Brain Tumor Detection

Capstone Project Documentation

Identify Brain Tumor through Deep Learning

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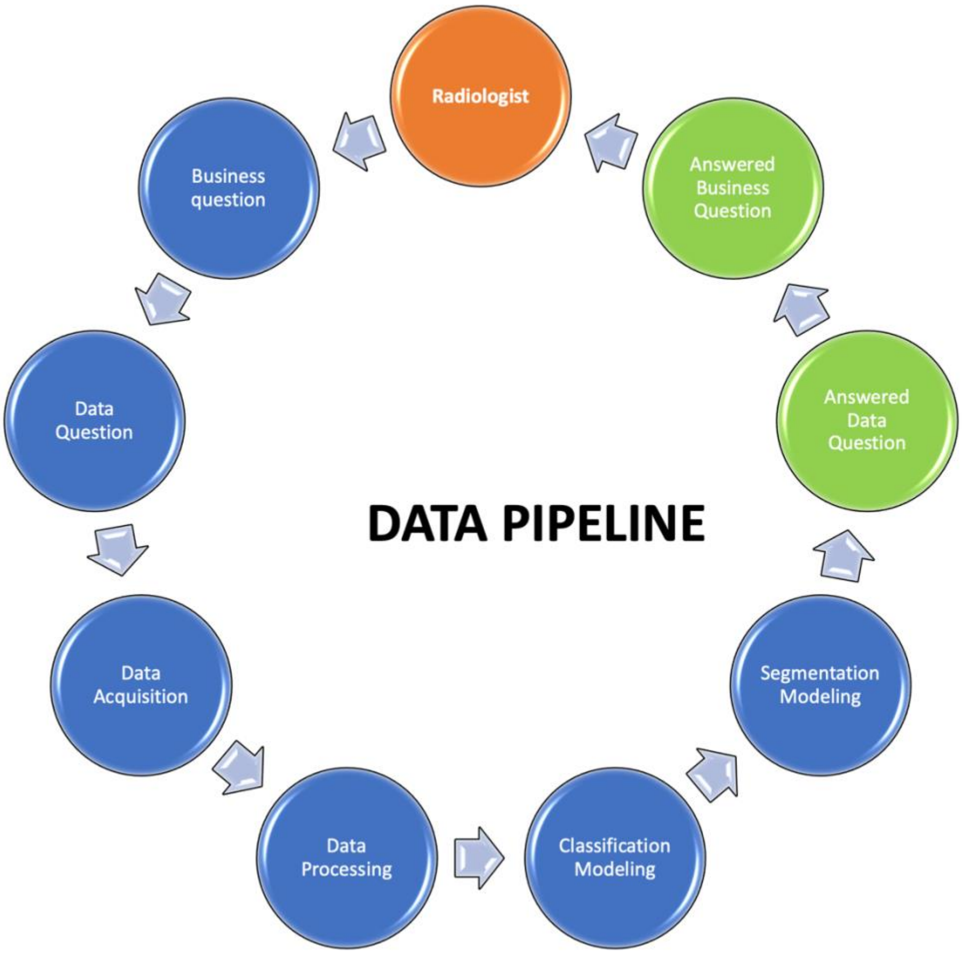
Table of Contents

Introduction

Today, clinical practice is an area of interest and research where extensive research and technical recommendations have been developed in response to increasingly complex challenges. Identifying and analyzing diseases is increasingly difficult because they are ever more sophisticated. Fortunately, artificial intelligence has revolutionized clinical practice in many areas such as cancer diagnosis with medical imaging, automatic classification diseases based on descriptions, and maximizing hospital efficiency. Among many approaches, deep learning has been proven superior in a wide range of clinical data and practice scenarios. Regarding MRI, the complex feature can be represented effectively by utilizing deep learning-based models in detection, registration, classification, and segmentation problems.

Process overview

The following diagram shows the overall end-to-end process for defining, designing and delivering the Capstone project.



Problem statement

- This project is concerned with training a convolutional neural network to detect lower-grade glioma brain tumours on MRI-scans.
- **Low-grade gliomas** (LGGs) are a diverse group of primary brain tumours that often arise in young, otherwise healthy patients and generally have an indolent course with longer-term survival in comparison with high-grade gliomas.
- In this type of brain tumour with a relatively good prognosis and prolonged survival, the potential benefits of treatment must be carefully weighed against potential treatment-related risks.
- It is therefore of vital importance that they can be accurately detected from MRI images.
- Although the field of deep learning is not yet advanced enough to fully replace radiologists at this task, significant progress has been made in the field with classification CNN's reaching accuracies of over 95%.

