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Brain MRI Tumor Analysis and Classification using Deep Learning

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Brain MRI Tumor Analysis and Classification using Deep Learning

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ABSTRACT

Magnetic Resonance Imaging (MRI) is a medical imaging technique frequently used to produce a pictorial view of internal body parts, structure and functionality. Radiologists usually perform manual analysis on a large number of MR images for brain tumor detection. It is very hard to correctly segment the tumor tissues present in the MR images due to the similarity, noise, complex texture, poor sampling and image distortions. With the advent of more powerful computing devices, system automation plays a pivotal role. In the medical industry, automated image classification and segmentation is an important task to assist medical experts in the correct diagnosis of a certain disease. Most of the recent research studies focus on binary classification of brain MR image into tumorous and non-tumorous images in addition to tumor segmentation. The extracted tumor is further classified into four Glioma tumor classes which are Necrosis, Edema, Enhancing and Non-Enhancing tumors. This is referred as multiclass classification, and it is an area that is yet to be explored. The current classification techniques proposed in the literature suffer from limited dataset size and overfitting problems. In this thesis, an automated multistage technique is proposed for the MR image classification into tumorous and non-tumorous images followed by brain tumor segmentation and classification in order to differentiate the tumors into these four classes using enhanced deep learning models. The experiments were performed using BraTS, AANLIB and PIMS-MRI datasets. In the first stage, the contribution of this study is a binary brain MR image classification, where two enhanced techniques are proposed to classify the images into tumorous and non-tumorous. The enhanced techniques are based on binary CNN features and binary Deep CNN classifier that resulted an average accuracy of 97.61% and 98.04%, respectively. In the second stage, the tumor region was segmented from the tumorous images using the proposed neighboring Fuzzy C-means (FCM) based

technique which resulted an average dice similarity coefficient (DSC) score of 90.87%. In the third stage, the segmented tumor was classified into four Glioma tumor classes using an enhanced multiclass CNN features and Deep CNN model as classifier. The experimental results using CNN features and Deep CNN model as classifier for multiclass Glioma tumor classification into Necrosis, Edema, Non-enhancing tumor, and enhancing tumor indicated an average accuracy of 96.19% and 96.30% respectively, which outperformed results reported in previous literature.

Keywords: Glioma tumor classification, convolutional neural networks, deep learning, magnetic resonance image classification, tumor segmentation

Analisis Tumor MRI Otak dan Klasifikasi Menggunakan Pembelajaran Mendalam

ABSTRAK

Pengimejan Resonans Magnetik (MRI) adalah teknik pengimejan perubatan yang sering digunakan untuk menghasilkan gambaran bahagian dalaman, struktur dan fungsi badan. Ahli radiologi biasanya melakukan analisa manual pada sebilangan besar pengimejan resonans magnetik untuk pengesanan tumor otak. Kaedah manual ini adalah sangat sukar untuk mengenal pasti tisu tumor yang terdapat dalam gambar MR kerana kesamaan, kebisingan, tekstur kompleks, persampelan yang tidak baik dan gangguan gambar. Dengan adanya peranti pengkomputeran yang lebih hebat, automasi sistem memainkan peranan penting. Dalam industri perubatan, klasifikasi dan segmentasi gambar automatik adalah tugas penting untuk membantu pakar perubatan dalam memberi diagnosis penyakit dengan betul. Sebilangan besar kajian penyelidikan bidang ini hanya tertumpu kepada pengkelasan binari gambar MR otak kepada gambar tumor dan bukan tumor selain segmentasi tumor. Tumor yang diekstrak kemudian dikelaskan kepada empat kelas tumor Glioma iaitu Necrosis, Edema, Enhancing dan Non-Enhancing. Ini disebut sebagai klasifikasi multikelas, dan merupakan skop kajian yang masih belum banyak diterokai. Teknik klasifikasi semasa yang dicadangkan dalam literatur mengalami masalah set data yang terhad dan overfitting. Dalam tesis ini, teknik automatik pelbagai peringkat adalah diusulkan untuk mengklasifikasikan gambar MR menjadi gambar tumor dan bukan tumor diikuti dengan segmentasi dan klasifikasi tumor otak untuk membezakan tumor kepada empat kelas tersebut menggunakan model pembelajaran mendalam yang dipertingkatkan. Eksperimen dilakukan menggunakan set data BraTS, AANLIB dan PIMS-MRI. Pada peringkat pertama, sumbangan kajian ini adalah klasifikasi gambar MR otak binari, di mana dua teknik

