



Faculty of Engineering

**DETECTION AND CLASSIFICATION OF BRAIN CANCER
USING DEEP LEARNING**

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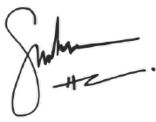
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DETECTION AND CLASSIFICATION OF BRAIN CANCER
USING DEEP LEARNING

ASVIN KUMAR A/L MOGHAN

A dissertation submitted in partial fulfilment
of the requirement for the degree of
Bachelor of Engineering
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ABSTRACT

Brain cancer is a serious medical condition that requires an accurate and timely diagnosis for effective treatment planning. In recent years, deep learning techniques have shown great potential in the field of medical image analysis. In this study, a brain cancer detection and classification system based on deep learning algorithms is proposed. The system utilises a convolutional neural network (CNN) architecture trained on a large dataset of brain MRI images. The images were preprocessed to enhance relevant features and remove noise. The CNN architecture chosen was GoogleNet. To validate the robustness of the system, a 5-fold cross-validation approach was employed, ensuring reliable and consistent results. The proposed system has the potential to assist medical professionals in the early detection and classification of brain tumours, aiding in accurate diagnosis and treatment decision-making. By automating the classification process, it reduces the burden of manual analysis, potentially saving time and improving the overall efficiency of the diagnostic process. The proposed model achieved an accuracy of $97.5522 \pm 0.2739\%$, a precision of 0.9498 ± 0.0054 , a recall of 0.9494 ± 0.0057 , a specificity 0.9839 ± 0.0018 and an F1 Score of 0.9493 ± 0.0057 across the 5-fold cross-validation iterations, demonstrating its effectiveness in accurately classifying brain MRI.

ABSTRAK

Kanser otak merupakan keadaan perubatan yang serius yang memerlukan diagnosis yang tepat, dan tepat pada waktunya untuk perancangan rawatan yang berkesan. Dalam beberapa tahun terakhir, teknik pembelajaran mendalam telah menunjukkan potensi besar dalam bidang analisis imej perubatan. Dalam kajian ini, satu sistem pengesanan dan pengelasan kanser otak berdasarkan algoritma pembelajaran mendalam dicadangkan. Sistem ini menggunakan jaringan saraf terkonvolusi (CNN) berdasarkan senibina GoogleNet yang dilatih menggunakan dataset yang besar dari imej MRI otak. Imej-imej tersebut telah melalui pra-pemprosesan untuk meningkatkan ciri-ciri yang relevan dan mengurangkan kebingaran data. Pendekatan 5-lipatan validasi persilangan diterapkan untuk mengesahkan kebolehpercayaan sistem dengan hasil yang boleh diandalkan dan konsisten. Sistem yang dicadangkan mempunyai potensi untuk membantu profesional perubatan dalam pengesanan awal dan pengelasan tumor otak, membantu dalam diagnosis yang tepat dan membuat keputusan rawatan. Dengan mengautomatikkan proses pengelasan, ia mengurangkan beban analisis manual, berpotensi menjimatkan masa dan meningkatkan kecekapan keseluruhan proses diagnostik. Model yang dicadangkan mencapai ketepatan sebanyak $97.5522 \pm 0.2739\%$, kefahaman sebanyak 0.9498 ± 0.0054 , pemulihan sebanyak 0.9494 ± 0.0057 , khususiti sebanyak 0.9839 ± 0.0018 dan Skor F1 sebanyak 0.9493 ± 0.0057 , melintasi iterasi persilangan, sekali gus membuktikan menunjukkan keberkesanannya dalam mengelaskan imej MRI otak secara tepat.

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Equation	Formulas	
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3.3	Accuracy for Meningioma (M)	$\frac{TP_M + TN_M}{TP_M + TN_M + FP_M + FN_M}$
3.4	Accuracy for Pituitary Tumour (P)	$\frac{TP_P + TN_P}{TP_P + TN_P + FP_P + FN_P}$
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3.23	Weighted Precision (Prc)	$\frac{Prc_G N_G + Prc_M N_M + Prc_P N_P + Prc_N N_N}{W_G + W_M + W_P + W_N}$
3.24	Weighted Recall (Rcl)	$\frac{Rcl_G N_G + Rcl_M N_M + Rcl_P N_P + Rcl_N N_N}{W_G + W_M + W_P + W_N}$
3.25	Weighted Specificity (Spc)	$\frac{Spc_G N_G + Spc_M N_M + Spc_P N_P + Spc_N N_N}{W_G + W_M + W_P + W_N}$
3.26	Weighted F1 Score (F1 S)	$\frac{F1S_G N_G + F1S_M N_M + F1S_P N_P + F1S_N N_N}{W_G + W_M + W_P + W_N}$
4.1	Recall	$\frac{TP}{TP + FN}$
4.2	F1 Score	$\frac{2(Precision * Recall)}{Precision + Recall}$