- Skilled radiologists reach accuracies of between 92 and 95%. It can take up to 1-2 weeks to get result.

Industry

- The use of Artificial Intelligence, or AI, is growing rapidly in the medical field, especially in diagnostics and management of treatment. To date there has been a wide range of research into how AI can aid clinical decisions and enhance physicians' judgement.
- Accurate diagnosis is a fundamental aspect of global healthcare systems. In the US, approximately 5% of outpatients receive an incorrect diagnosis, with errors being particularly common for serious medical conditions, and carrying the risk of serious patient harm.
- It can be used to diagnose cancer, triage critical findings in medical imaging, flag acute abnormalities, provide radiologists with help in prioritizing life threatening cases, diagnose cardiac arrhythmias, predict stroke outcomes, and help with the management of chronic diseases.
- AI is a rich realm of data, algorithms, analytics, deep learning, neural networks and insights that's constantly growing and adapting to the needs of the healthcare industry and its patients.
- Over the past few years, artificial intelligence in medical diagnosis has shown immense promise in changing the standards of medical care while reducing the extreme pressures felt by the medical industry.

Stakeholders

The main stakeholder is:

- Radiologists
- Doctors
- Physicians
- Neuropathologists

Business Question

“How can we detect tumor more accurately than radiologist and faster?”

Data Question

"Can we use Artificial Intelligence to detect brain tumor based on MRI-scan images?"

Data science process

Data extraction

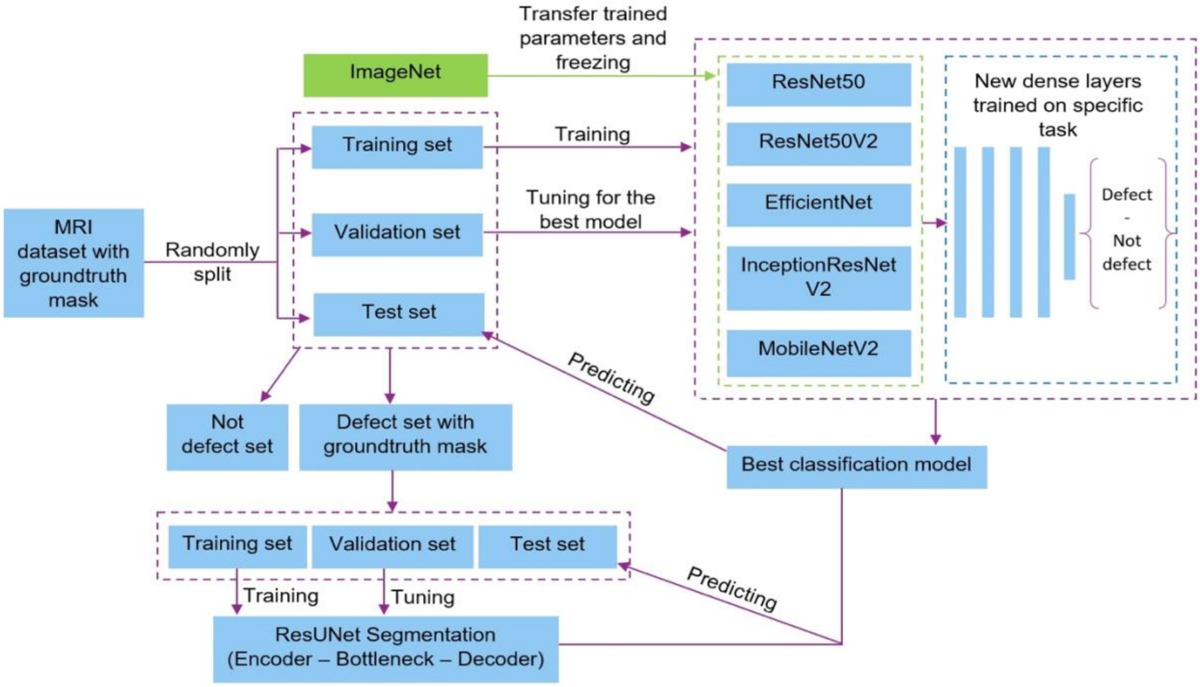
- Images were extracted from Kaggle.com
- The data is in .tif format
- Size of data is 1.08GB

Images Pre-processing

- Resize images to 256x256 pixels to preserve features and less computational power.
- Visualize MRI image and Mask to locate the tumor in brain.
- Normalization images by 255 to reduce the variance in pixel.
- Based on csv file about patient's information. Find out age range of patients.

