Deep Learning Assignment Fall 2024

Dr. Gorkem Saygili

Deadline: September 27, 2024

1 Practical Aspects

This is a **group** assignment. Please consider the rubric on the canvas page for this assignment before the submission. The sections below describe important practical aspects of the assignment for the TiU Deep Learning Course, BLOCK 1, 2024-2025. The groups should be formed by a minimum of **four** or a maximum of **six** students. Students need to mention **their contribution** to the project in their reports explicitly. In case no contribution explicitly mentioned for a student, the grade of that student will be set as 1/10 where 10 represents the maximum grade. Students who are unable to assign themselves to a group but are willing to complete the assignment should contact the course T.A. within one week of the assignment's release. They will be placed in groups with fewer than four members or with other students in a similar situation. Students who fail to contact the T.A. within this timeframe will be randomly assigned to a group one week after the assignment's release.

1.1 Grading

The hands-on assignment will count for **30% of your total course grade**. The grades will be based on the quality of your work as judged by the instructor based on your report and code. There might be hardware limitations in order to train very complex neural networks. You are encouraged to mention improvements to your classifier that you could implement if you had more resources available.

The assignment itself does not necessarily require access to high-end GPUs or a very powerful machine. If you do want to experiment with GPUs or TPUs, you could use the facilities provided by Google Colab[1] or GPU4EDU clusters.

Passing the assignment is not mandatory to pass the course but it is highly advisable.

The assignment will be graded on 10 points (may be scaled to 100 by multiplying with 10 on Canvas), a detailed description of all the required components can be found in Section 2. The grades of each component are outlined as below:

- A baseline model along with the required plots and performance metrics (2 points).
- An improved model, with required plots and performance metrics, an explanation/justification, and discussion of the experiments, implementation choices, and the results obtained, including class-based performance variations and underlying reasons (4 points).

[1] https://colab.research.google.com

- An extensive discussion about possible different networks or improvements to further enhance the performance of the algorithms relying on the existing literature (2 point).
- Using transfer learning (VGG16, ResNet50, or DenseNet) to improve performance (1 point).
- Good coding standards with explanatory comments (1 points)

2 Task Description

The assignment focuses on the task of detecting and diagnosing various brain tumours using computer vision techniques.

2.1 Brain Tumor MRI Classification

Image classification is one of the most studied tasks in computer vision. The milestone paper [1], AlexNet, proposed a CNN architecture with ReLU activation functions and dropout layers to achieve accurate image classification results on the ImageNet classification challenge. For the assignment, you will be using Brain Tumor MRI Dataset [2] which had been also used in the work of Gómez-Guzmán et al. [3].

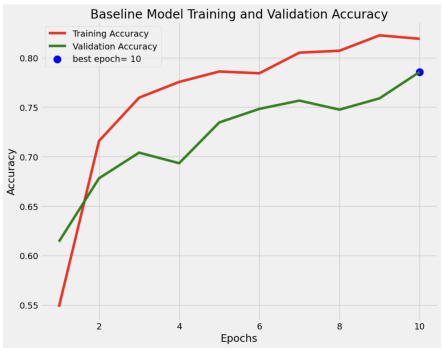
After downloading and preparing the datasets using the provided notebook file, your assignment is to:

- Create a virtual environment and install tensorflow, matplotlib, pandas, keras, seaborn libraries. These are the libraries we recommend but you can also install the ones of your choice.
- Convert the target values using the proper function for one hot encoding.
- Randomly select 15 samples from the dataset. For each selected sample, display the image along **with its corresponding label** as text on top of the image. Arrange these images and labels in a single figure, ensuring that they are visually clear and labeled properly.
- Create a bar plot to visualize the class label distribution of the dataset. (Hint: this bar plot reveals how many samples the dataset has for each class)
- Apply **20% of the training set** as a validation set to validate the hyperparameters that you have chosen.
- Implement the baseline CNN algorithm (exactly, **without any modification** for both model and dataset) that is shown in Fig. 1. It is a network consisting of: a Convolutional layer with 32 filters and kernel size of 3×3 with ReLU activations that is followed by a max pooling layer of size 2×2 and again a convolutional layer of 32 filters of size 3×3 with ReLU activations. Each convolutional layer is followed by a MaxPooling layer with a size of 2×2. Finally, a dense layers of sizes 32 and with Relu

