

Detection and Classification of Brain Tumours from MR Images Using Texture Features and Machine Learning

A.V.S. Deepak¹, B. Mahalakshmi², K. Uma Shankar³, Padi Devi⁴, Koda Manikanta⁵, Chukka Balaji⁶

¹⁻³ Assistant Professor, Department of Electronics and Communication Engineering Avanthi Institute of Engineering & Technology, Tamaram, Makavarapalem, Narsipatnam, Anakapalli District – 531113, Andhra Pradesh, India

⁴⁻⁶ UG Student, Department of Electronics and Communication Engineering Avanthi Institute of Engineering & Technology, Tamaram, Makavarapalem, Narsipatnam, Anakapalli District – 531113, Andhra Pradesh, India

Abstract

Brain tumour is among the more lethal forms of cancer, and its position close to the neuronal centre of the body means that even a small lesion can have serious consequences. Early detection substantially raises the chance of successful treatment, but expert evaluation of every patient is costly and impractical at scale, which is what motivates computer-aided detection. This paper describes a system for detecting and classifying brain tumours from magnetic resonance images. The pipeline comprises four stages. Pre-processing with a Gaussian low-pass filter removes low-frequency background noise and normalizes intensity. Segmentation using Otsu thresholding partitions the image by selecting the grey-level threshold that minimizes intra-class variance, separating the region of interest from the background; because it operates directly on the grey-level histogram it is fast and reasonably noise-tolerant. Post-processing applies morphological erosion and dilation to remove the imperfections that simple thresholding leaves in the binary regions. Feature extraction computes fourteen Haralick texture descriptors from the grey-level co-occurrence matrix, including contrast, correlation, energy, entropy and homogeneity, using a formulation that is asymptotically invariant to the quantization step. Classification into benign and malignant is performed using K-nearest neighbours and support vector machine classifiers on a database of 180 brain MR images, of which 144 are benign and the remainder malignant.

Index Terms— Brain tumour, computer-aided detection, feature extraction, Haralick texture features, KNN, magnetic resonance imaging, Otsu thresholding, segmentation, support vector machine.

I. INTRODUCTION

A brain tumour is a mass or accumulation of abnormal cells in the brain. These cells differ from healthy brain cells, and as they grow inside the rigid skull they press on the surrounding brain tissue and cause pain and neurological problems. Common symptoms include headaches, personality changes, loss of balance and difficulty concentrating.

Tumours are classified along two axes. By pathology they are benign, meaning non-cancerous, or malignant, meaning cancerous and considerably more dangerous. By origin they are primary, originating in the brain and generally benign, or secondary, also called metastatic, originating in another organ such as the lung and spreading to the brain through the blood or lymph. Both types are harmful because both occupy space within a skull that cannot expand.

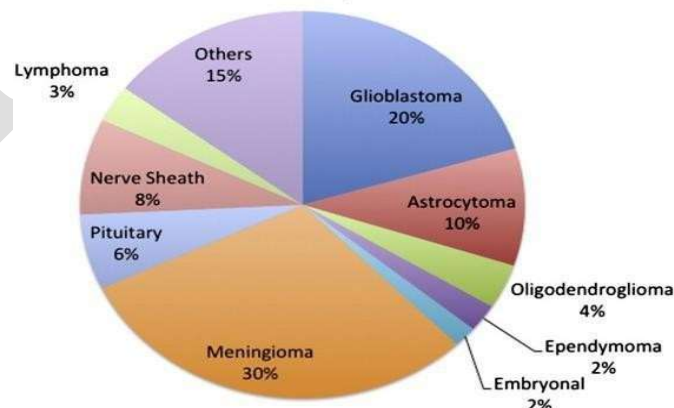


Fig. 1. Classification of brain tumours.

Early detection is the key factor in outcome, raising the chances of successful treatment substantially. But early detection requires expert evaluation of the patient, which is expensive and cannot be provided to the whole population that might benefit from screening. This is the argument for computer-aided detection: MRI generates the images, and software performs the first stage of analysis, flagging regions that differ from normal brain tissue so that the human expert's time is spent on the cases that need it.

