

**BRAIN TUMOR MRI IMAGES DETECTION AND
CLASSIFICATION ALGORITHM BASED ON DEEP
CONVOLUTION NEURAL NETWORK TECHNIQUES**

BY

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ABSTRACT

The substantial progress of medical imaging technology in the last decade makes it challenging for medical experts and radiologists to analyse and classify them. Medical images contain massive information that can be used for diagnosis, surgical planning, training, and research. The ability to estimate conclusions without direct human input in healthcare systems using computer algorithms is known as Artificial intelligence (AI) in healthcare. Deep Learning (DL) approaches are already being employed or exploited for healthcare purposes. There is, therefore, a need for a technique that can automatically analyze and classify the images based on their respective contents. DL algorithms open a world of opportunities, and it has been recently used for medical images analysis. Although DL techniques have demonstrated a breakthrough in medical images analysis, research still ongoing to improve the accuracy rate. This research focuses on DL in the context of analysing Magnetic Resonance Imaging (MRI) brain medical images. A comprehensive review of the state-of-the-art processing of brain medical images using DL is conducted in this research. The scope of this research is restricted to three digital databases: (1) the Science Direct database, (2) the IEEEExplore Library of Engineering and Technology Technical Literature, and (3) Scopus database. More than 400 publications were evaluated and discussed in this research. The research focus on both binary classification and multi-class classification. For binary classification, the dataset used is from the brain tumor classification project which contains tumorous and non-tumorous images, and it is available for research and development. For multi-class classification, the dataset contains T1-weighted contrast-enhanced MRI medical images from 233 patients with three types of tumours: meningioma, glioma, and pituitary which is also available for research and development. The proposed neural model is fully automatic brain tumour MRI medical images classification model that uses Convolutional Neural Network (BTMIC-CNN). The model's excellent performance was confirmed using the evaluation metrics and reported a total accuracy of 99%. It outperforms existing methods in terms of classification accuracy and is expected to help radiologists and doctors accurately classify brain tumours' images. This study contributes to goal 3 of the Sustainable Development Goals (SDGs), which involves excellent health and well-being.

ملخص البحث

التقدم الكبير في تكنولوجيا التصوير الطبي في العقد الماضي يجعل من الصعب على الخبراء الطبيين وأخصائي الأشعة تحليلها وتصنيفها. تحتوي الصور الطبية على معلومات ضخمة يمكن استخدامها في التشخيص، والتخطيط الجراحي، والتدريب، والبحث. تُعرف القدرة على تقدير الاستنتاجات دون المدخلات البشرية المباشرة في أنظمة الرعاية الصحية باستخدام خوارزميات الحاسوب باسم الذكاء الاصطناعي (AI) في الرعاية الصحية. يتم بالفعل استخدام مناهج التعلم العميق (DL) لأغراض الرعاية الصحية. لذلك، هناك حاجة إلى تقنية يمكنها تحليل الصور وتصنيفها تلقائيًا بناءً على محتويات كل منها. تفتح خوارزميات DL عالماً من الفرص، وقد تم استخدامها مؤخرًا لتحليل الصور الطبية. على الرغم من أن تقنيات DL أظهرت تقدمًا كبيرًا في تحليل الصور الطبية، إلا أن الأبحاث لا تزال جارية وهناك العديد من الطرق لتحسين معدل الدقة. يركز هذا البحث على خوارزميات DL في سياق تحليل الصور الطبية للدماغ بالتصوير بالرنين المغناطيسي (MRI) يتم إجراء نظرة عامة شاملة على أحدث معالجة للصور الطبية للدماغ باستخدام الشبكات العصبية العميقة في هذا البحث. يقتصر نطاق هذا البحث على ثلاث قواعد بيانات رقمية: (1) قاعدة بيانات Science Direct، (2) مكتبة IEEEXplore للأدب الفني الهندسي والتكنولوجيا، و (3) قاعدة بيانات Scopus. تم تقييم ومناقشة أكثر من 400 منشور في هذا البحث. يركز البحث على كل من التصنيف الثنائي والتصنيف متعدد الفئات. بالنسبة للتصنيف الثنائي استخدمنا مجموعة البيانات من مشروع تصنيف أورام المخ والذي يحتوي على صور أورام وغير أورام، وهي متاحة للبحث والتطوير. من أجل التصنيف متعدد الفئات، تم استخدام النموذج العصبي المقترح لتصنيف الصور الطبية بالرنين المغناطيسي المعززة بالتباين الموزونة T1 المأخوذة من 233 مريضًا يعانون من ثلاثة أنواع من الأورام: الورم السحائي والورم الدبقية والغدة النخامية. النموذج العصبي المقترح هو نموذج تصنيف صور التصوير الطبي بالرنين المغناطيسي لورم الدماغ التلقائي بالكامل والذي يستخدم الشبكة العصبية التلافيفية (BTMIC-CNN). الدقة الإجمالية قدرها 99%. حيث تتفوق على الأساليب الحالية من حيث دقة التصنيف ومن المتوقع أن يساعد أطباء الأشعة والأطباء في تصنيف صور أورام الدماغ بدقة. تساهم هذه الدراسة في الهدف 3 من أهداف التنمية المستدامة (SDGs).