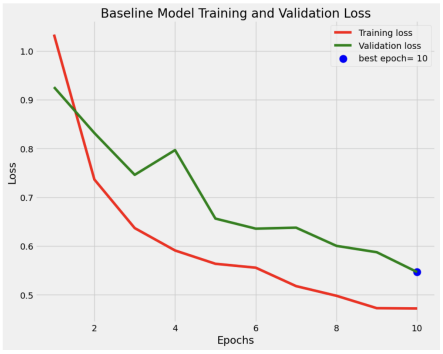
Figure 1: Baseline CNN Algorithm for image classification

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_5 (Conv2D)	(None, 12, 12, 32)	9,248
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 32)	0
flatten_2 (Flatten)	(None, 1152)	0
dense_4 (Dense)	(None, 32)	36,896
dense_5 (Dense)	(None, 4)	132

Total params: 46,596 (182.02 KB)
Trainable params: 46,596 (182.02 KB)
Non-trainable params: 0 (0.00 B)



(a) Training and validation accuracy



(b) Training and validation loss

Figure 2: Examples of accuracy and loss plots. They shouldn't have to be in this format exactly.

activation function and an output layer with the proper activation function (you are expected to find out) are added. The number of epochs should be set as 10 and batch size as 32 (is already set in the preprocessing code). The optimizer should be Adam, the metric should be accuracy and the loss function is expected from you :-).

- Analyze the performance of the baseline by plotting: (i) the training and validation losses and accuracies on the training and validation set through epochs (similar to Fig. 2a and Fig. 2b), (ii) the Receiver Operator Characteristic (ROC) curve with the Area under the Curve (AUC) score and a confusion matrix **for the validation and test sets**. Examples of accuracy and loss plots are shown in Fig. 2, and an example of a ROC curve and confusion matrix is shown in Fig. 3, respectively. Report performance measures (accuracy, precision, recall, and F1-score) **for both validation and test sets**. You can find the hint for plotting multi-class ROC curve here.

- Once you have a baseline model, adapt/fine-tune the network to improve its performance by: (i) changing the hyper-parameters. It is critical to intentionally tweak at least six different hyperparameters, ensuring that these adjustments are not randomly chosen. You are expected to make purposeful selections based on the intricacies of

the problem at hand, and conduct optimization within a logical framework. Consider changes such as the addition of more layers, alterations in filter sizes and numbers, adjustments to activation functions, fine-tuning the learning rate together with different optimizers, and experimenting with the number of neurons in Dense layers. Document and analyze the rationale/reasoning behind each modification in your report. Illustrate the improvements of your new network over the baseline by: (a) plotting the ROC curve with the AUC score; and (b) reporting performance measures. Compare and explain the differences between the two models as well as potential reasons behind the increase/decrease in performance.

- Add an extensive discussion about possible different networks or improvements to further enhance the performance of the algorithms relying on the existing literature (such as hybrid architectures and architectures that have been specifically used for similar problems before).

- Next, train a new model using transfer learning. Utilize either VGG16, ResNet50, or DenseNet121 architecture for feature extraction. Freeze the layers until the fully connected layer such that these layers will not be updated through training. Add your fully connected layers (as many as you like) and present the results that you obtained on the test set (ROC curve with AUC score, performance measures, and confusion matrix). Comment on the performance with respect to the baseline and the network that you designed in the previous step.

Tip: As you work on your assignments, please bear memory constraints in mind, especially when using platforms like Google Colab. While normalization is a common preprocessing step, it may not always be necessary and can impact memory usage. So you can skip the normalization process in this assignment, to prevent potential memory issues.

2.2 Dataset

The dataset is available online and can be downloaded from:

https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset?resource=download.\

This dataset contains 5712 training and 1311 test MRI images with four classes. All images are in varying sizes, in gray scale and are in jpeg file format. The classes are; glioma, meningioma, no tumor, and pituitary. No tumor class images were taken from the Br35H dataset.

For the sake of reducing computational workload and memory requirements, you will be working on a smaller dimension of 30×30 rather than the original resolution of the images.

You should use the provided code to load the images. You are expected to use the same notebook(ipynb) file for the rest of the tasks.

