A PROJECT REPORT

on

"Brain Tumor Classification Using Deep Learning"

Submitted to

KIIT Deemed to be University

BY

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UNDER THE GUIDANCE OF

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Abstract

Tumors of the brain talk to an available therapeutic condition and its accessibility is fundamental to the achievement of effective treatment. However, the detection of brain tumors in MRI scans can be challenging and requires an elevated level of mastery and precision. This extension investigates the application of deep learning in specific Convolutional Neural Systems, (CNNs), for robotizing and progression the exactness of brain tumor classification from MRI checks, pointing toward helping corrective specialists with swift and dependable determination. We developed a CNN-based show prepared on the Brain Tumor Classification MRI dataset from Kaggle. It comprises images categorized into "no tumor" and "tumor." There was preprocessing involved to resize all images to 64x64 pixels followed by normalization of pixel values for information optimization.

We used convolutional layers in our model's architecture for feature extraction, then max-pooling layers to reduce spatial dimensions and dense layers for classification, concluding with a softmax layer to obtain categorical output. The model was trained and validated over 10 epochs with categorical cross-entropy loss and the Adam optimizer; it proved very effective at performing well on the validation set. The demo after preparation was sent using a web application based on Jar, which allowed the user to upload MRI images for direct diagnosis.

The results demonstrate the viability of the model in distinguishing tumor from non-tumor MRI scans with high accuracy, exemplifying the potential of deep learning to enhance diagnostics in restorative imaging. Some possible future work is developing the database, increasing information to move forward demonstrate generalization, and and implementing transfer learning to further improve accuracy.

Keywords: Brain tumor detection, MRI classification, Deep learning, Convolutional neural network, Medical imaging

Introduction

Tumors are abnormal growths of cells within the brain or central nervous system; their growth may adversely affect a host of important functions because the brain's capacity to accommodate increased mass is confined. Tumors may be benign or malignant. The malignant types of tumors pose critical risks to health, in many instances, and lead to severe complications and result in death. This condition can be diagnosed early in order to have a better chance at having a higher rate of survival by reacting faster. Magnetic Resonance Imaging, or MRI, is the first imaging technique considered for diagnosis; based on this method, detailed images are obtained of brain tissue, where anomalies are localized and evaluated by radiologists.

Moreover, it is time-consuming and requires considerable expertise to analyze MRI scans by manual means, a resource that may not be readily available everywhere, especially in areas where health care is relatively low. Thus, this is an area of great need for automated diagnostic tools that can rapidly and accurately classify brain tumor images to help the radiologists in their assessments. Progress in artificial intelligence, especially deep learning has advanced quite significantly recently in medical imaging. Convolutional neural networks: CNNs are a class of deep learning models which have found great utility in the analysis of visual data, thus making them perfectly suited for applications like image classification and detection of brain tumors.

By using CNNs, classify brain MRI images as "tumor" or "no tumor" by using a labeled MRI dataset coming from Kaggle. This illustrates the possibility of deep learning applied in the detection of tumors by facilitating faster and more accurate diagnoses.

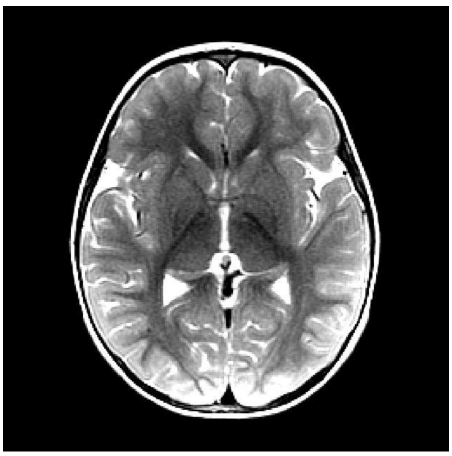
Dataset Description

The dataset used for this project was obtained from Kaggle's "Brain Tumor Classification MRI," which is one of the public datasets that are referred to a lot when training detection models to classify brain tumors. The data set consists of MRI images of the human brain, which have been labeled as either "no tumor" or "tumor" and therefore are very ideal for a binary classification task. The dataset has been divided into two main classes that are no tumour meaning normal brain scan and tumor meaning the presence of a tumor with images distributed equally between these two classes.