Modelling

The Blueprint Classification-Segmentation Pipeline for Brain Tumour MRI Detection



This project aims to combine the classification and segmentation of brain MRI into a single clinical practice.

Phase 1: Train classification model

- For the task of classification, i have deployed 5 well-known CNN models in computer vision community (ResNet50, ResNet50V2, InceptionResNetV2, EfficientNetB0, and MobileNetV2).

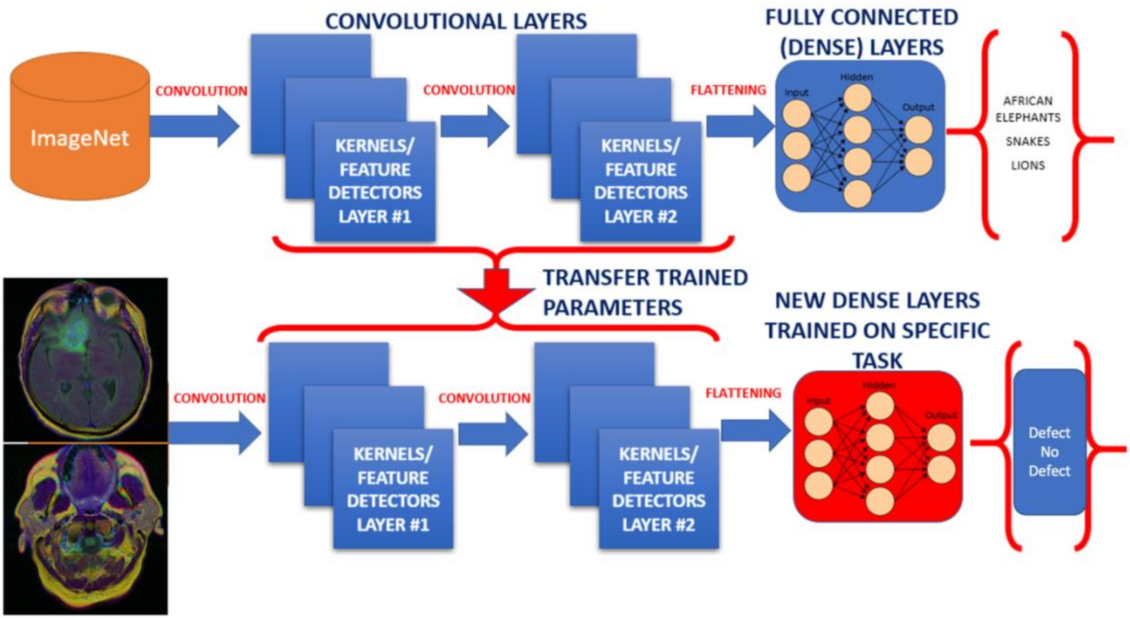
- Splitting MRI dataset into 70%-15%-15% training, validation (val.), test sets.
- For each model to apply transfer learning to do transfer pretrained weights from ImageNet to the CNN part and freeze it.

Model	Accuracy	Recall	Precision	AUC	F1-Score
Resnet50	0.96	0.91	0.97	1	0.94
Resnet50V2	0.95	0.90	0.93	0.98	0.91
InceptionNetV2	**0.98**	**0.96**	**0.98**	**0.99**	**0.97**
EfficientNetB0	0.95	0.87	0.93	0.97	0.9
MobileNetV2	0.97	0.97	0.93	1	0.95

- The model was train on Kaggle notebook with accelerated GPU.

- InceptionNetV2 model was selected as it gave a best performance.