APPROVAL PAGE

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DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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*This thesis is dedicated to my beloved parents for laying the foundation of what I
turned out to be in life.*

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LIST OF ABBREVIATION

AI	Artificial Intelligence
ANN	Artificial Neural Network
BRATS	Brain Tumors Segments Challenges
BTMIC	Brain Tumor MRI Medical Images Classification
CNN	Convolutional Neural Network
CNS	Central Nervous System
CT	Computerized Tomography
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
ISLES	Ischemic Stroke Lesion Segmentation Challenge
ML	Machine Learning
MRI	Magnetic Resonance Imaging
MRS	Magnetic Resonance Spectroscopy
NBTS	National Brain Tumor Society
PET	Positron Emission Tomography
SDGs	Sustainable Development Goals
SPECT	Single-photon emission computed tomography
SVM	Support Vector Machine
TL	Transfer Learning
VGG	Visual Geometry Group
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

A brain tumour is the result of abnormal and uncontrolled development of brain cells. The National Brain Tumour Society reports that ~700,000 people in the United States of America (USA) suffer from brain tumours, and that number will increase by 85,000 in 2021. The world's 10th most common cause of death; ~3460 children under 15 were also diagnosed this year with a brain or central nervous system (CNS) tumour (NBTS, 2021). The early detection and classification of brain tumours is an important research domain in medical imaging, because it aids in the selection of the best treatment choice to save the patients' lives. Medical images are critical towards surgical planning, as it is a crucial information source for many diseases. It can also be used for research and training purposes.

The demand for digital medical images is steadily increasing. For example, CT imaging rates in older adults were 428 per 1000 person-years in 2016, compared to 204 per 1000 in 2000 in US health care systems and 409 per 1000 vs 161 per 1000 in Ontario; MRI rates were 139 per 1000 vs 62 per 1000 in the US and 89 per 1000 vs 13 per 1000 in Ontario; and ultrasound rates were 495 per 1000 vs 324 per 1000 in the US and 580 per 1000 vs 332 per 1000 in Ontario (Smith-Bindman et al., 2019). Therefore, an efficient and precise medical image analysis scheme is needed for operational planning, preparation of medical reports, and medical research and development.

Medical imaging is essential for the early identification and diagnosis of cancer. Cancer is an abnormal and uncontrolled division of cells in any part of the body. If these abnormal cells appear in the brain tissue, it is called a brain tumor. Brain tumors, similar to other types of cancers, can be benign (non-cancerous) or malignant (cancerous). Brain tumors can also be classified into primary and secondary tumors, where the former originates in the brain and is mostly benign, while the latter (known as a metastatic brain tumor) occurs when the abnormal cells spread from other organs to the

brain (Johnson et al., 2017). One common type of primary brain tumor is Glioma, which develops from glial cells (DeAngelis, 2001).

Tumors and strokes have been the world's second and third leading causes of death, respectively, after heart disease. According to the World Health Organization (WHO), 40,000–50,000 people are diagnosed with a brain tumor annually in India, out of which ~20% are infants (Saman & Jamjala Narayanan, 2019). One of the most common forms of cancers is brain cancer, with a ~70% mortality rate. Early detection would help increase the survival rates of brain cancer patients (Brunese, Mercaldo, Reginelli, & Santone, 2020).

There are many types of early detection applicable for medical imaging, such as Single-Photon Emission Computed Tomography (SPECT), Magnetic Resonance Spectroscopy (MRS), Positron Emission Tomography (PET), Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). The Eurostat reports indicated that one person out of ten in Europe is subject to CT imagery annually, one in 13 to MRI, and one out of 200 for PET tomography (Aiello, Cavaliere, D'Albore, & Salvatore, 2019). The majority of prior research involved MRIs (Işın, Direkoğlu, & Şah, 2016; Kong et al., 2019).