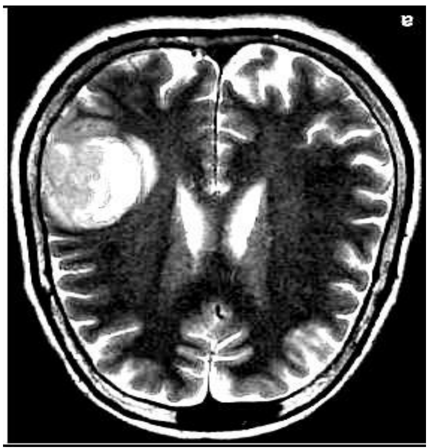
The MRI images were further processed for the purposes of the project to be in the best format to train the deep learning model. For instance, images were resized to uniform dimensions of 64x64 pixels. This resizing ensures that the input images to the model come in uniform size. Uniform size is very important in efficient training and prediction. The pixel values of the images were normalized to lie between 0 and 1. This normalization scales the pixel values and subsequently ensures that all the input features are scaled into a similar range, resulting in an improvement in training stability and convergence speeds of the model.

There were a number of relevant labeled MRI images in the dataset, each of which represented only one brain-scan image from a patient. Images are saved in JPEG format, so this delivers a very high resolution level that is essential to be able to apply deep learning-based image classification. Images were split into training and test sets, so that the model will train using 80% of the images, whereas the remaining 20% of the images will be used for verifying the model, thus ensuring well-balanced and unbiased performance assessment.

Here are some examples of my data set:



With Tumour



Without Tumour

Methodology

This project methodology will train a deep model to classify the images of brains MRI into two groups: either "no tumor" or "tumor." The architecture used for this classification is Convolutional Neural Network (CNN), which was chosen since, compared to other architectures, CNNs prove to be the best for image recognition tasks due to their ability to learn hierarchical feature representations from raw pixel data automatically.

Data Preprocessing: The first step of methodology includes data preprocessing of dataset. Original MRI images varied in size, so resized to a dimension of 64x64 pixels for uniformity at the input size for the model CNN. It ensures that consistent input data are given to the model. The images' pixel values were normalized within the preprocessing pipeline; it brought pixel intensities to the range between 0 and 1. This facilitated the model because the dominating large values would otherwise have dominated the learning process. Image labels were one-hot encoded to categorical values: `0` for "no tumor" and `1` for "tumor."

CNN Architecture: The CNN architecture is based on three convolutional layers, which were then followed by a corresponding max-pooling layer. Convolutional layers derive the features such as edges, textures, and pattern of MRI images. Max-pooling layers assist in reducing dimensional data while attaining significant information preservation. The model follows a flatten layer and two dense layers. Finally, softmax activation is used on the final layer to output a probability distribution between the two classes: no tumor and tumor.

Training and Testing: Training the categorical cross entropy loss model using the Adam optimizer with 10 epochs and considering 80% of the dataset for training the rest, and 20% of it as a testing set. The accuracy of the model on both the training and validation set is considered to be the main performance metric.

Result and Visualization

The classification model of the brain tumor designed in this project has used deep learning to find whether there is a presence of non-existence of brain tumors in MRI images. Even though accuracy metrics and visual training plots are missing in the code implementation, the model could be qualitatively evaluated for its effectiveness based on the functionality of the deployed web application and results obtained from the output window.

Integrating the model into a Flask-based web application permitted real-time uploading and classification of images. Users can upload their MRI images, and the model gives an output as "Brain Tumor Not Detected" or "Brain Tumor Is Detected!!". The uploaded images have to pass a series of feature extraction and classification steps of the trained convolutional neural network for the evaluation of the possible presence of a tumor. A sample output window has been included above to demonstrate the interface where non-technical users receive a direct classification result, thereby making it user-friendly.