LIST OF ABBREVIATIONS

No.	Abbreviations	Full Sentence
1	AI	Artificial Intelligence
2	ML	Machine Learning
3	NN	Neural Network
4	DL	Deep Learning
5	MRI	Magnetic Resonance Imaging
6	CT	Computed Tomography
7	CNN	Convolutional Neural Network
8	SVM	Support Vector Machine
9	3D	Three Dimensional
10	FLAIR	Fluid Attenuated Inversion Recovery
11	CE	Contrast-enhanced
12	SNR	Signal-to-noise Ratio
13	SIST	Shift-invariant Shearlet Transform
14	RGB	Red-green-blue
15	FC	Fully Connected
16	RBF	Radial Basis Function
17	NB	Naïve Bayes
18	K-NN	K-nearest Neighbour
19	RF	Random Forest
20	DAE	Deep Autoencoder
21	BFC	Bayesian Fuzzy Clustering
22	JOA	Jaya Optimization Algorithm
23	DNN	Deep Neural Network
24	ANN	Artificial Neural Network
25	ReLU	Rectified Linear Unit
26	GLCM	Gray Level Co-occurrence Matrix
27	OFPA	Oppositional Flower Pollination Algorithm
28	PFCM	Possibilistic Fuzzy C-means
29	DWT	Discrete Wavelet Transformation

30	KMFCM	K-means with Fuzzy C-means
31	PCA	Principal Component Analysis
32	ACLS	Active Contour by Level Set
33	BWT	Berkeley Wavelet Transformation
34	ERT	Extremely Randomised Trees
35	EM	Expectation-maximisation
36	FFT	Fast Fourier Transform
37	MRMR	Minimal-redundancy-maximal-relevance
38	ELM	Extreme Learning Machine
39	LRF	Local Receptive Fields
40	ELM-LRF	Extreme Learning Machine with Local Receptive Fields
41	FFBPNN	Feed Forward Back Propagation Neural Network
42	WHO	World Health Organisation
43	RAM	Random-access Memory
44	Adam	Adaptive Moment Estimation
45	TP	True Positive
46	FP	False Positive
47	TN	True Negative
48	FN	False Negative

CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 Brain Cancer

The brain, which is displayed in Figure 1.1, is the control centre of the human body and its most complex part. It is responsible for all the body's functions. This organ is the centre of intelligence and controls behaviour, movement, and the interpretation of the senses. It is made up of billions of cells called neurons and glial cells, which work together to transmit and process information.



Figure 1.1: Human Brain [1]

One of the most serious and deadly diseases that can affect the brain is brain cancer. Brain cancer arises when abnormal cells in the brain divide and grow out of control. These cells can combine to generate benign or malignant tumours. Brain tumours that are

malignant are more aggressive and can spread to other regions of the body, whereas benign tumours are often less dangerous and do not spread.

According to the Cancer Council of New South Wales [2], brain tumours can be classified into four grades based on their level of aggressiveness. These grades are used to help patients with brain tumours forecast their prognosis and guide treatment options. Brain cancer is classified into four categories based on their malignancy: Grade I, Grade II, Grade III, and Grade IV. Grade I tumours are the least aggressive and are characterised by slow growth and a low risk of recurrence. They can be treated surgically or with a mix of surgery, radiation treatment, and chemotherapy. Grade II tumours are more aggressive than grade I tumours but still have a relatively low risk of recurrence. They may be treated with surgery, radiation therapy, or chemotherapy, depending on the specific characteristics of the tumour. Grade III tumours are more aggressive than grade II tumours and have a higher risk of recurrence. They may be treated with surgery, radiation therapy, and chemotherapy, but the prognosis for these tumours is generally worse than for lower-grade tumours. Grade IV tumours are the most aggressive and have a high risk of recurrence. They may be treated with surgery, radiation therapy, and chemotherapy, but the prognosis for these tumours is generally poor.