The traditional technique of manually analysing medical images is time-consuming, and its interpretation imprecise (prone to human error)(Jyoti Patil & Pradeepini, 2019). Artificial intelligence (AI) is on the verge of transforming medicine in the next years. AI systems will be used frequently to diagnose diseases early, enhance prognoses, and give more effective, individualised treatment regimens, all while saving time and resources. Algorithms that can interpret medical images for doctors in the near future, provide decision assistance for practitioners without specialist expertise, and power AI-driven telemedicine services. Beyond the hospital, AI will be used to continually monitor the health of millions of patients, as well as route them to physician consultations and follow-ups on a massive scale.

Deep Learning is a type of Machine Learning that uses artificial neural networks to learn representations. It is considered a state-of-the-art algorithm for medical image analysis and has been successfully applied in many areas (J. Zhang, Xie, Wu, & Xia, 2019). Deep Learning (DL) has been demonstrated to be significantly superior to

manual image analyses in terms of medical image segmentation, classification, detection, registration, biometric measurement, and quality evaluation (S. Chen, Ding, & Liu, 2019). The current work focus on Deep Convolution Neural Network (DCNN), which has resulted in significant advances in the analysis of medical images (Wachinger, Reuter, & Klein, 2018).

Deep Neural Networks (DNNs) is widely used for brain image analysis. Many studies tended to classify brain diseases, brain tissue segmentation, and anatomy. According to the literature, image analytics are mostly done by DNNs. In Brain Tumors Segments Challenges (BRATS), the longitudinal MSLS 2015, the 2015 Ischemic Stroke Lesion Segmentation Challenge (ISLES), and the MR Brain imaging challenge (MRBrains) in 2013, all of the top teams used CNNs, focusing on the abovementioned techniques of MRI scans of the brain (Litjens et al., 2017). Brain tumor is an abnormal cell growth in the brain. The classification of brain tumours aids in predicting their potential behaviour and improving health-care systems.

Tumors are classified based on their cellular origin and actions, ranging from less active (benign) to aggressive (malignant), malignant tumor are graded from I (least malignant) to IV (most malignant) based on their rate of growth (DeAngelis, 2001). Classification of brain medical images can be binary classification, as the name refers binary classification is for two classes a normal class and an abnormal one. It is used in medical testing to detect whether or not a patient has a certain condition.

In brain MRI medical images for a tumor detection this task involve classifying the images to normal and affected by a tumor. Another task could be classifying the tumor itself to benign or malignant tumor (Kumari & Kr., 2017). Another type of classification is Multiclass classification, this task involves categorising objects into one of multiple classes. In medical imaging this task is widely used to classify different types of diseases. For instance, brain tumor has more than 120 different types. The main goal in this task is to classify one class out of three or more classes (Irmak, 2021; Johnson et al., 2017). Meningiomas are brain tumor that develops in the small walls that generally surround the brain and is mostly non-cancerous, Gliomas are one of the most common types of primary brain tumors. Most pituitary tumors are noncancerous (benign) growths (adenomas). Adenomas remain in the pituitary gland or surrounding tissues and don't spread to other parts of the body (S. Chen et al., 2019). Generally, one

of the life-threatening disorders that can directly damage human lives is brain tumors (Thillaikkarasi & Saravanan, 2019).

One of the most important challenges in computer vision and pattern recognition is image classification. Researchers have previously investigated brain tumor MRI (Magnetic resonance imaging) classification using Machine Learning algorithms. In traditional Machine Learning the classification task need prior step which is features extraction. While in Deep Learning algorithms the process can be completed without the use of handcrafted features, and both the feature extraction and classification steps are combined (Aiello et al., 2019; Brunese et al., 2020). In recent years. In the field of medical image analysis and disease detection, the development of artificial intelligence and Deep Learning-based new technologies has had a significant impact. Deep Convolutional Neural Network (DCNN) is one of the most extensively utilized image processing techniques (Işın et al., 2016; Kong et al., 2019; B. Menze et al., 2014). The use of CNN applications to classify different types of brain tumors has demonstrated a good performance and promising results (Havaei, Davy, Warde-Farley, et al., 2017).

1.2 STATEMENT OF THE PROBLEM

In this technological age, medical specialists are in a position to provide patients with more efficient health care using latest technologies. Brain is the most complicated component of the human body, with millions of cells working together (Guo et al., 2011). Brain tumor is an uncontrolled brain disorder which causes abnormal brain cell groups to develop. MRI employs a powerful magnetic field and waves to generate accurate pictures of the body's organs and cells. The Brain MRI scan is the best means for scientists to detect and follow the progress of the brain tumor (Mamta Mittal et al., 2019; Muhammed Talo, Baloglu, Yıldırım, & Rajendra Acharya, 2019). In high resolution MR images, brain tumor can be detected. But when there are a huge number of images (big data) (Aiello et al., 2019), it is difficult for experts to check and analyse every single image, so here it comes the need of an automatic classification and detection tools. Therefore, the computer-aided methods for analysis and detections of these information must be applied.

