International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Integration of DCNN Model for Brain Tumor Detection with PPIR Simulator

Dafina Xhako*[1], Elda Spahiu[3], Niko Hyka[2], Suela Hoxhaj[1], Partizan Malkaj[1]

Submitted: 04/10/2023 **Revised**: 26/11/2023 **Accepted**: 09/12/2023

Abstract: For several years we are focused in use of simulation in radiotherapy in Matlab environment establishing the first module for called PPIR 2014. This program uses Matlab to implement a number of simulation and computation techniques and applications in radiation and medical imaging. Important features for processing, visualizing, and calculating medical pictures in radiotherapy are offered by this program. With an emphasis on estimating the tumor normal tissue complication probability through the analysis of radiation interactions with individual tumor cells using virtual simulations and control probability, we enhanced the Eudmodel for histogram of dose and volume, in 2019. The 2019 release of the PPIR previews gave students additional chances to do realistic simulations of a fractioned treatment, based on the radiation sensitivity of tumor cells, tumor volume, cell density, and number of fractions. In 2023, under the project "*Development of simulation and forecasting models and integration with the TCIA database of medical images*", we created a DCNN model that includes a thorough ontology of the various kinds of the most prevalent cancer types. In this work we represent the DCNN model and its applications on dataset loading, preparation for training, regularization, and other parameters. We integrated the PPIR 2023 adding the DCNN module as integral part of PPIR. The process of creation of the DCNN structure, reading the data, training, displaying the results and performance evaluation of the trained, using the validation dataset, is performed through PPIR GUI which can be enabling easy use by students, imaging technicians and radiological medicine professionals. The model that we proposed with DCNN, is adapted to function with large number of input data which are medical images taken with CT, MRI and PET technics. We offer a technique to facilitate the brain tumor detection simulation by altering the network's architecture. However, we seek to further the application of artificial neural networks in clinical diagnosis and decision-making.

Keywords: *ANN, cancer, Convolutional Deep Neural Nets, medical imaging, PPIR, forecast, training, simulation.*

1. Introduction

Establishing the PPIR module for training and simulation with interface in Albanian language, was our first work on application of Matlab for trainings and simulations. Dose Response Explorer System (DREES) and Computational Environment for Radiotherapy Research (CERR) are two apps that are included within the PPIR module. It is set up and customized to carry out the key tasks involved in using radiation therapy to treat tumours, including importing medical photos, defining structural boundaries, administering treatment, managing drug dosage, and more. Matlab, a sophisticated graphical analysis and programming tool, is used to create CERR and DREES. [1]. Both packages are accessible as an Matlab environment to develop and programming different treatment planning tools and also visualise with graphical tools on Matlab The fundamental structure of various forms of information in various cell array elements is what makes the CERR module most famous. In the meantime, in order to make it easier to navigate and analyse intricate radiobiological interactions and how they relate to treatment results, DREES is specifically designed for modelling and investigating dose response in radiation oncology. At the first version, PPIR provide most of CERR and DREES applications including also analytical and normal tissue complication probability and tumour control probability [2]. These modules also contain principal component analysis, actuarial analysis, hazard regression, dimensionality reduction, and multi-metric regression modelling of dose-volume variables, biomarkers, and patient-specific clinical factors.

The more recent DICOM extensions for items relevant to radiation therapy make it a desirable way to import treatment planning data into Matlab. Once the plan archive is translated into the CERR format, it can be interactively modified using the Matlab system with the help of the provided application and related tools, as will be covered in more detail below. It is simple to query ASCII data fields in RTOG format using the Matlab command line. The plan viewing applications also provide comprehensive examples of how to easily retrieve treatment planning data in the CERR format from within Matlab, in addition to these features [3]. A Matlab structure can be constructed for any type of treatment planning item, including dose distributions and image scans, with fields matching those defined for that type of object. For radiation oncology, DREES is specifically designed for modelling and investigating dose

[1] *Polytechnic University of Tirana, Albania*
ORCID ID : 0000-0002-0937-2471
[2]*University of Medicine, Tirana, Albania*
ORCID ID : 0000-0002-4645-3844
[3] *Institute of Applied Physics, Tirana, Albania*
** Corresponding Author Email: dafinaxhako@yahoo.com*

response. DREES contains a number of graphical and analytical tools that make it easier to navigate and analyse intricate radiobiological interactions and how they relate to treatment outcomes. Among these characteristics are the following: nomogram representation; actuarial analysis and hazard regression; multimeric regression modelling of biomarkers, dose-volume variables, and patient-specific clinical factors; principal component analysis, dimensionality reduction, fitting of the analytical normal tissue complication probability, and tumour control probability. The effectiveness of the various prediction models is measured using metrics such as rank correlations, chi-square and area under the ROC curve, and bootstrap plots. DREES provides reliable estimates of the optimal model order and related parameters by combining information-theoretic techniques with sophisticated statistical resampling techniques (cross-validation and bootstrap).