dicadangkan untuk mengklasifikasikan gambar kepada tumor dan bukan tumor. Teknik yang dicadangkan adalah berdasarkan ciri CNN binari dan pengelasan CNN binari yang masing-masing menghasilkan ketepatan purata 97.61% dan 98.04%. Pada peringkat kedua, kawasan tumor yang disegmentasi dari gambar tumor menggunakan teknik berasaskan Fuzzy C-means (FCM) yang menghasilkan skor koefisien kesamaan dadu (DSC) 90.87%. Pada tahap ketiga, tumor yang disegmentasi diklasifikasikan menjadi empat kelas tumor Glioma menggunakan ciri CNN multikelas yang dipertingkatkan dan model Pendalaman CNN sebagai pengelasan. Hasil eksperimen menggunakan ciri CNN dan model Pendalaman CNN sebagai pengelasan untuk klasifikasi tumor Glioma multikelas kepada Necrosis, Edema, Enhancing dan Non-Enhancing menunjukkan ketepatan 96.19% dan 96.30%, di mana ianya adalah lebih baik dari hasil kajian yang dilaporkan dalam sorotan kajian sebelum ini.

Kata kunci: *Klasifikasi tumor glioma, rangkaian konvolusi neural, pembelajaran mendalam, klasifikasi imej resonans magnetik, segmentasi tumor*

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CHAPTER 1

INTRODUCTION

In recent years, most fatalities are caused by brain tumors which are abnormal growth of brain cells (McCance & Huether, 2018). According to the global cancer statistics report 2018, it is estimated that more than 18.1 million people will be diagnosed with cancer, while 9.6 million deaths would be attributed to cancer (Bray et al., 2018). Most of these deaths would be expected to occur in developing countries like Afghanistan, Kenya, and some other African countries, bringing the percentage of cancer-related deaths to 70% of deaths worldwide. Currently, 13 million US citizens are suffering from a malignant brain tumor, as reported in the cancer statistics provided by the Surveillance, Epidemiology, and End Results (SEER) Program (Navi & Iadecola, 2018). The treatment of brain tumors is challenging due to the complex brain structure in which all the tissues and cells are interconnected. The life expectancy of patients strictly depends on the size, type, and location of the tumor. Therefore, an early diagnosis of the tumor is extremely important to start the treatment in a proper direction.

The brain is like the human body's central processing unit, which controls all the activities; it has trillions of nerves that communicate with the whole body through chemical and electrical signals. Although brain tumors can grow in any part of the brain, it mainly grows in the tissues and nerves that cover the brain's outer boundary. The tumors that develop in the central nervous system of the brain are known as primary tumors and usually do not spread. Still, the tumors that develop in the remaining parts of the brain can spread to the rest of the brain and are known as metastatic tumors (Pan et al., 2015).

A tumor is an abnormal growth of cells that can either be Malignant or Benign. Malignant tumors usually cause brain cancer while the benign tumor is harmless. To diagnose and interpret different body parts, an advanced medical imaging modality named Magnetic Resonance Imaging (MRI) is used. A brain MRI uses hundreds of sequences and interpretations to identify normal and affected brain tissues. Around 400 MR images are extracted through the magnetic field of the MRI machine and the interpretation process by doctors takes around 40 to 50 minutes. The interpretation of these MR images is a highly complex task, and it is extremely difficult to specify the exact location of the tumor inside the brain due to hard overlapping tissues (Usman & Rajpoot, 2017).