Previous studies implemented supervised Machine Learning (ML) algorithms (hand-designed features) for brain tumor classification and segmentation (B. Menze et al., 2014). These techniques use the classical ML algorithm, which first retrieves then provides the features to a classifier whose training does not influence their nature. Alternatively, they develop a task-adapted algorithm, which is a hierarchy of increasingly complicated features to learn directly from within the domain (Havaei, Davy, Warde-Farley, et al., 2017). DL network performed better relative to the classical ML algorithms. Previous studies confirmed that the most efficient way to analyse big datasets is to use DL (Mallick et al., 2019; M. Mittal et al., 2019; M. Talo, Baloglu, Yıldırım, & Rajendra Acharya, 2019). According to (B. H. Menze et al., 2015), there has been an exponential increase in the number of publications dedicated to automated brain tumor classification and segmentation. This study not only highlights the need for automatic analysis of brain tumors, but it also demonstrates that research in this field is ongoing.

The detection and classification of a brain tumor are challenging tasks. It is often not enough to have a good forecast scheme, particularly in medicine, where accountability is essential and can have severe legal implications (Lecun, Bengio, & Hinton, 2015). Another obstacle researchers may face is the lack of a large datasets (Litjens et al., 2017). However, that can be solved with the use of data pre-processing and data augmentation. Classification or detection in medical imaging often is described as a binary: ordinary vs abnormal, object versus context (Rouhi, Jafari, Kasaei, & Keshavarzian, 2015). But it is often a big simplification as both classes can be extremely heterogeneous and so it needs more sophisticated techniques. A closer look to the literature on brain tumor MRI medical images, however, reveals a number of gaps and shortcomings on the accuracy, performance and inconsistencies in data formats and lack of reliable training data, which need to be addressed. Therefore, there is a need to develop more accurate and reliable image detection and classification algorithm.

To sum up, these are the main points:

- i. There are a huge number of medical images, it is difficult for experts to check and analyze every single image (Talo, Baloglu, Yıldırım, & Rajendra Acharya, 2019).

- ii. The traditional technique of manual medical images analysis has limitation of time consuming and interpretation (human error) (Talo et al., 2019)
- iii. Although ML and DL techniques have demonstrated a breakthrough when compared to manual analysis, but research still ongoing to improve the accuracy rate (Menze et al., 2015).

1.3 RESEARCH OBJECTIVES

The main aim of this research is to improve the classification and detection accuracy of brain tumor MRI medical images based on using Deep Learning techniques. The main concerns of the research have been summarized on four objectives as listed below:

1. To identify the current methodologies and algorithms exist to analyze brain MRI medical images.
2. To develop Deep Learning algorithms for detection of a brain tumor MRI medical images through binary classification with a better accuracy.
3. To develop Deep Learning algorithms for classification of a brain tumor MRI medical images through multiclass classification with a better accuracy.
4. To validate and evaluate the proposed algorithms with the current state-of-art algorithms.

1.4 RESEARCH QUESTIONS

The questions of this research are as follow:

1. What are the current methodologies and techniques that are used in analyzing brain MRI medical images?
2. How to develop a Deep Learning algorithm for brain abnormalities MRI medical images detection with a better accuracy?
3. How to develop a Deep Learning algorithm for brain tumor MRI medical images classification with a better accuracy?

4. How effective the proposed algorithms when compared to the other current state-of-art algorithms?

1.5 SIGNIFICANCE OF THE STUDY

This thesis will make a number of significant contributions to the field of medical images analysis. Medical imaging technologies generally have a significant impact on medical diagnosis as well as AI field. Previously, a process was carried out manually, but this technique is deemed costly and time consuming based on the big number of medical images generated daily. Therefore, there is a need to use automatic classification systems for medical image processes, in which these systems can process a great number of images with minimal effort and more accurate result. This research will contribute to develop detection and classification Deep Learning algorithms for brain tumor MRI medical images that may not only imitate experts, but it may outperform them. Another key benefits of the algorithm is that the early detection of the disease that result in saving human life and increasing the survival rate of the patients. This study contributes to goal number 3 of the Sustainable Development Goals (SDGs), which involves excellent health and well-being.

1.6 SCOPE OF THE STUDY

Recent theoretical developments have employed Deep Learning algorithms in the field of medical images analysis. Deep Learning has many architectures, in this study, new architecture using Convolution Neural Network (CNN) is going to be developed. CNN is one of the most prevalent profound Deep Learning algorithms. And among the medical images different types we have decided to apply MRI medical images. So, the analysis will mainly focus on brain tumor MRI medical images. The literature will cover the last five years.