In order to replicate the biological effects of radiation on a tumour that has been uniformly exposed to n fractions of radiation at a dose of d per fraction, we have included a new function in 2019 that is characterized by volume, cell density, radio sensitivity for cell death, and sublethal damage to cells. This program also utilizes statistical ideas, as it generates a random integer < 1 using the Matlab function rand. With a final count of dead cells equal to the initial count of cancer cells to arrive at TCP, the total count of possible outcomes for all tumour cells throughout the second and subsequent fractions is divided by the total number of simulations. Together with the primary radiobiological indices for a real radiation oncology therapy, the virtual simulation calculates the cancer control probability and the likelihood of problems involving normal tissue.

The *TumorRBEf* function's model allows for the evaluation of up to three organs at risk (OAR), which is frequently quite similar to how radiation treatment actually works [4]. Using virtual simulations, we contrasted the model to determine the tumour control probability by examining how radiation interacts with individual tumour cells. Through virtual simulations of a fractioned therapy for a homogeneously irradiated tumour, we calculate the TCP as the ratio between the total number of simulations and the simulations with 100% of killed cells. Typically, we utilize the formulas to compute TCP and NTCP with respect to PPIR. Here, we made use of the following parameters: The TCP model's power (pT) for the stomach, bladder, and liver is 0.9, and the minimum dosage for The Tumour Control Probability (TTD_{min}) is 15 Gy. The minimum dose for The Tumour Control Probability (TTD_{max}) is 75 Gy. As demonstrated in our research published in 2019 [5], the function *tumorrbef.m* computes the biological effects of radiation on normal tissues by probabilistic modelling, accounting for the tumour's radiosensitivity for cell death and its radiosensitivity for cell sub-lethal damage. number of virtual simulations, volume of the tumour cell density, and number of fractions.

Following various modifications, we have integrated *tumorrbef.m* with the PPIR 2019 module, a new version that is frequently used by students for dosage calculations and simulations. because of the expertise our working group has in applying numerical techniques to Matlab-based ANNs and biological pictures. With financial backing from the Albanian National Agency for Research and Innovation (NASRI), we began work on the project "Development of simulation and forecasting models and integration with the TCIA database of medical images" [5], [6], and [7]. The primary goal of this study was to develop a CNN model to identify a tumour in its early stages using deep neural network applications. Since this model is still in its early stages, medical physicists, radiologists, and oncologists can only use it for research purposes to hone their artificial intelligence application skills in identifying the correct diagnosis in medical images.

2. Methodology and Results

As mentioned, under the project "Development of simulation and forecasting models and integration with the TCIA database of medical images", we established a DCNN model with different types and forms of cancer [6]. To access and use the ANN model, it's important to have good knowledges of using MATLAB. Starting from the difficulty that medical professionals such as imaging technicians and radiologists have, it is necessary to create an interface that enables modifications in the structure of the neural network, reading and importing data, training the network and then reading the results and comparing them with desired values.

For this reason, we integrated the DCNN module as integral part of new PPIR called from Matlab with "*ppir*" command [9], [10], [11]. The process of creation of the DCNN structure, reading the data, training, displaying the results and performance evaluation of the trained, using the validation dataset, is performed through PPIR GUI which can be enabling easy use by students, imaging technicians and radiological medicine professionals. An enormous amount of picture data can be used with the suggested DCNN model. We offer a technique to facilitate the brain tumor detection simulation by altering the network's architecture. Conversely, our goal is to advance the application of artificial neural networks in clinical diagnosis and decision-making.