This research focused on developing an autonomous system that performs the classification, segmentation, and visualization of all images. This will make the job of radiologists and doctors much more manageable. An essential task in the medical imaging field is to segment the tumorous portion of the MR image for proper diagnosis. Segmentation is important in breast MR images, segmentation of CT-scans of the lung, and brain MRI (Gambino et al., 2019). There are three major tissue types in the human brain: white matter, gray matter, and cerebrospinal fluid (Prust et al., 2018). These tissue types are quite similar in appearance in MR images. Therefore, it is a difficult task to differentiate among such types. Our main focus in this research was on the classification of brain images as tumorous or non-tumorous images (binary classification), segmentation of tumorous portion of the image, and further classifying the tumor into four classes (multiclass classification); Necrosis, Edema, Non-enhancing tumor, and enhancing tumor. In the classification phase, enhanced techniques based on machine learning and particularly convolutional neural networks (CNNs) were used.

Although extensive research has been conducted in the field of tumor classification and segmentation, early diagnosis remains poor (Morgan et al., 2017). High-Grade Gliomas (HGG) is known to be the most aggressive form of this disease in which the survival rate is two or fewer years and immediate treatment is required (Sauwen et al., 2016). There are Low-Grade Gliomas (LGG) with a slow-growing rate of tumorous cells. In this case, the treatment can be delayed because the life expectancy is several years. In the human brain, there are tissues known as “Glial” which are supportive tissues and keep the brain neurons in place and intact for functioning well. Any tumor which is caused by such tissues is termed as “Glioma”. This tumor mainly occurs in the brain and spinal cord. The type of Glioma tumor depends on the nature of the glial cells involved. Gliomas have different types, and each type has specific traits that could affect brain function and could be life-threatening (Hsieh et al., 2017). The classification of Glioma brain cancer and the location of the tumorous portion of the brain is vital for the timely treatment and prognosis that may be prescribed, which may include chemotherapy, surgery, targeted or radiation therapy (Wen et al., 2010). This is why the focus on the HGG is heterogamous in nature with irregular shape and boundary, but experiments are performed on both HGG and LGG. Furthermore, the location and size vary considerably, which makes the segmentation task more challenging. This is a crucial task to follow up on the treatment of HGG and LGG patients. The manual segmentation of such tumors through MR Imaging (MRI) is still a trusted process performed by a neuro-radiologist. The MRI process is still preferred over other radiology methods as it is more accurate to locate the tumor cells (Giedd, 2004). The manual process for radiologists to classify, diagnose and locate tumorous portions of the brain is a long, expensive, and tedious process. Thus, the research's importance is to automate brain tumor classification (Menze et al., 2015). Such methods are further categorized into

Supervised and Unsupervised classification methods. Supervised classification methods need prior knowledge from training data sets, and from this learning process, algorithms take the decision. Still, the training data sets are extensive and require time-consuming pre-processing. In contrast, unsupervised classification methods can directly be applied to images without any labeling on the data set. The tumor is classified into different classes after segmentation. Other classification methods are discussed in Bauer et al. (2013), e.g., Random Forest (RF), Multi-Layer Perceptron (MLP), Support Vector Machines (SVM), Naïve Bayes, and Deep Learning. These methods perform the classification by incorporating different tumor features. The most commonly used methods for feature extraction are Texture Feature, Discrete Cosine Transform (DCT), Deep Convolutional Neural Network Features and Discrete Wavelet Transform (DWT) (Latif et al., 2017). Recently, the interest in deep learning techniques has been revived due to the advances in computing power, which allows for the execution of more complex algorithms. Many researchers have applied deep learning algorithms for the classification of brain tumors. However, gaps still exist within current literature due to overfitting problems and a lack of sufficiently sized datasets.

1.1 Motivation

Radiologists and physicians are always keen on correctly diagnosing and identifying the brain tumor's location as it is a disease that caused 9 million deaths in 2015. This death rate is increasing with an estimated 11.5 million dying in 2030 (Dwivedi et al., 2016). MR images are currently used for diagnosis and detection of tumors, but this is done through a tedious process in which radiologists analyze a large amount of MR Images for a single patient. This manual classification depends on the human judgment of the radiologist, their expertise, and experience. Human judgment is always prone to mistakes. Therefore, due to the importance of correctly diagnosing and segmenting a Glioma Tumor, an automated

system is required in which computers do most of the tedious work of analysis and assist the radiologists and physicians in making the correct diagnosis and appropriate treatment. In summary, brain tumor diagnosis is a complicated task due to the following reasons:

- i. the classification and segmentation of brain MR images is a very important and complicated task for proper diagnosis and treatment of the brain tumor;
- ii. experienced radiologists perform the manual segmentation of MR images which is a time consuming and expensive method (Krishna et al., 2018);
- iii. manual segmentation of the images varies among different experts due to level of experience and could also include possible human error; and
- iv. the location and type of the brain tumor vary from case to case, making the task even more challenging (Anaraki et al., 2019).