Model Architecture



Metrics used:

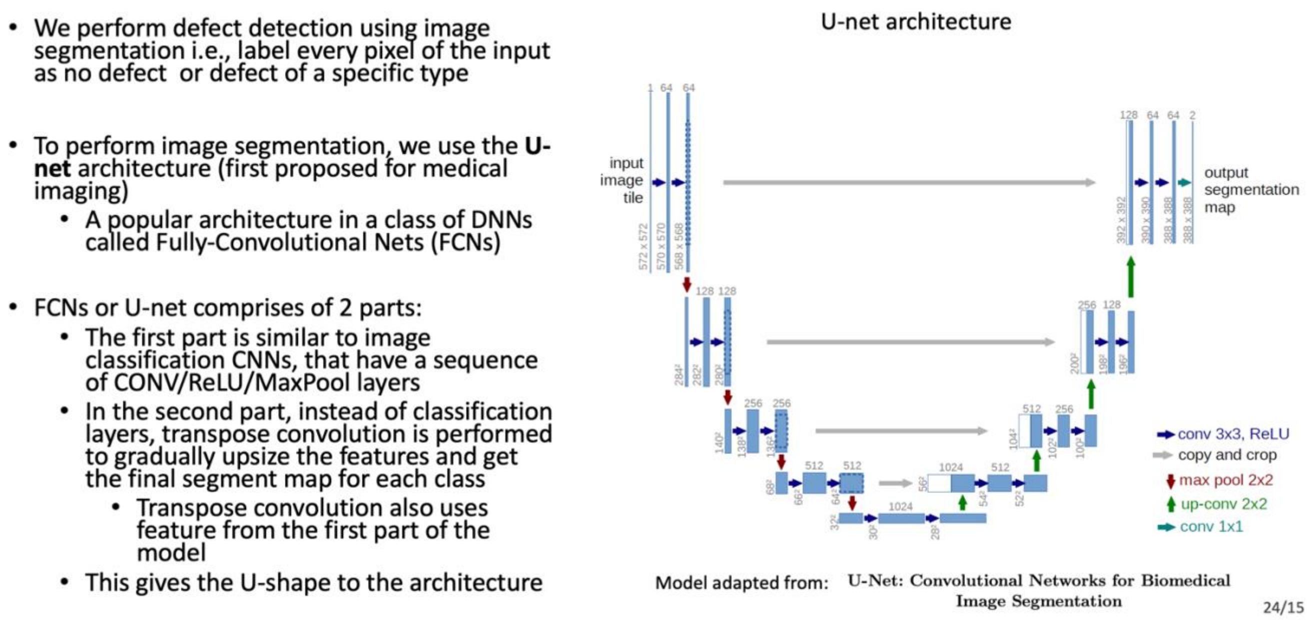
- Accuracy Score: 98%
- Recall: 97%
- F1 Score: 96%
- Epochs: 28
- Time: 19 minutes 55 seconds.

Phase 2: Train segmentation model

Segmentation Model (RESUNET)

- Defect MRI images are split into 70%-15%-15% training, val., test sets
- In the segmentation task, ResUNet model, one of the most state-of-the-art segmentation models.

Model Architecture:



Metrics used:

- Tversky Score: 96%
- Focal Tversky Loss: 0.17
- Epochs: 44
- Time: 5 minutes 52 seconds.

Outcomes

- The Classification model correctly predicted 98% accuracy, and 96% F1 score on unseen data

- The Segmentation model was also performce well with customize accuracy score funtion tversky score 96% and 90% on unseen data.

Implementation

- Developing software that can be installed on a computer, doctors can upload MRI images and report results within minutes.

Data answer

- Take advantage of Computer Vision in object detection we can accurately identify tumor based on MRI images.
- By using AI, the processing of dianogsis has been faster and more accurately than radiologist with 97% accuracy and within minutes to get result

Business answer

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- Neuropathologists, radiologist can review the images without the need for a pathology lab, eliminating the long wait time needed for traditional processing, staining and interpretation.

Response to stakeholders

- AI takes full advantage of the data and increases the speed and objectivity of diagnoses. The result of the AI evaluations is a suggested diagnosis that still needs to be verified by the physician or doctor.

End-to-end solution

- The project has been described and implemented the proposed Class- Seg workflow by leveraging transfer learning and residual network together with several state-of-the-art convolutional neural models.
- The project has integrated the classification and segmentation of brain MRI into a single clinical practice and combined two research directions on the well-known Kaggle brain MRI dataset, in which more than 40 code solutions have been investigated. Intensive experiments have been conducted to develop a clinically acceptable automatic workflow for better brain MRI diagnosis.

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