In the preparatory phase, users can select a category of images from patients' examinations obtained from the same diagnostics technique. The model at this stage offers the possibility to detect only brain tumors in examinations with MRI or CT. The DCNN model can be fed with related clinical and demographic data from the brain image

datasets. are linked to manual fluid attenuated inversion recovery abnormality segmentation masks for the collection of MRI brain pictures. With 1200 photos of lower-grade gliomas such as medulloblastomas, meningiomas, oligodendrogliomas, glioblastomas (GBM), and so on, the dataset's content is actually quite limited. We have predetermined the tumor diagnosis for each image utilized in the network training. There is a distinct trained when the user chooses a certain type of cancer and view. In addition to a series of images and some basic metadata, the data input will yield a list of candidate tumor kinds, additional plausible non-cancer explanations, and a probability for each alternative diagnosis. Numerous investigations on the most prevalent types of brain cancer, including their variants, and comparable findings in non-cancerous conditions are crucial [12], [13].

In the second stage of the process, DCNN compose, the number of hidden layers and neurons varies according to the particular architecture and tasks. We suggest beginning with a 5-layer CNN structure to carry out segmentation for simulation purposes. Every filter is often repeated across the whole visual field of a CNN. By sharing the same characteristics with regard to the weight vector and bias, these repeating units combine to form a typical map. As a result, within their own response field, every neuron in a convolutional layer reacts to the same typical feature. By repeating units in this way, the typical map that is produced can remain unchanged even if input characteristics' placements within the visual field change. The features in each rectangular sub-region of the hidden layers' characteristic maps are independently reduced to a single value, typically by taking the rectangle's average or maximum value. The merging process minimizes the sizes of the characteristic maps and increases the CNN's resistance to changes in their placements by applying a level of translational invariance to the features included within the characteristic maps [6]. CNNs are able to do greater generalization for vision-related issues thanks to all these qualities. By learning fewer free parameters, weight partitioning lowers the amount of memory needed to run the network and creates opportunities for training bigger, more capable networks. The process of editing involves adding details to address a problem that isn't clearly stated or to avoid duplication [4]. We are now experimenting with several mesh models in Matlab while keeping these parameters in mind. In parallel, we are enhancing computer processing power in order to eventually transition to Pytorch and Python. The best-performing DCNN model will be incorporated into PPIR 2023. In order to improve the model's training, we first separated the images into two categories: theoretically clean photos and images with a tumor structure that has varying tumor sizes, positions, forms, and intensities. Initially, we transformed the pictures into arrays. Thus, the array form should be 150 x 256 x 256 if each image is 256 x 256. The training procedure makes use of these data sets. We use Matlab to detect brain tumors in each image [14], [15]. With the aid of the brain MRI tumor identification and classification tool, we were able to separate the previously described images into two groups. Regarding the performance of the model, several types of errors can be identified and classified using the confusion matrix. The confusion matrix's goal is to display the percentages of accurate and incorrect responses for each division. Longer training sessions resulted in an increase in the quantity of hidden neurons.

It is possible to teach a neural network to function correctly using a randomly chosen portion of its neurons.

