Cancer Cell Detection in Brain – A Systematic Literature Review

Coursework Group 02

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# Introduction

## A brain tumour is an abnormal development of tissues in the brain that interferes with normal brain functions. Several techniques have been introduced to detect these abnormal cells. Brain tumours can either be benign or malignant. Some of the cancers related to the brain are gliomas, pituitary adenomas, carcinoma, glioblastoma and pituitary tumours. More information about the types of brain tumours can be found at Cancer Research UK[[1]](#footnote-2). This study is a systematic literature review to analyse the image processing techniques used in the detection of cancer cells in the brain. This review principally benefits cancer patients and health practitioners.

## Since the brain abnormalities cannot be detected with the naked eye and the only indicators are the physical symptoms such as headaches, seizures and vomiting (National Health Services, 2021). The diagnosis of these abnormalities can be done by using imaging techniques. The techniques such as X-Ray, positron emission tomography, gamma-ray, UV, and so on make use of image processing techniques for disorder identification and cancer detection, verifying the abnormalities in the brain. The goal of imaging is to extract accurate information from the generated images with minimum possible errors.

## Multiple image processing techniques exist that accurately identify the malignant cells in the brain. Picking the optimal technique among the multitudes of techniques is a challenge. These techniques on application to an image refines it or extract useful information. It is a form of signal processing in which the input is an image, and the output is either that image or its characteristics/features.

## It is one of the most rapidly evolving technologies today. In this study, several pieces of literature are analysed to answer the question, "how do different image processing techniques detect cancer cells in the brain?".

The protocol and the processing of literature are executed according to the guidelines provided by Kitchenham and Charters (2007). The search string, derived from the research question was applied in the IEEE Xplore digital library. The resulting literature was then refined using the inclusion and the exclusion criteria and the synthesis of data was done to obtain data to answer the research question. By applying the inclusion and exclusion criteria on the initially obtained 422 papers from the search string, 14 papers were finalized for review. After parsing the contents of the papers, 5 themes were retrieved for the papers. It can be concluded that the MR imaging technique is the most popular.

The remainder of the document is organized as follows: Section 2 contains the background, section 3 introduces the method, section 4 presents the results, section 5 discusses the resulting literature and section 6 provides the conclusion.

# Background

Cancer cells in the brain were detected by preparing the cell image and is fed into the soft computing techniques after applying the Gabor filter to identify the cells (Thammasakorn et al., 2016). Another technique that applies image processing, Histogram Orientation Gradient and Extreme Learning Machine to detect cancer cell images in the brain (W. Phusomsai et al., 2016). K-means clustering algorithm delimits the tumour tissue boundary for real-time processing on hyperspectral images (Torti et al., 2018).

A review was conducted on the disordered physiological processes associated with brain cancer and the machine learning and deep learning algorithms available for brain cancer (Tandel et al., 2019). In (Al-shamasneh and Obaidellah, 2017), a review is carried out on the detection of cancer in the lung, breast and brain using artificial intelligence techniques and medical imaging. It analysed that the MRI scan yielded the most accurate result of 100%. By using various literature, brain tumour detection was proposed by using segmentation on MRI scanned images (Laddha and Ladhake, 2014). Brain cancer diagnosis in (Abd-Ellah et al., 2019) is done using machine learning techniques and deep learning techniques on MRI images.

Several image techniques are used to detect cancer in the body. In this review, an attempt is made to compare the different image processing techniques to find the optimal technique that can be used to find cancer in the brain. This literature attempts to answer the following research question: *How do different image processing detect cancer cells in the brain?*

# Method

# The following describes the research question based on context, population, intervention, comparison and outcome.

# *Context*: Cancer cell detection in the brain

# *Population*: Cancer cells

# *Intervention*: Image processing algorithms

# *Comparison*: Magnetic resonance imaging vs optical imaging

# *The outcome of interest*: Accuracy

# Based on the above breakdown, the keywords identified for the search are “tumour" and "image processing". The US form of writing tumor to broaden the search as most publications are usually written in US English. For the identified keywords, the following are their synonyms:

# *Cancer* –sarcoma, malignant

# *Detect* - Spot

# Hence, the search string that was created from the keywords and their synonyms is

# (cancer OR {tumor} OR {tumour} OR {sarcoma} OR {malign\*}) AND (detect\* OR {spot\*}) AND ("image processing") AND (accura\*) AND (brain)

# The digital library that was used to search for the publications is IEEE Xplore[[2]](#footnote-3). To be included, the publication should be a journal paper that was published in the last 10 years. The inclusion criteria and exclusion criteria for the publication to be included in the review is provided in Table 1. In case of duplicate studies, the paper with the latest results is to be included.

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| Table 1: Inclusion and exclusion criteria | |
| Inclusion Criteria (the paper…) | Exclusion Criteria |
| Answers the research questionIs published between 2011 – 2021Is a journal articleMust show empirical evidence | No duplicate study to be included. |

# The resulting papers after applying the search string were 36. These papers were divided into 2 groups among the members of the group i.e. 18 each. The title of the papers was checked against the inclusion criteria, if the paper satisfied the criteria or if the reviewer were unsure, then the paper was included. A similar process was done in the next step, where the papers that have passed the title check were checked again. The abstract was checked against the inclusion criteria. If the papers satisfied the criteria or if the reviewer were unsure, then the paper was included. After this process, 8 papers were rejected.

# Next, the contents of the paper were checked against the criteria. If the paper does not satisfy the criteria, then a reason is provided for why the paper was not included in the review. A redundancy check was done to search for any duplicate papers. The 14 papers that passed the inclusion and exclusion criteria were divided into 2 groups of 7 papers. The full text of the papers was analysed, and 5 themes were finalized after discussion among the team members. Table 2 shows the summarized view of the paper selection process.

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| Table 2: Paper selection process | |
| Selection Stage | Number of papers |
| First pass: Boolean search string as used in IEEE Explore (cancer OR {tumor} OR {tumour} OR {sarcoma} OR {malign\*}) AND (detect\* OR {spot\*}) AND ("image processing") AND (accura\*) AND (brain) | 34 |
| Check Title | 30 |
| Check Abstract | 28 |
| Whole paper | 14 |

# Results

# The number of papers that were identified by our search string was 422. As one of our inclusion criteria was to consider all the journal papers, 36 papers were identified after applying the criteria. Since we are considering the years starting from 2011-2021, two papers were excluded.

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| Table 3: Paper exclusion process | | |
| Selection Stage | Number of papers | Reference |
| Check Title | 6 | (Acharya et al., 2019; Asiedu et al., 2019; Chung et al., 2018; Hu and Soleimani, 2020; Meng et al., 2019; Rister et al., 2017) |
| Check Abstract | 2 | (Albahli et al., 2020; Khan et al., 2021) |
| Whole paper | 12 | (Jafari-Khouzani, 2014; G. Li et al., 2019; Liu et al., 2019; Monti et al., 2017; P. Schucht et al., 2020; Pattison et al., 2014; Sukovich et al., 2020; Sultan et al., 2019; Tang et al., 2019; Zhong et al., 2020; Zhou and Rivaz, 2016; Zhou et al., 2020) |

# Table 3 shows the paper exclusion process along with the reference to the excluded papers. After checking the title, six papers were excluded since they were not related to brain cancer detection and were failing to answer the research question directly. After checking the abstract, two papers were rejected since some of them did not talk about the techniques and brain cancer detection. After reading the contents of the paper, a total of twelve papers have been rejected as some of them were not showing empirical results, answering the research question directly or yielding any solution to the research question. Thus, fourteen papers passed all the inclusion and exclusion criteria. Table 4 shows the articles that passed the inclusion and exclusion criteria.

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| Table 4: Papers included in the review | |
| Title of the paper | Reference |
| A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor | (Noreen et al., 2020) |
| A Noninvasive System for the Automatic Detection of Gliomas Based on Hybrid Features and PSO-KSVM | (Song et al., 2019) |
| A Novel Approach to Improving Brain Image Classification Using Mutual Information-Accelerated Singular Value Decomposition | (Al-Saffar and Yildirim, 2020) |
| Automated Brain Metastases Detection Framework for T1-Weighted Contrast-Enhanced 3D MRI | (Dikici et al., 2020) |
| BAT Algorithm With fuzzy C-Ordered Means (BAFCOM) Clustering Segmentation and Enhanced Capsule Networks (ECN) for Brain Cancer MRI Images Classification | (Alhassan and Zainon, 2020) |
| Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network | (M. Li et al., 2019) |
| Hybrid Segmentation Method With Confidence Region Detection for Tumor Identification | (Ejaz et al., 2021) |
| Label-Free Detection of the Architectural Feature of Blood Vessels in Glioblastoma Based on Multiphoton Microscopy | (S. Wang et al., 2021) |
| Multi-Level Canonical Correlation Analysis for Standard-Dose PET Image Estimation | (L. An et al., 2016) |
| Optimized Multistable Stochastic Resonance for the Enhancement of Pituitary Microadenoma in MRI | (M. Singh et al., 2018) |
| Robust Cell Detection of Histopathological Brain Tumor Images Using Sparse Reconstruction and Adaptive Dictionary Selection | (H. Su et al., 2016) |
| Segmentation of Tumor and Edema Along With Healthy Tissues of Brain Using Wavelets and Neural Networks | (A. Demirhan et al., 2015) |
| Towards Real-Time Computing of Intraoperative Hyperspectral Imaging for Brain Cancer Detection Using Multi-GPU Platforms | (G. Florimbi et al., 2020) |
| Visualization of White Matter Fiber Tracts of Brain Tissue Sections With Wide-Field Imaging Mueller Polarimetry | (P. Schucht et al., 2020) |

# Discussion

Table 5.1 illustrates how each of the papers answers the review questions and the themes that were identified in each of the paper. The themes that were identified as the image processing techniques such as magnetic resonance (MR) imaging, second harmonic generation (SHG) imaging, optical imaging, optical imaging, hyperspectral (HS) imaging and general imaging technique. Table 5.2 illustrates the themes that were extracted from the papers.

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| Table 5.1: Data Extraction to Data Synthesis for RQ: “*How do different image processing detect cancer cells in the brain?*” | | |
| How did the paper answer RQ? | Reference | High-Level Theme |
| Brain Metastases lesion detection using a single-sequence gadolinium-enhanced T1-weighted 3D MRI dataset | (Dikici et al., 2020) | General imaging |
| Segmentation of tumour in MRI images to enhance the efficiency of segmentation and classification | (Alhassan and Zainon, 2020) | General imaging |
| Tumour detection using CNN and multimodal information fusion | (M. Li et al., 2019) | MR imaging |
| Multi-level features extraction and concatenation for early diagnosis of brain tumour | (Noreen et al., 2020) | MR imaging |
| Diagnosis system for gliomas based on the machine learning methods | (Song et al., 2019) | MR imaging |
| proposes of mutual information-accelerated singular value decomposition to classify the MRI brain images into three classes: high-grade glioma, low-grade glioma and, healthy brain | (Al-Saffar and Yildirim, 2020) | General imaging |
| Hybrid Segmentation Method detects tumour by a hybrid cluster of three unsupervised learning techniques | (Ejaz et al., 2021) | MR imaging |
| Detected using label-free MPM blood vessel feature from normal brain | (S. Wang et al., 2021) | SHG imaging |
| Detects by estimating a standard-dose positron emission tomography (PET) image from a low-dose PET | (L. An et al., 2016) | MR imaging |
| Uses MSSR-MOALO to enhance MRI images for diagnosis of microadenomas and lesions in the pituitary gland | (M. Singh et al., 2018) | MR imaging |
| Presents an automatic cell detection algorithm by detecting multiple cells on a single image patch | (H. Su et al., 2016) | General imaging |
| Proposes a new tissue segmentation algorithm that segments brain MR images into a tumour, edema, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) | (A. Demirhan et al., 2015) | MR imaging |
| Uses multi-GPU platforms for real-time detection by acquiring a hyperspectral image of the brain | (G. Florimbi et al., 2020) | HS imaging |
| Uses a non-invasive and non-contact optic technique called Mueller polarimetry to detect the boundary between the white matter of the tumour and the healthy brain | (P. Schucht et al., 2020) | MR imaging |

*MR imaging*

# In the paper proposed by E. Dikici and others (2020), a Brain Metastases (BM) method has been proposed which needs high MR imaging. The BM method focuses on the detection of smaller (<:15mm) BM lesions. It has two stages of classification candidate selection stage and detection stage.

# A BAT automated segmentation technique has been introduced by Alhassan and Zainon (Alhassan and Zainon, 2020). The pre-processing and segmentation process for the segmentation of tumour/tissue is done by expanding the range of data and clustering. For automated segmentation BAT algorithm with Fuzzy C-Ordered Means (BAFCOM) has been recommended for segmenting tumour and Enhanced Capsule Network (ECN) is used to categorize the output as normal or brain tumour.

# In (Ejaz et al., 2021), the MRI image will be subjected to hybrid segmentation resulting in a determined confidence region on the MRI image. The accurate localization of the tumour will be done using the contour detection algorithm.

In (P. Schucht et al., 2020), the tumour boundary is delineated using the Mueller polarimeter by constructing an azimuth map, reconstructing it from Mueller matrix images. A segmentation algorithm uses unsupervised self-organizing maps and learning vector quantization to classify areas of the brain in T1, T2 and FLAIR MR images of glial tumour (A. Demirhan et al., 2015). (M. Singh et al., 2018) proposes a post-processing algorithm of MRI images using a multi-stable stochastic resonance technique for the diagnosis of microadenoma in the pituitary gland. Standard-dose positron emission tomography (PET) image is estimated by combining the information from a low-dose PET image and an MR image (L. An et al., 2016).

# Li et al (2019) talk about the mutual information-singular value decomposition (MI-ASVD) method for selecting a significant subset of features as the input to a classifier and then the MRI images will be classified into 3 classes as healthy, high-grade glioma and, low-grade glioma.

*SHG imaging*

Glioblastoma can be detected by using label-free multiphoton microscopy and two-photon excited fluorescence on second harmonic generation (SHG) images (S. Wang et al., 2021).

*HS imaging*

Real-time detection of brain cancer during neurosurgery is carried out by making classifying each pixel of the Hyperspectral image into a multi-Graphic Processing Unit platform (G. Florimbi et al., 2020).

*General imaging*

# In (Noreen et al., 2020), two pre-trained deep learning models Inception-v3 and DenseNet201 are subjected to multi-level feature extraction and concatenation and the extracted results will be subjected to classification using a softmax classifier. The results of both the pre-trained models were compared which gave 93.4% and 99.51% of accuracy respectively.

# The images will be standardized by size normalization and background removal, (Song et al., 2019) uses the KSVM and particle optimization for the classification of the modified images. Hybrid features including grey-level-occurrence matrix and pyramid histogram of the oriented gradient and other features are extracted together from the enhanced images.

# To solve low accuracy in detection, (M. Li et al., 2019) has proposed an approach of multimodal information fusion along with CNN detection called Multi-CNNs. Here the extension of 2D CNN will be done to multimodal 3D-CNN to obtain brain lesions under different modal characteristics of 3D space.

(H. Su et al., 2016) detects malignant cells automatically by training on the images of different brain tumour patients and reconstructs a trivial template to identify the tumour cells at the testing stage.

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| Table 5.2: Data Extraction to Data Synthesis for RQ: “How do different image processing detect cancer cells in the brain?” | |
| High-Level Theme | Reference |
| MR Imaging | (A. Demirhan et al., 2015; Alhassan and Zainon, 2020; Al-Saffar and Yildirim, 2020; Dikici et al., 2020; Ejaz et al., 2021; L. An et al., 2016; M. Li et al., 2019; P. Schucht et al., 2020) |
| SHG Imaging | (S. Wang et al., 2021) |
| HS Imaging | (G. Florimbi et al., 2020) |
| General | (Al-Saffar and Yildirim, 2020; H. Su et al., 2016; M. Li et al., 2019; Noreen et al., 2020; Song et al., 2019) |

# Conclusions

This review answers the research question, "how do different image processing techniques detect cancer cells in the brain?". From the search string, 14 papers passed the inclusion and exclusion criteria. MR imaging, SHG imaging, HS imaging and general imaging were retrieved from the finalized papers. From the themes, it can be concluded that MR imaging in combination with singular value decomposition, brain metastases method, networks and algorithms is the most commonly used technique. This technique was supported by 5 of the 14 papers. Though other imaging techniques detect brain cancer, MR imaging proved to be popular. More research needs to be conducted in the area of brain tumour detection using SHG imaging and HS imaging.

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1. [Cancer Research UK](https://www.cancerresearchuk.org/about-cancer/brain-tumours/types) [↑](#footnote-ref-2)
2. IEEE Xplore: [https://ieeexplore.ieee.org](https://ieeexplore.ieee.org/) [↑](#footnote-ref-3)