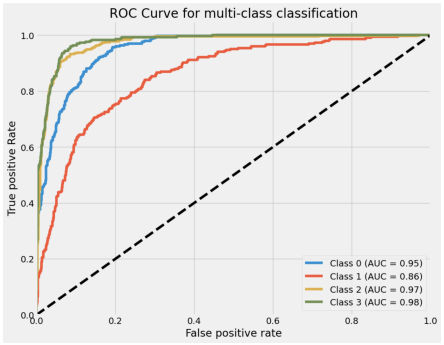
3 Important Dates and Deliverables

3.1 Report

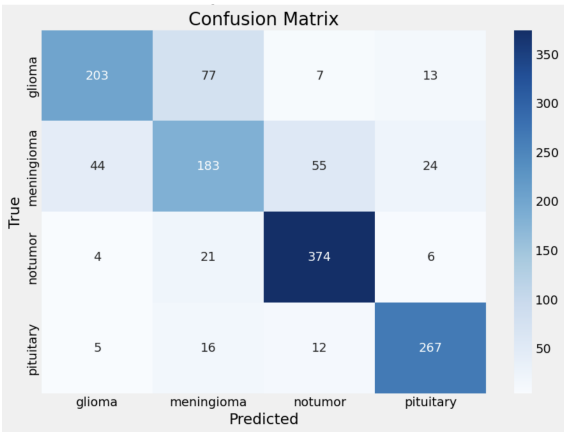
A **6-page (excluding references, title page)** group report should be submitted by **Sunday, September 27, 2024 until 23:59 (sharp)**. **Assignments exceeding the page limit will not be considered for evaluation.**

The report should include the following information:

- Title
- Student names and numbers
- **Explicitly mentioned contribution of each student.**
  For instance:
  student A: Hyperparameter optimization, Results Section, Discussion Section.
  Student B: Baseline implementation, Results Section, Discussion Section.
  Student C: Plotting test results, Introduction Section, Results Section.
  Student D: Preprocessing of images, Methodology Section, Discussion Section, Conclusion.
  Student E: Hyperparameter optimization, Results Section, Discussion Section, Future improvements, Limitations.
- A summary of your models (excluding the baseline model) - similar to the one provided in Fig. 3. To make optimum use of the page limit, you do not need to include the information about the Baseline model (model summary) in the report. You only need to include the results you use for model evaluation/comparison.
- A brief description of your experiments, including possible pre-processing steps, training, hyperparameters, activation functions, optimization/regularization techniques so on or any other changes you made such as **justification about your choices for further improvements**. Since specific values for all hyperparameters of the baseline model are explicitly requested in the assignment, there is no need to provide explanations and justifications for baseline hyperparameters. **Please reserve explanations and justifications only for your own choices.**
- The graphs/results requested in the task description, see Sec. 2.1.
- All the .ipynb code (that produces the results presented in your report) (ipython notebook file) which includes your results. Important: The results that you present in the report have to be in the ipynb file. Otherwise, **results not included in the ipynb file will not be considered for evaluation**.
- Bibliography



(a) ROC curve



(b) Confusion Matrix

Figure 3: Examples of ROC curve and confusion matrix.

3.2 Code

You can find an ipynb notebook including the codes which will help you to read and resize the data. You are expected to use the provided code to read and resize datasets, add the required exploratory data analysis and validation an test steps that were mentioned above, and continue implementing your algorithms which can be run to generate your results. **Your plots from your run should be observable in the .ipynb file** that you submit together with your report (you should provide the results that are in your report). You do not need to submit your training data or the trained model.

3.3 Submission format

Each group is required to upload their Jupyter Notebook (.ipynb) file to the ' Assignment Code Submission' section on Canvas. If you plan to upload more than one notebook file (it is better to have it in a single file) please merge them into a zip file before uploading and make sure to put your group name in each file. Ensure that all outputs, including results, code execution outputs, and any printed or displayed information, are visible in the notebook. The code parts that give an error will not be considered for evaluation. At the top of your file, please reference any code, methods, or ideas that are not your own or not provided in this course. Remember that these codes must be publicly available and free to use. You do not have to reference the course worksheets, the textbook nor the lecture slides. Please also include any special instructions that are required to run your code. Every result that you showed in your report should be also in the .ipynb notebook. Otherwise, you will not receive any credit for that result.

Every group must submit their reports as a .pdf file to the 'Assignment Report Submission' section on Canvas.

Very important remark: It is imperative for each group to produce their work independently from other groups. Deliverables will be run through plagiarism software to compare them to the literature, and deliverables of other students in this or other assignments. Any instances of academic fraud or plagiarism will be dealt with seriously. These changes are

in effect to ensure a fair assessment for each group. Please adhere to these guidelines for a smooth and transparent evaluation process.

References

[1] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Communications of the ACM 60.6 (2017): 84-90.

[2] Brain Tumor MRI Dataset: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset?resource=download, accessed on 07/09/24.

[3] Gómez-Guzmán, M. A., Jiménez-Beristaín, L., García-Guerrero, E. E., López-Bonilla, O. R., Tamayo-Perez, U. J., Esqueda-Elizondo, J. J., ... & Inzunza-González, E. "Classifying brain tumors on magnetic resonance imaging by using convolutional neural networks." Electronics, 12(4), (2023): 955.