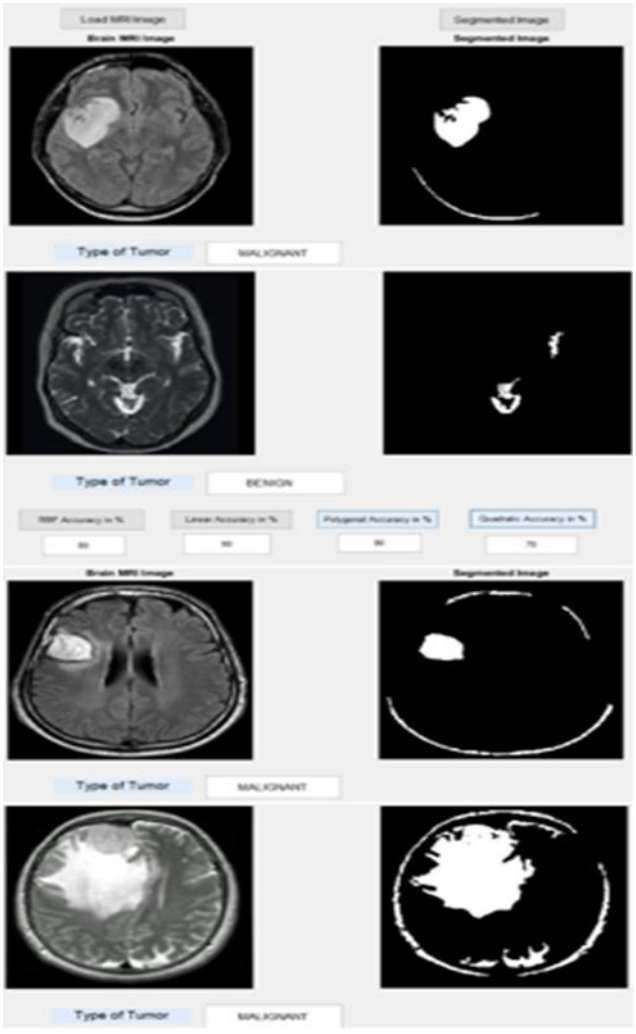

Fig 1. Brain MRI tumor detection and classification

The optimal course of action is to avoid training every neuron on every training set in a way that would minimize overfitting through dropout. Overfitting can be reduced by using a neural network with a larger number of training instances.

This can be done by altering the existing data in order to produce new ones, for as by rotating, scaling, or shifting it. One of the greatest ways to prevent a network from overfitting is to simply stop the training process before

overfitting can happen. This is one of the explicit regularization techniques. Another is early stopping. Plotting the parameter known as the Receiver Operating Characteristic is another technique to assess how well the neural network has suited the data. With outputs that are thresholder from 0 to 1, the relationship between false positive and true positive rates is displayed using a ROC plot. To get a high true positive rate, less false positives must be allowed the further left and up the line one goes. A line that runs from the lower left corner to the upper left corner and finally to the upper right corner is what the best classifiers display. Patients in class 1 are those with tumors, and patients in class 2 are those without tumors. We demonstrated that the DCNN model can significantly aid physicians in rapidly and more accurately identifying features in images. The mean squared error is calculated on a logarithmic scale to determine the network's performance. As the network was educated throughout the training phase, this error steadily decreased. This performance is displayed for every training and validation test set.

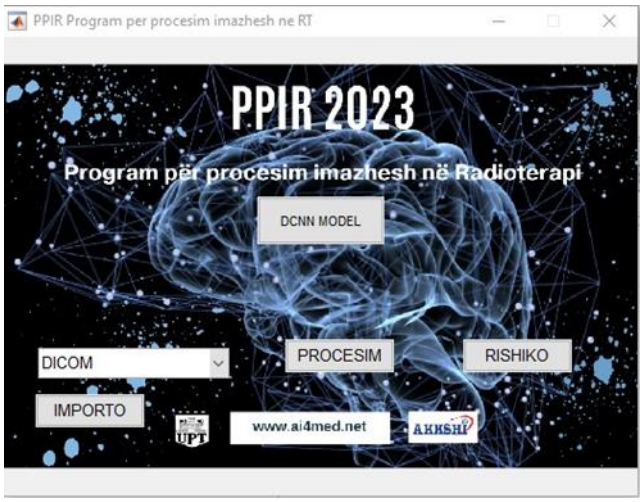

Fig 2. PPIR 2023 Graphical user interface

3. Conclusions

In this work we represented the integration of the DCNN model and its applications on dataset loading, preparation for training, regularization, and other parameters with PPIR 2023. The process of creation of the DCNN structure, reading the data, training, displaying the results and performance evaluation of the trained, using the validation dataset, is performed through PPIR GUI which can be enabling easy use by students, imaging technicians and radiological medicine professionals. An enormous amount of medical imaging data can be used with the suggested DCNN model. We offer a technique to facilitate the brain tumor detection simulation by altering the network's architecture. Conversely, we seek to advance the application of artificial neural networks in clinical diagnosis and decision-making. This study presents a CNN model for image-based brain tumor identification. While our suggested model is still in its early stages, preliminary findings show promise for tumor detection-based picture categorization. We can still address a number of these issues in our next efforts. For instance, the need for a very big dataset addresses one of the primary barriers to using deep learning-based automated brain tumor identification. Furthermore, by utilizing few-shot learning approaches, a deep learning model can extract information from even a limited number of labeled cases per class. Another drawback of this work is that, despite the suggested method's success in identifying and classifying the tumor image, it still produced subpar results. We tested the module with MRI images taken from American Hospital. Tirana but the model needs more improvement. Our model is designed and modified to operate on a vast quantity of image data. We've already set up a dataset on ai4med.net. We believe that the architecture of the network can be altered to enhance the detection of brain cancers. As new opportunities arise, it will be continuously refined throughout time to support the development and implementation of standardized, safe, and effective AI to support clinical decision making and diagnosis. Our goal is to keep using the PPIR 2023 mostly for trainings and simulations for medical professionals and students. For people with little experience with the Matlab environment and its applications, having a graphical user interface makes things considerably easier.