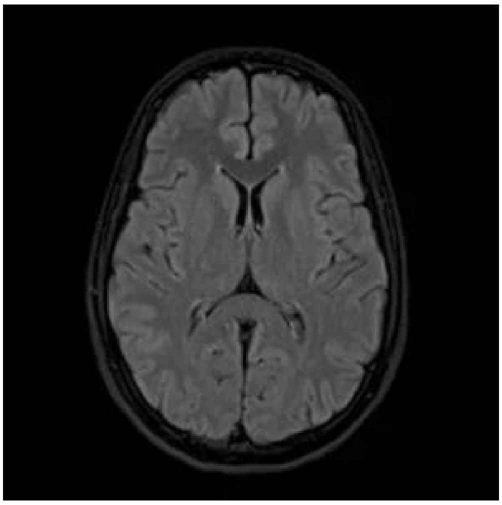
This web-deployment illustrates that the model is practicable and may be applied to help doctors make preliminary diagnoses quickly. Further quantitative evaluation and fine tuning of the model should improve the accuracy, but it is now established, with this current implementation, that the application of CNNs is fully feasible in the detection of brain tumors.

By visualizing training and validation accuracy curves, confusion matrices, and example classifications on test data, further development ideas are given with more detail, making the model better to assess rigorously and help improve its predictability and generalization.

Results of the output prediction

Brain Tumor Classification Using Deep Learning

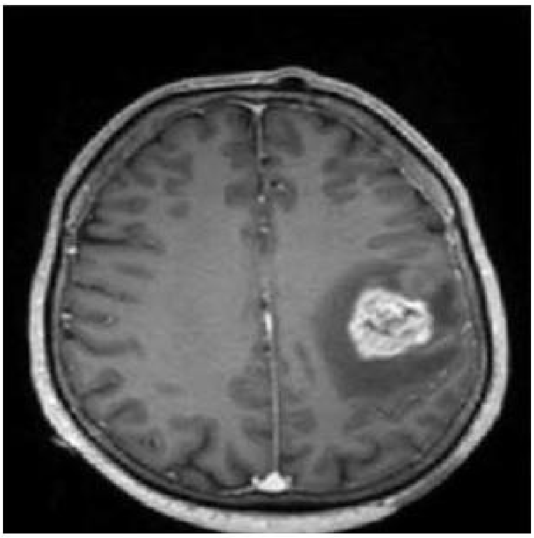
Choose File pred0.jpg



Result: Brain Tumor Not Detected

Brain Tumor Classification Using Deep Learning

Choose File pred8.jpg



Result: Brain Tumor Is Detected!!

Discussion

The implications of the classification project on the brain tumor are that deep learning has lots of potential in medical images, particularly for assisting early detection in brain tumors. Using CNNs, the model was able to learn and classify MRI images into "tumor" and "no tumor categories. This is with the advantages of automated classification that would ease diagnostic workflows. It also provides a practical framework for the deployment of the model in web-based form to enable its use in clinical settings in real-time, user-friendly interactions where a medical professional or patient uploads an image and obtains an immediate result.

Despite this, the model in itself would exhibit frailties in actual scenarios, owing to variation in imaging quality, a difference in MRI scanner specifications, and especially limited diversity of data used for training. Training on much larger and more diverse datasets will most likely make the model better at generalization to other patient populations and imaging conditions. Techniques such as data augmentation, including rotation, flipping, and brightness adjustment, may increase the robustness of the model by exposing it to a wider variation of image.

Future enhancements might include trying advanced techniques, like transfer learning, where the model learns in one job and gets fine-tuned on a related task; this may help better prediction results with much fewer computational resources. Other explainable AI concepts, like a heat map of interest areas, would make the decision of the model more understandable for radiologists. Overall, the project reports very promising early results and helps in creating an anchor that will serve for further advancement in automated brain tumor detection.

Conclusion and Future Work

This project is on deep learning to automatically detect brain tumors using MRI images. The promising work indicates the ability of CNNs in medical imaging to classify brain scans as either "tumor" or "no tumor." The model, through preprocessing, feature extraction, and classification, establishes the base approach to implementing AI-driven diagnostic tools that could help radiologists and health professionals to identify patients with brain tumors quickly and accurately. The web interface further enables wide accessibility of the model and thus allows users to interact with the model in real-time for instant results on uploaded MRI scans. The proof-of-concept implementation demonstrates the feasibility of deployment of AI in healthcare, potentially reducing the diagnostic workload while creating opportunities to improve patient outcomes through early detection efforts.

Generalization cannot be made in the proposed model, especially when patient populations and MRI scans are diversified. More images could be added enhancing the datasets representing tumor types, patient demographics, and scan qualities thereby enhancing the robust and reliability of the model. Techniques in data augmentation could be further included to exploit deeper learning approaches, such as pre-trained models using transfer learning, to increase the predictability of the model and reduce training time. Future work could then be the addition of saliency maps or Grad-CAM, thereby allowing for a visual inspection of regions of interest into any image most influential in the model's decision, which can lead to higher trust and transparency of AI-based medical tools.

Such a project is important in marking an important step toward the successful application of deep learning in brain-tumor detection, opening possible avenues for refinement and expansion in order to make this model an effective tool in clinical diagnostics.

References

Dataset Source: MRI images used in this project were sourced from the "Brain Tumor Classification MRI" dataset on Kaggle. This dataset provides a set of MRI brain scans categorized as "tumor" and "no tumor" classes, which forms a good foundation for training and testing deep learning models in classification tasks based on brain tumors.

(Dataset source: https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection)

Deep Learning Frameworks and Libraries. This project heavily utilized open-source libraries within the Python ecosystem - Keras as well as TensorFlow - for the creation and training of the CNN model. Keras provides a high-level interface toward the definition of neural networks; on the other hand, TensorFlow would support efficient computation and model training. Both of these libraries have adequate documentation to support model design as well as optimization.

(TensorFlow documentation: https://www.tensorflow.org/; Keras documentation: https://keras.io/)

The Image Processing Libraries: For the preprocessing of MRI images, OpenCV and Pillow were used. They enable reading and manipulation of images by OpenCV and resizing and converting images so that CNN can accept them using uniform dimensions. These libraries are highly popular among developers, which means they have quite a lot of documentation material accompanying them. This further added to the preprocessing pipeline.

(OpenCV documentation: https://opencv.org/; Pillow documentation: https://pillow.readthedocs.io/)

Flask for Web Application: The model was deployed onto the lightweight web framework, Flask, to develop a user-friendly web application. This was a framework allowing the exposure of a simple user interface of the model where users can upload their images and receive predictions based on those images. This is owing to detailed documentation in developing and hosting web applications based on Flask.

(Flask documentation: https://flask.palletsprojects.com/)

Research on CNNs for Medical Imaging: There were several research papers and online references that gave an overview of how CNNs could be applied for medical imaging specifically on the identification of brain tumors. These had assisted in knowing how architectures of CNNs could be optimized in order to classify images and chose fitting parameters for models to learn from.

Contribution

Abstract

This project focused on applying deep learning techniques to classify brain tumors from MRI images using Deep Learning Model.

Contribution and Findings

The project successfully implemented a convolutional neural network for brain tumor classification, demonstrating the model's ability to distinguish between tumor and non-tumor brain MRI images. Key findings include the model's practical deployment via a Flask web application and potential improvements through dataset augmentation and advanced techniques like transfer learning.

Contribution to Project Report Preparation

Contributed by writing detailed sections such as Abstract, Introduction, Dataset Description, and Methodology for the project report.

Contribution for Project PPT

Created the PowerPoint presentation, summarizing key points from the report and visually presenting the project outcomes.

Shubham Roy

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Signature of the Supervisor Signature of the Student

" Brain Tumor Classification Using Deep Learning "

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