The motivation of this work is to develop automated processes that could analyze and classify MR Images into tumorous and non-tumorous images (binary classification), correctly segment the tumor from the tumorous images, and then further classify the segmented tumorous images into the four types, namely Glioma tumors; Necrosis, Edema, Non-enhancing tumor, and enhancing tumor (Multiclass classification). Recently, the field of image processing has gained momentum and a lot of research has been done on developing automated processes for these tasks (Vardhana et al., 2018). In this research, enhanced processes have been proposed and developed to increase the above-mentioned tasks' accuracy and outperform all methods reported in previous literature. The enhanced proposed models include deep learning models that were proposed based on carefully selected parameters to achieve 100% accuracy for multiclass brain Glioma tumor classification. Deep learning algorithms have been around for decades. However, due to the computational requirements of these algorithms, they were never utilized to the full potential

(Ullah et al., 2017). In recent years, the technological advances in hardware computer technology rolled out systems capable of processing deep learning algorithms in a reasonable time. Therefore, researchers in image recognition are now concentrating on the use of deep learning algorithms that outperform feature-based classification methods. Researchers are redesigning deep architectures according to the application to enhance accuracy. In this thesis, improved deep learning architectures are proposed for Glioma tumor classification to achieve enhanced classification results. In both cases, the fact that human judgment is removed from the process with the error-prone variable makes the automated process of diagnosis of glioma brain tumor through classification and segmentation a more appealing alternative.

1.2 Research Problem

The diagnosis of images for the human brain is one of the most complex tasks because brain tissue images can overlap due to inconsistency in brain MR images' anatomy (Despotović et al., 2015). The challenges of using brain MR images for the manual diagnosis and the possibility of human error in the diagnosis process made it necessary to research automated alternatives that can diagnose and segment tumors with better accuracy than the most experienced doctors and radiologists. The main problem faced when applying deep learning in radiology is the limited data set size and overfitting due to the lack of effective application dependent model designs (Yamashita et al., 2018). Several studies are presented in this thesis to show the problems faced in terms of overfitting and data availability. Many researchers tackle these problems using data augmentation for data availability or using architectures based on the optimization of parameters that generalize the model. The regularization of the model by adding more dropout layers and reducing the architecture complexity also plays a vital role in reducing the overfitting problem. The proposed

techniques in this thesis overcome the problems associated with the use of deep learning in radiological applications. Though many researchers have proposed binary classification techniques using the same dataset, very limited work has been done in the multiclass brain tumor classification. Most previous literature propose the use of feature extraction based methods for the classification of brain tumors providing researchers the possibility to enhance and propose new methods for higher accuracy. This study focuses on developing deep learning architectures through parameter manipulation that can correctly diagnose Glioma tumors and Glioma tumor types with high accuracy. Within this context, enhanced image processing techniques are also proposed within this research.

1.3 Research Questions

The following are the research questions addressed in this thesis:

- i. How to enhance the existing feature extraction and classification techniques for the brain MR images in order to classify the image into tumorous and non-tumorous to overcome the limitations of existing deep learning models that suffer from overfitting and limited dataset problems?
- ii. How to utilize deep learning architectures to classify Glioma tumors from MR images into Necrosis, Edema, Enhancing, and Non-Enhancing?
- iii. Is the proposed enhanced deep learning model better than the existing feature-based classification techniques and deep learning architecture such as LeNet, AlexNet and GoogleNet?

1.4 Research Objectives

A comprehensive research was conducted on brain tumor segmentation and classification of tumors in this thesis. The utmost goal of this research is to propose an