Some common types of brain tumours include gliomas, meningiomas, pituitary tumours, craniopharyngiomas, primary brain lymphomas, and metastatic brain tumours. Gliomas are tumours that originate in the glial cells, which support and protect the nerve cells of the brain. Gliomas can be either benign or malignant and include astrocytomas, oligodendrogliomas, and ependymomas. Meningiomas are tumours that develop in the meninges. Meningiomas are usually benign but can sometimes be aggressive. Pituitary tumours are cancers that originate from the pituitary gland, a tiny endocrine gland situated at the base of the brain. Pituitary tumours can be either benign or malignant. Craniopharyngiomas are tumours that arise from cells in the pituitary gland and are usually benign. Primary brain lymphoma is a type of cancer that originates in the brain and is usually associated with non-Hodgkin's lymphoma. Tumours that have progressed to the brain from another area of the body, such as the lungs or breast, are known as metastatic brain tumours.

For this research and writing process, the brain cancer detection and classification will cover three types of brain cancer, which are gliomas, meningiomas, and pituitary tumours. Symptoms of brain cancer can differ based on the tumour's location and size.

Common symptoms include headaches, seizures, changes in mood or behaviour, weakness or numbness in the limbs, and difficulty with balance and coordination. A physical assessment, imaging tests including MRI or CT scans, and a biopsy to study a sample of tumour tissue are all used to detect brain cancer. The specific treatment and prognosis for a brain tumour will depend on the type and stage of the tumour, as well as the overall health of the patient.

1.1.2 Deep Learning

DL is a sort of ML that analyses and recognises patterns in data using ANNs with several layers. The difference between AI, ML, NN, and DL is shown in Euler's diagram in Figure 1.2.

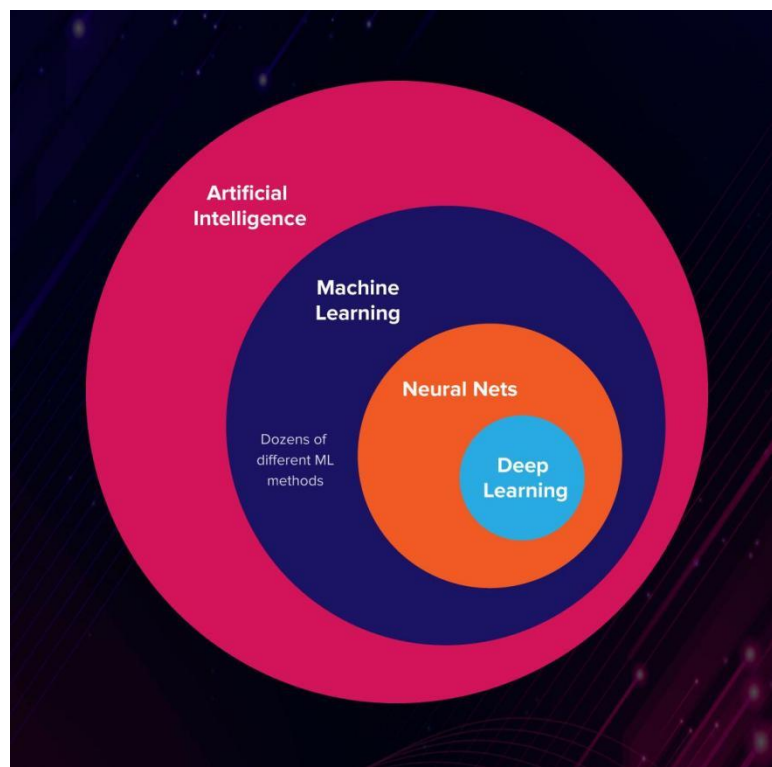


Figure 1.2: Euler's Diagram on AI, ML, NN and DL [3]

The key characteristic of DL is the utilisation of DNNs, which are composed of multiple layers of interconnected neurons. These networks are designed to mimic the structure and functioning of the human brain, allowing them to learn and model highly complex relationships within the data. Each layer of neurons in a DNN performs specific computations and progressively learns more abstract and high-level representations as information flows through the network.

