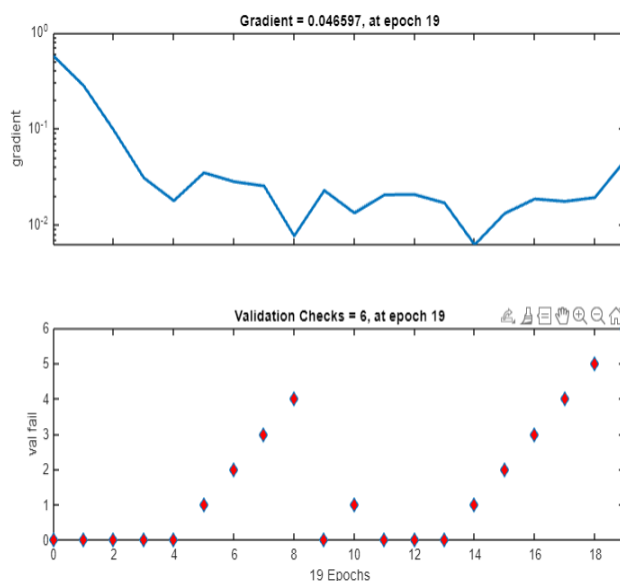
4986

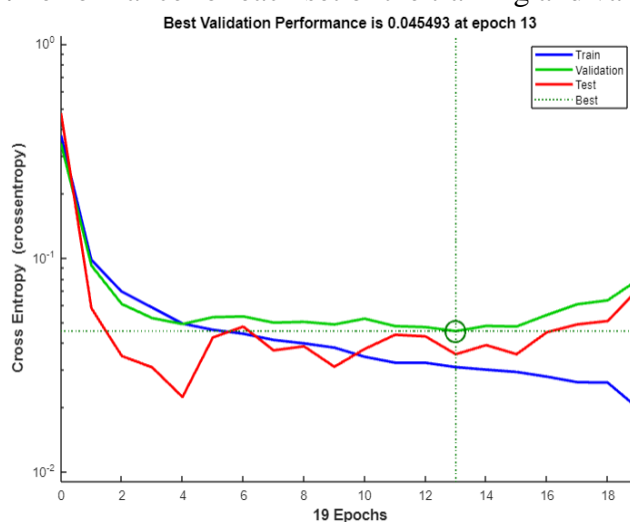**Fig. 8.** Performance for each set of the training and validation

Fig. 9. Best validation performance of network

4. Conclusion

This research introduces a CNN model for identifying brain tumors from MRI images. Although our proposed model is in the first stage, some first results are promising for image classification through tumor detection. In our work we showed some important applications of AI in medical imaging such as medical interpretation, tumor detection, following tumor development, the determination and visualization of blood flow etc.

There are yet a number of problems that can be resolved in our future work. For example, resolving one of the main obstacles in using deep learning-based automated brain tumor detection is the request for a very large dataset. TCIA is one of the most complete medical image archives that can be used for training and simulations on the network.

Also, a deep learning model can take information even from a small number of labeled instances per class by using a few-shot learning techniques.

Another disfavor of this work is that even the proposed method achieved a good result in in the identification and the classification of the tumor image. We are currently testing the module in MRI imaging but the model needs improvement.

The proposed CNN model is adapted and created to work with a very large number of image data. Output results demonstrated that the achieved performance of the network was between 80 % - 92 %. By modifying the architecture of the network, we believe that the level of brain tumor detection can be increased. In order to promote the development and use of standardized, safe and effective AI to aid in clinical decision making and diagnosis, it will be continuously improved over time as new opportunities are developed. Among the top use cases for artificial intelligence in the imaging world is screening for common cancers.

5. Acknowledgments

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4989

Eur. Chem. Bull. 2023,12(Special Issue 7), 4979-4989