Acknowledgements

This paper was completed as part of the research for the project "Development of simulation and forecasting models and integration with the TCIA database of medical images" with funding from the National Agency for Scientific Research and Innovation (NASRI) [Decision Nr.01, dt. 05/07/2022, of NASRI Board]. The authors also acknowledge Albmedtech, EFOMP, READ (Research Expertise from Academic Diaspora), AAMP, and READ.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Joseph O Deasy, (2003); "A computational environment for radiotherapy research", Med Phys. May; 30 (5): 979-85.

[2] Brad Warkentin (2004), A TCP-NTCP estimation module using DVHs and known radiobiological models and parameter sets. University of Alberta, 11560 University Ave., Edmonton, AlbertaT6G IZ2 Canada

[3] M. Goitein (1985), Calculation of the uncertainty in the dose delivered during radiation therapy, Medical Physics, Volume12, Issue5, September, Pages 608-612.

[4] M. Zaider, L. Hanin, Med Phys. 38(2), 574-583 (2011).

[5] Niko Hyka; Dafina Xhako, New method to calculate the tumor control probability for PPIR, https://doi.org/10.1063/1.5135450.

[6] Niko Hyka et.al (2023), Using deep convolutional neural network to create a DCNN model for brain tumor detection, European Chemical Bulletin (ISSN 2063-5346), Volume -12, Special Issue-7: Page: 4979-4989.

[7] Xhako, D., & Hyka, N. (2022). Artificial neural networks application in medical images. International Journal of Health Sciences, 6(S2), 10632–10639. https://doi.org/10.53730/ijhs.v6nS2.7829.

[8] Jinming Zou, Yi Han, Sung-Sau So. Overview of Artificial Neural Networks, PubMed, January 2009, Methods in molecular biology (Clifton, N.J.) 458:14-22, DOI: 10.1007/978-1-60327-101-1_2.

[9] Niko, H. et al. "Calculation Methods in Radiotherapy Using MATLAB." Journal of International Environmental Application and Science 9 (2014): 205-210.

[10] Dafina Hyka (Xhako), Niko Hyka, Developing numerical methods and simulations for trainings in radiotherapy. Science & Technologies, Nautical and environmental studies, Volume VIII, 2018, Number 2:

[11] Nyoman Abiwinanda et al, Brain Tumor Classification Using Convolutional Neural Network, DOI: 10.1007/978-981-10-9035-6_33

[12] Louis, David N et al. "The 2021 WHO Classification of Tumors of the Central Nervous System: a summary." Neuro-oncology vol. 23,8 (2021): 1231-1251. doi:10.1093/neuonc/noab106

[13] Clark, K., Vendt, B., Smith, K. et al. The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository. J Digit Imaging 26, 1045–1057 (2013). https://doi.org/10.1007/s10278-013-9622-7

[14] Aggarwal, M., Tiwari, A.K., Sarathi, M. et al. An early detection and segmentation of Brain Tumor using Deep Neural Network. BMC Med Inform Decis Mak 23, 78 (2023). https://doi.org/10.1186/s12911-023-02174-8

[15] Manu BN (2023). Brain MRI Tumor Detection and Classification. https://www.mathworks.com/matlabcentral/fileexchange/55107-brain-mri-tumor-detection-and-classification), MATLAB Central File Exchange. Retrieved AI4MED (2023) Artificial intelligence for medicine, https://ai4med.net

[16] Dhabliya, D., Ugli, I.S.M., Murali, M.J., Abbas, A.H.R., Gulbahor, U. Computer Vision: Advances in Image and Video Analysis (2023) E3S Web of Conferences, 399, art. no. 04045, .

[17] Tonk, A., Dhabliya, D., Sheril, S., Abbas, A.H.R., Dilsora, A. Intelligent Robotics: Navigation, Planning, and Human-Robot Interaction (2023) E3S Web of Conferences, 399, art. no. 04044, .