Artificial neural networks and machine learning methods have been widely applied to medical imaging, performing tasks that would otherwise require expert judgement. This work applies image processing and classification techniques to brain MR images, covering their processing, segmentation and classification into benign or malignant.

II. LITERATURE SURVEY

Rajesh and Malar combined rough set theory with a feed-forward neural network for brain tumour detection in magnetic resonance images, using rough sets to handle the uncertainty inherent in region boundaries before classification.

Machhale et al. proposed a hybrid SVM-KNN classifier for MRI brain cancer classification, combining the margin-based separation of the support vector machine with the instance-based decision of nearest neighbours. The hybrid approach is relevant here, since the present work also uses both classifiers.

Shasidhar et al. used a modified fuzzy C-means clustering algorithm for MRI brain image segmentation, allowing a pixel to hold partial membership in more than one cluster, which suits tissue boundaries where the transition is gradual rather than sharp. Goswami and Bhaiya applied unsupervised learning through a neural network for tumour detection, removing the need for labelled training data at the segmentation stage.

Badran et al. presented an algorithm for detecting brain tumours in MRI images, and Parameshwari and Aparna developed an efficient algorithm for textural feature extraction and tumour detection for a class of brain MR imaging applications, establishing texture as a discriminative property for this problem. Kumar and Selvi used image mining techniques for feature extraction to identify brain tumours.

Noureddine et al. addressed segmentation and extraction of brain injury lesions from MRI images with a MATLAB implementation. Sumithra and Deepa analysed the performance of various segmentation techniques for detecting brain abnormality, providing a comparison of the segmentation options available. Kaur et al. applied a neural network ensemble approach to tumour detection.

The methods surveyed divide broadly into those that emphasize segmentation quality and those that emphasize the discriminative power of the extracted features. The present work draws on both: Otsu thresholding with morphological refinement for the first, and Haralick texture descriptors for the second.

III. MEDICAL IMAGING BACKGROUND

Several imaging modalities are used clinically, divided into anatomical and functional types. Radiography, following the discovery of X-rays, produces an image on a screen or film from the differential absorption of radiation by tissues of different density. Fluoroscopy produces real-time images using a continuous low-rate X-ray input, useful for catheter guidance, while projectional radiography establishes the nature and extent of fractures and detects deformation in the lungs.

Magnetic resonance imaging uses the relaxation properties of magnetically excited hydrogen nuclei in water molecules. Powerful magnets excite the nuclei to a higher energy state, and as they relax they emit a signal that is spatially encoded. Different tissues relax at different rates, and it is this difference that produces contrast in the image. MRI is preferred over computed tomography for brain imaging because it uses non-ionizing radiation and gives better soft-tissue contrast, which is precisely what is needed to distinguish tumour tissue from healthy brain.

Nuclear medicine uses radioactive substances to assess physiology rather than anatomy, showing the function of the system under investigation rather than only its structure.

IV. PROPOSED METHODOLOGY

The proposed approach proceeds through pre-processing, segmentation, post-processing, feature extraction and classification.

A. Pre-Processing

Pre-processing removes low-frequency background noise, normalizes the intensity of individual images, masks portions of the image that are not of interest and removes reflections. A Gaussian low-pass filter is used, chosen because MRI noise is broadly distributed across the spectrum while the structures of interest are relatively large, so attenuating the high-frequency content removes noise disproportionately to signal.

B. Segmentation

Segmentation partitions the image into multiple regions, simplifying its representation into something more meaningful and easier to analyse. Threshold segmentation is among the simplest techniques: pixels are separated according to their intensity value, and the task reduces to selecting an appropriate grey-level threshold.

Otsu's method is used here. It is a global thresholding technique depending only on the grey values of the image, and it selects the threshold that minimizes the intra-class variance of the resulting black and white pixel populations — equivalently, that maximizes the separation between them. It is implemented in MATLAB as `graythresh`. Because it operates directly on the grey-level histogram rather than on the spatial image, it is fast, and it has reasonable noise immunity. Choosing the threshold from the image's own histogram rather than fixing it in advance is what allows the same procedure to work across images whose overall intensity differs.

The result of segmentation is a set of contours, with the pixels in each region similar with respect to intensity and adjacent regions significantly different.

C. Post-Processing

Binary images produced by simple thresholding contain imperfections: the regions are distorted by noise and by texture within the tissue. Morphological processing removes these by accounting for the form and structure of the image. Erosion shrinks region boundaries, removing small isolated pixels and thin protrusions that thresholding produced from noise. Dilation expands boundaries, filling small holes within a region that thresholding left. Applied in sequence, the two clean the segmentation without substantially changing the size of the regions that matter.

D. Feature Extraction

Haralick texture features are standard texture descriptors in image analysis. Computing them requires the image grey-levels to be reduced, a process called quantization, and the resulting features normally depend heavily on the quantization step, so that features computed with different quantization are not comparable. Here a formulation invariant to the number of quantization grey-levels is used: by redefining the grey-level co-occurrence matrix as a discretized probability density function, the features become asymptotically invariant to the quantization. This matters in practice because MR images from different scanners or protocols may not share an intensity scale, and features that shift with quantization would not transfer between them.

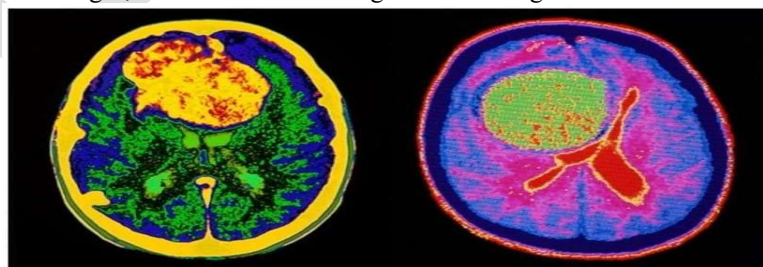
Fourteen texture features are extracted from the approximated subband: autocorrelation, cluster prominence, cluster shade, contrast, correlation, dissimilarity, energy, entropy, homogeneity, sum of squares variance, inverse difference, sum average, sum entropy and sum variance. Texture is an appropriate basis for this problem because tumour tissue differs from healthy brain tissue in the spatial arrangement of intensities as much as in intensity itself.

E. Classification

The extracted features are classified using K-nearest neighbours and support vector machine classifiers, separating benign from malignant cases. KNN classifies by majority vote among the nearest training examples in feature space, making no assumption about the shape of the class distributions. SVM finds the hyperplane that maximizes the margin between classes, which generalizes well when the number of features is comparable to the number of training samples — the situation here, with fourteen features and a database of moderate size.

V. DATABASE

The database comprises two types of brain MR image: benign and malignant. Because of the limited availability of public brain tumour image databases, images from several sources were combined and processed to a common form. The total is 180 brain MR images, of which 144 are benign and 36 malignant.



Meningioma and Glioma

Fig. 2. Sample images from the database: malignant tumour and normal brain.

The class imbalance in this database — four benign images for every malignant one — should be borne in mind when reading classification results, since a classifier that predicted the majority class for every input would already score

80% accuracy. Sensitivity on the malignant class is therefore the more informative measure for this data, and the total of 180 images is small enough that results should be treated as indicative rather than conclusive.

VI. RESULTS

The system was implemented and run on the assembled database. Fig. 3 shows the output of the processing pipeline on a test image.

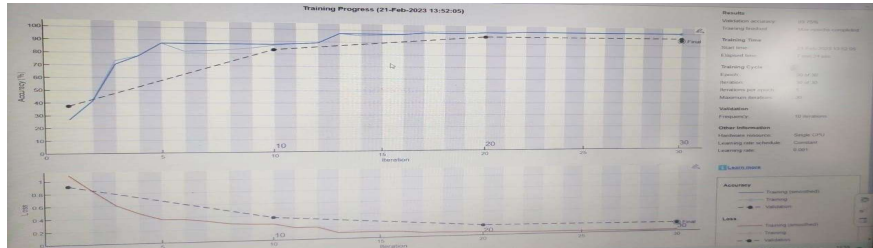


Fig. 3. Output of the detection and classification system.

Tumour features were extracted from the MR images and passed to the classifiers, which separated the images into benign and malignant classes. The low-pass filter together with the morphological operations removed noise and non-brain tissue from the images, which is a necessary step: skull, scalp and background all produce regions that survive thresholding and would otherwise be measured as though they were tissue of interest.

VII. CONCLUSION AND FUTURE SCOPE

Features of tumour cells were extracted from MR images and classified using KNN and SVM classifiers. A low-pass filter together with morphological dilation and erosion removed noise and non-brain tissue from the images before feature extraction. The pipeline demonstrates that a classical image processing and machine learning approach can separate benign from malignant cases on this data without requiring the large annotated datasets that a deep learning approach would need.

Two limitations bound what can be claimed. The database of 180 images is small and imbalanced, so the results indicate feasibility rather than establishing performance. And the system classifies a whole image rather than localizing the tumour within it, so it assists a radiologist in triage rather than in delineation.

The natural extension is to classify brain tumours using convolutional neural networks and deep learning, which learn features from the data rather than requiring them to be specified in advance, and which have consistently outperformed hand-designed texture features on comparable medical imaging tasks. That direction would require a substantially larger annotated database than the one used here, which is the practical obstacle to be addressed first.

References

- [1] T. Rajesh and R. S. M. Malar, "Rough set theory and feed forward neural network based brain tumor detection in magnetic resonance images," in Proc. Int. Conf. Advanced Nanomaterials and Emerging Engineering Technologies (ICANMEET), 2013, pp. 240–244.
- [2] K. Machhale, H. B. Nandpuru, V. Kapur, and L. Kosta, "MRI brain cancer classification using hybrid classifier (SVM-KNN)," in Proc. Int. Conf. Industrial Instrumentation and Control (ICIC), 2015, pp. 60–65.
- [3] M. Shasidhar, V. S. Raja, and B. V. Kumar, "MRI brain image segmentation using modified fuzzy C-means clustering algorithm," in Proc. Int. Conf. Communication Systems and Network Technologies (CSNT), 2011, pp. 473–478.
- [4] S. Goswami and L. K. P. Bhaiya, "Brain tumour detection using unsupervised learning based neural network," in Proc. Int. Conf. Communication Systems and Network Technologies (CSNT), 2013, pp. 573–577.
- [5] E. F. Badran, E. G. Mahmoud, and N. Hamdy, "An algorithm for detecting brain tumors in MRI images," in Proc. Int. Conf. Computer Engineering and Systems, 2010, pp. 368–373.
- [6] D. S. Parameshwari and P. Aparna, "An efficient algorithm for textural feature extraction and detection of tumors for a class of brain MR imaging applications," in Proc. 19th Int. Conf. Digital Signal Processing, 2014, pp. 339–344.
- [7] B. S. Kumar and R. A. Selvi, "Feature extraction using image mining techniques to identify brain tumors," in Proc. Int. Conf. Innovations in Information, Embedded and Communication Systems (ICIIECS), 2015, pp. 1–6.

- [8] R. Nouredine, K. Tarhini, and S. Saleh, "Segmentation and extraction of brain injury lesions from MRI images: MATLAB implementation," in Proc. Int. Conf. Advances in Biomedical Engineering (ICABME), 2015, pp. 45–48.
- [9] M. G. Sumithra and B. Deepa, "Performance analysis of various segmentation techniques for detection of brain abnormality," in Proc. IEEE Region 10 Conference (TENCON), 2016, pp. 2056–2061.
- [10] K. Kaur, G. Kaur, and J. Kaur, "Detection of brain tumor using NNE approach," in Proc. IEEE Int. Conf. Recent Trends in Electronics, Information and Communication Technology (RTEICT), 2016, pp. 1864–1868.
- [11] N. Otsu, "A threshold selection method from gray-level histograms," IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62–66, 1979.
- [12] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6, pp. 610–621, 1973.
- [13] A. Amsaveni, N. N. Singh, and J. Dheeba, "Detection of brain tumor using neural network," in Proc. Int. Conf. Computing, Communication and Networking Technologies, 2012.
- [14] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed. Pearson, 2018.