One of the major breakthroughs in deep learning has been in the field of computer vision, where CNNs have demonstrated exceptional performance in tasks such as image classification, object detection, and segmentation. CNNs can automatically learn spatial hierarchies of features from images, enabling them to identify and distinguish objects with remarkable accuracy. This has opened new possibilities in areas such as autonomous driving, facial recognition, and medical imaging.

In recent years, DL techniques have emerged as powerful tools for medical image analysis, offering the potential to revolutionise brain cancer detection and classification. By leveraging large amounts of data, as can be seen in Figure 1.3, and complex NN architectures, DL models have demonstrated remarkable capabilities in extracting meaningful features from medical images and making accurate predictions.

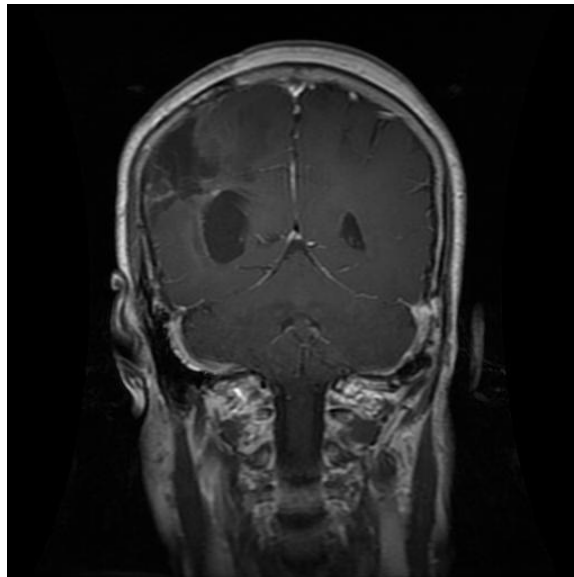


Figure 1.3: DL can be used to detect the presence of brain cancer in this MRI [4]

The implementation of DL in the identification and classification of brain cancer holds great promise for improving the accuracy and efficiency of these processes and could greatly enhance patient outcomes. However, further study is required to properly comprehend the capabilities and limitations of this approach and to develop robust and reliable methods for implementing it in clinical practise.

1.2 Problem Statement

Detecting and classifying brain cancer manually is a time-consuming process that requires extensive analysis and interpretation of medical imaging data. Radiologists and

medical professionals typically examine brain MRI's to identify the presence of brain cancer in them and classify them into specific types. However, this manual approach can be slow and labour-intensive, leading to delays in diagnosis and treatment planning. The interpretation of brain MRI images involves visually analysing intricate details, patterns, and abnormalities in the scans. Radiologists need to meticulously examine multiple slices of the brain to accurately identify and characterise tumors. This process is not only time-consuming but also susceptible to human error and subjectivity, which can impact the accuracy and consistency of diagnoses. Addressing the time-consuming nature of manual brain cancer detection and classification is crucial to improve patient outcomes and optimize healthcare resources. By leveraging automated techniques, such as DL algorithms, we can develop a system that assists radiologists in the efficient and accurate detection and classification of brain cancer, decreasing the time required for diagnosis and enabling timely treatment interventions.

Other than that, detecting and classifying brain cancer often requires the processing of vast amounts of medical imaging data. This task can present challenges due to the substantial computational resources required. The size and complexity of the datasets, along with the computational demands of sophisticated analysis algorithms, can strain the capabilities of available resources. Limited computational power, memory, or storage capacity may hinder the timely and efficient analysis of brain cancer imaging data. These constraints can lead to longer processing times, delays in diagnosis, and potential limitations in the accuracy and effectiveness of the detection and classification processes. Overcoming these computational resource constraints is crucial for developing efficient and scalable brain cancer detection and classification systems that can handle the increasing volume and complexity of medical imaging data.

1.3 Objectives

There is a need for further research to address these challenges and develop reliable and effective DL approaches for the detection and classification of brain cancer. This will require a multidisciplinary approach that brings together experts in DL, medical imaging, and brain cancer research, as well as clinicians who can provide valuable insights into the needs and constraints of real-world clinical practise. The following are the primary goals of a study on the detection and classification of brain tumours with DL: