# Multi-spectral Imaging Analysis of Brain Tissue Dissection During Neurosurgery

MRes Thesis Literature Review

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# 1 Introduction

Brain tumours are tumours that affect the central nervous system and can develop in both children and adults. These tumours can be classified based on their biopsy sample characteristics under the microscope. However, some tumours are very hard to distinguish, as they are visually indifferent to their surrounding tissue [2]. Maximal tumour resection through surgical operation is still one the main treatment for brain tumour [1]. However, the indifferent visual appearance of a tumour might make it difficult to delineate the margin between the tumour and healthy tissue.

Images that mimic visible light or colours are often represented digitally as a combination of three colour values: red, green and blue (RGB). However, producing an image with RGB values introduces information loss as it does not store information on the wavelengths between each colour. Multi-spectral imaging minimises the information lost in the imaging process by storing the data of multiple bands of visible light instead of only three as found in RGB. This project will explore the use of multi-spectral imaging to aid surgeons during surgical procedures.

# 2 Multi-spectral Imaging

## Image Preprocessing

Preprocessing is a crucial first step before analysing image data since raw data collected using a multi-spectral camera is not ideal to be used directly for analysis [18]. This is the case since the images collected might not share the same attributes, such as noise levels and illumination values. Preprocessing the images will ensure the data is within a certain expectation, minimising any variability in the later stages of the process.

There are some methods that can be utilised to preprocess multi-spectral image data. In some processes, the number of bands is filtered in an effort to minimise data size without omitting important information [4, 14]. Another reason for using band filtering is to remove known poor-quality bands on each end of the spectrum (400–440nm and 900—1000nm), which are specific to the camera performance used [9, 11, 12, 15]. White and dark reference images are also acquired and used in the processing stage, mainly to get room illumination conditions and avoid dark current from the camera system [5, 6, 9, 11, 12, 15, 17]. The white reference image is taken by taking an image of an object that reflects 99% of the incoming light, while the dark image is taken by closing the shutter. Other methods that are used in the preprocessing stage are spectral normalisation [4, 9, 17, 19] and hyperspectral signal identification by minimum error filter (HySIME) [9, 15].

## Image Analysis

Semantic segmentation is the process of assigning labels or finding regions of interest in an image. This process can be achieved by using a learning model, which can be categorised into two main approaches, classical machine learning and deep learning [18].

Some classical machine learning models have been tried to accomplish segmentation for brain multi-spectral images. One paper tested support vector machine (SVM), random forest (RF) and multi-layer perceptron (MLP) to classify tissue types during brain operation with RF having the highest accuracy [4]. However, another paper also tested the same models but had MLP as the model with the highest accuracy [7]. The discrepancy in accuracy might be caused by different data and preprocessing techniques used by both papers. One other paper also mentions the use of k-means clustering for in-vivo and ex-vivo brain tumour analysis [11].

In the recent decade, there has been an increase in the number of published deep-learning models and their application for multi-spectral images [10]. While the U-Net model [16] is used in tissue segmentation [17], most tumour analyses used basic convolutional neural network (CNN) architecture [7, 8, 12]. CNN is also used in tandem with a secondary model such as CNN+SVM [12], CNN+Transformer [19] and CNN+Spectral Phasor [9].

## Evaluation

Evaluation metrics are needed to compare the performance between learning models. For a given model, the evaluation will be done by comparing the output image of the model with its ground truth pair. There are multiple metrics that are used to evaluate segmentation models. For pixel-by-pixel comparison, some papers used accuracy with sensitivity and specificity as the main metrics [4, 12]. Other papers [8, 17, 19] used metrics based on intersecting or overlapping areas, such as the Sørensen–Dice coefficient [3] and Jaccard similarity coefficient [13].

# References


[1] N. A. O. Bush, S. M. Chang, and M. S. Berger. Current and future strategies for treatment of glioma. *Neurosurgical Review*, 40(1):1–14, Jan. 2017. ISSN 1437-2320. doi: 10.1007/s10143-016-0709-8. URL https://doi.org/10.1007/s10143-016-0709-8.

[2] V. P. Collins. Brain tumours: classification and genes. *Journal of Neurology, Neurosurgery & Psychiatry*, 75(suppl 2):ii2–ii11, 2004. ISSN 0022-3050. doi: 10.1136/jnnp.2004.040337. URL https://jnnp.bmj.com/content/75/suppl_2/ii2.

[3] L. R. Dice. Measures of the amount of ecologic association between species. *Ecology*, 26(3):297–302, 1945. doi: https://doi.org/10.2307/1932409. URL https://esajournals.onlinelibrary.wiley.com/doi/abs/10.2307/1932409.

[4] H. Fabelo, S. Ortega, S. Kabwama, G. M. Callico, D. Bulters, A. Szolna, J. F. Pineiro, and R. Sarmiento. HELICoiD project: a new use of hyperspectral imaging for brain cancer detection in real-time during neurosurgical operations. In *Hyperspectral Imaging Sensors: Innovative Applications and Sensor Standards 2016*, volume 9860, page 986002. SPIE, May 2016. doi: 10.1117/12.2223075. URL https://www.spiedigitallibrary.org/conference-proceedings-of-spie/9860/986002/HELICoiD-project--a-new-use-of-hyperspectral-imaging-for/10.1117/12.2223075.full.

[5] H. Fabelo, S. Ortega, R. Lazcano, D. Madroñal, G. M. Callicó, E. Juárez, R. Salvador, D. Bulters, H. Bulstrode, A. Szolna, J. F. Piñeiro, C. Sosa, A. J. O'Shanahan, S. Bisshopp, M. Hernández, J. Morera, D. Ravi, B. R. Kiran, A. Vega, A. Báez-Quevedo, G.-Z. Yang, B. Stanciulescu, and R. Sarmiento. An Intraoperative Visualization System Using Hyperspectral Imaging to Aid in Brain Tumor Delineation. *Sensors*, 18(2):430, Feb. 2018. ISSN 1424-8220. doi: 10.3390/s18020430. URL https://www.mdpi.com/1424-8220/18/2/430. Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.

[6] H. Fabelo, S. Ortega, A. Szolna, D. Bulters, J. F. Piñeiro, S. Kabwama, A. J-O'Shanahan, H. Bulstrode, S. Bisshopp, B. R. Kiran, D. Ravi, R. Lazcano, D. Madroñal, C. Sosa, C. Espino, M. Marquez, M. De La Luz Plaza, R. Camacho, D. Carrera, M. Hernández, G. M. Callicó, J. Morera Molina, B. Stanciulescu, G.-Z. Yang, R. Salvador, E. Juárez, C. Sanz, and R. Sarmiento. In-Vivo Hyperspectral Human Brain Image Database for Brain Cancer Detection. *IEEE Access*, 7:39098–39116, 2019. ISSN 2169-3536. doi: 10.1109/ACCESS.2019.2904788. Conference Name: IEEE Access.

[7] T. Giannantonio, A. Alperovich, P. Semeraro, M. Atzori, X. Zhang, C. Hauger, A. Freytag, S. Luthman, R. Vandebriel, M. Jayapala, L. Solie, and

S. de Vleeschouwer. Intra-operative Brain Tumor Detection with Deep Learning-Optimized Hyperspectral Imaging, Feb. 2023. URL http://arxiv.org/abs/2302.02884. arXiv:2302.02884 [cs, eess].

[8] H. Haj-Hassan, A. Chaddad, Y. Harkouss, C. Desrosiers, M. Toews, and C. Tanougast. Classifications of Multispectral Colorectal Cancer Tissues Using Convolution Neural Network. *Journal of Pathology Informatics*, 8(1): 1, Jan. 2017. ISSN 2153-3539. doi: 10.4103/jpi.jpi_47_16. URL https://www.sciencedirect.com/science/article/pii/S2153353922004059.

[9] Q. Hao, Y. Pei, R. Zhou, B. Sun, J. Sun, S. Li, and X. Kang. Fusing Multiple Deep Models for In Vivo Human Brain Hyperspectral Image Classification to Identify Glioblastoma Tumor. *IEEE Transactions on Instrumentation and Measurement*, 70:1–14, 2021. ISSN 1557-9662. doi: 10.1109/TIM.2021.3117634. Conference Name: IEEE Transactions on Instrumentation and Measurement.

[10] U. Khan, S. Paheding, C. P. Elkin, and V. K. Devabhaktuni. Trends in Deep Learning for Medical Hyperspectral Image Analysis. *IEEE Access*, 9:79534–79548, 2021. ISSN 2169-3536. doi: 10.1109/ACCESS.2021.3068392. Conference Name: IEEE Access.

[11] R. Leon, S. H. Gelado, H. Fabelo, S. Ortega, L. Quintana, A. Szolna, J. F. Piñeiro, F. Balea-Fernandez, J. Morera, B. Clavo, and G. M. Callico. Hyperspectral imaging for in-vivo/ex-vivo tissue analysis of human brain cancer. In *Medical Imaging 2022: Image-Guided Procedures, Robotic Interventions, and Modeling*, volume 12034, pages 525–534. SPIE, Apr. 2022. doi: 10.1117/12.2611420. URL https://www.spiedigitallibrary.org/conference-proceedings-of-spie/12034/1203429/Hyperspectral-imaging-for-in-vivo-ex-vivo-tissue-analysis-of/10.1117/12.2611420.full.

[12] F. Manni, F. van der Sommen, H. Fabelo, S. Zinger, C. Shan, E. Edström, A. Elmi-Terander, S. Ortega, G. Marrero Callicó, and P. H. N. de With. Hyperspectral Imaging for Glioblastoma Surgery: Improving Tumor Identification Using a Deep Spectral-Spatial Approach. *Sensors*, 20(23):6955, Jan. 2020. ISSN 1424-8220. doi: 10.3390/s20236955. URL https://www.mdpi.com/1424-8220/20/23/6955. Number: 23 Publisher: Multidisciplinary Digital Publishing Institute.

[13] A. H. Murphy. The finley affair: A signal event in the history of forecast verification. *Weather and Forecasting*, 11(1):3 – 20, 1996. doi: 10.1175/1520-0434(1996)011⟨0003:TFAASE⟩2.0.CO;2. URL https://journals.ametsoc.org/view/journals/wefo/11/1/1520-0434_1996_011_0003_tfaase_2_0_co_2.xml.

[14] S. Ortega, M. Halicek, H. Fabelo, R. Camacho, M. d. l. L. Plaza, F. Godtliebsen, G. M. Callicó, and B. Fei. Hyperspectral Imaging for the Detection of Glioblastoma Tumor Cells in H&E Slides Using Convolutional Neural Networks. *Sensors (Basel, Switzerland)*, 20(7):1911, Mar. 2020. ISSN 1424-8220. doi: 10.3390/s20071911. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7181269/.

[15] D. Ravì, H. Fabelo, G. M. Callic, and G.-Z. Yang. Manifold Embedding and Semantic Segmentation for Intraoperative Guidance With Hyperspectral Brain Imaging. *IEEE Transactions on Medical Imaging*, 36(9):1845–1857, Sept. 2017. ISSN 1558-254X. doi: 10.1109/TMI.2017.2695523. Conference Name: IEEE Transactions on Medical Imaging.

[16] O. Ronneberger, P. Fischer, and T. Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation, May 2015. URL `http://arxiv.org/abs/1505.04597`. arXiv:1505.04597 [cs].

[17] S. Seidlitz, J. Sellner, J. Odenthal, B. Özdemir, A. Studier-Fischer, S. Knödler, L. Ayala, T. J. Adler, H. G. Kenngott, M. Tizabi, M. Wagner, F. Nickel, B. P. Müller-Stich, and L. Maier-Hein. Robust deep learning-based semantic organ segmentation in hyperspectral images. *Medical Image Analysis*, 80:102488, Aug. 2022. ISSN 1361-8415. doi: 10.1016/j.media.2022.102488. URL `https://www.sciencedirect.com/science/article/pii/S1361841522001359`.

[18] Y. Wu, Z. Xu, W. Yang, Z. Ning, and H. Dong. Review on the Application of Hyperspectral Imaging Technology of the Exposed Cortex in Cerebral Surgery. *Frontiers in Bioengineering and Biotechnology*, 10, 2022. ISSN 2296-4185. URL `https://www.frontiersin.org/articles/10.3389/fbioe.2022.906728`.

[19] B. Yun, Y. Wang, J. Chen, H. Wang, W. Shen, and Q. Li. SpecTr: Spectral Transformer for Hyperspectral Pathology Image Segmentation, Mar. 2021. URL `http://arxiv.org/abs/2103.03604`. arXiv:2103.03604 [cs, eess].