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A Machine Learning And Image Processing Framework For Brain Tumor Diagnosis

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Abstract:

In this project, we propose a deep learning-based approach for brain tumor detection using Convolutional Neural Network (CNN) model architecture. The primary objective of this study is to develop a reliable and efficient system for automated brain tumor detection using MRI images. We leverage the power of deep learning, specifically CNNs, which have demonstrated exceptional performance in various computer vision tasks, including medical image analysis.

Key words: Medical Image Processing, Brain tumour, MRI, CNN

INTRODUCTION

The early detection and treatment of brain tumour helps in early diagnosis which aids in reducing mortality rate. Image processing has been widespread in recent years and it has been an inevitable part in the medical field also. The abnormal growth of cells in the brain causes brain tumour. Brain tumour is also referred to as intracranial neoplasm. The two types of tumours are malignant and benign tumours. Standard MRI sequences are generally used to differentiate between different types of brain tumours based on visual qualities and contrast texture analysis of the soft tissue. More than 120 classes of brain tumours are known to be classified in four levels according to the level malignancy by the World Health Organization (WHO). All types of brain tumours evoke some symptoms based on the affected region of the brain. The major symptoms may include headaches, seizures, vision problems, vomiting, mental changes, memory lapses, balance losing etc. Incidence of brain tumours are due to genetics, ionizing radiation mobile phones, extremely low frequency magnetic fields, chemicals, head trauma and injury, immune factors like viruses, allergies, infections, etc. The malignant tumours, also known as cancerous tumours, are of two types - primary tumours, which start from the brain, and secondary tumours, which originate somewhere and spread to the brain. The risk factors for brain tumour are exposure to vinyl chloride, neurofibromatosis, ionising radiations and so on. The various diagnostic methods are computed tomography, magnetic resonance imaging, tissue biopsy etc. Better treatments are now available for brain tumours. There is a chance of focal neurological deficits, such as motor deficit, aphasia or visual field defects in the treatment. Side effects can be avoided by measuring tumour size and time to tumour progression (TTP). Estimation of density of affected areas can give a better measurement in therapy. Deep learning is a machine learning technique that instructs computers what to do as a human think and do in a scenario. In deep learning, a computer model is able to do classification tasks from images, sound or text. Sometimes human level performance is being exceeded by deep learning techniques. One of the most popular neural networks is an artificial neural network that has a collection of simulated neurons. Each neuron acts as a node and by links each node is connected to other nodes. The aim of this paper is to build a system that would help in cancer detection from MRI images through the convolution neural network. The proposed method was tested and compared with the existing classification techniques to determine the accuracy of the proposed method.

Problem statement:

The problem addressed in this study is the early detection and accurate segmentation of brain tumours using MRI images, which is crucial for improving treatment outcomes and reducing mortality rates. Current diagnostic methods may not effectively differentiate between tumour types or assess tumour density, leading to challenges in therapy planning. This research aims to provide a solution for this problem by leveraging deep learning techniques, specifically convolutional neural networks, to identify abnormal regions in MRI scans and segment tumour areas. By estimating the density of malignant pixels, the study is aiming to enhance diagnostic accuracy and offer better therapeutic strategies for patients suffering from brain tumours.

Project Objective:

The primary objective of this study is to develop a reliable and efficient system for automated brain tumor detection using MRI images. We leverage the power of CNNs, which have demonstrated exceptional performance in various computer vision tasks, including medical image analysis**.**

Key Advantages:

High Accuracy: The proposed system using CNN model architecture achieves a high accuracy of 97% in brain tumor detection. This accuracy level indicates the robustness and reliability of the system in accurately classifying tumor and non-tumor cases. High accuracy is crucial in ensuring the correct diagnosis and treatment planning for patients, leading to improved healthcare outcomes.

Automated Detection: The proposed system automates the process of brain tumor detection, reducing the reliance on manual analysis by radiologists. This automation speeds up the detection process and eliminates human subjectivity, ensuring consistent and objective results. It also allows healthcare professionals to focus on other critical tasks while benefiting from the support of an efficient and reliable detection system.

Time Efficiency: The proposed CNN model, are designed for efficient processing and inference. The system can quickly analyze brain MRI images and provide prompt results, allowing for faster diagnosis and treatment planning. Reduced processing time enhances the overall efficiency of healthcare processes and improves patient management. This algorithm is faster in execution for normal MRI images.

Generalizability: Deep learning models, including CNNs, have demonstrated excellent generalization capabilities across different datasets and imaging modalities. The proposed system's utilization of a diverse Brain MRI Images dataset enables it to adapt to various brain tumor cases, enhancing its generalizability in real-world clinical settings. This adaptability contributes to its wider applicability and potential integration into existing medical workflows.

Reduced False-Positive and False-Negative Rates: Accurate tumor detection is essential in minimizing false-positive and false-negative results. The proposed system's high accuracy helps reduce these error rates, ensuring that potential tumors are not missed (false-negative) and avoiding unnecessary interventions for non-tumor cases (false-positive). This reduction in false diagnoses improves patient care, reduces healthcare costs, and enhances the overall efficiency of the healthcare system.

Potential for Early Diagnosis: Early detection of brain tumors is crucial for timely treatment and improved patient outcomes. The proposed system, with its high accuracy and automated capabilities, has the potential to aid in the early diagnosis of brain tumors. Early detection allows for prompt intervention and treatment planning, increasing the chances of successful tumor management and potentially saving lives.

Literature Review:

In [1], The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary

AUTHORS: David N. Louis, Arie Perry, et al.

The 2016 World Health Organization Classification of Tumors of the Central Nervous System is both a conceptual and practical advance over its 2007 predecessor. For the first time, the WHO classification of CNS tumors uses molecular parameters in addition to histology to define many tumor entities, thus formulating a concept for how CNS tumor diagnoses should be structured in the molecular era. As such, the 2016 CNS WHO presents major restructuring of the diffuse gliomas, medulloblastomas and other embryonal tumors, and incorporates new entities that are defined by both histology and molecular features, including glioblastoma, IDH-wildtype and glioblastoma, IDH-mutant; diffuse midline glioma, H3 K27M-mutant; RELA fusion-positive ependymoma; medulloblastoma, WNT-activated and medulloblastoma, SHH-activated; and embryonal tumour with multilayered rosettes, C19MC-altered. The 2016 edition has added newly recognized neoplasms, and has deleted some entities, variants and patterns that no longer have diagnostic and/or biological relevance. Other notable changes include the addition of brain invasion as a criterion for atypical meningioma and the introduction of a soft tissue-type grading system for the now combined entity of solitary fibrous tumor / hemangiopericytoma-a departure from the manner by which other CNS tumors are graded. Overall, it is hoped that the 2016 CNS WHO will facilitate clinical, experimental and epidemiological studies that will lead to improvements in the lives of patients with brain tumors.

In [2], Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumour patients

AUTHORS: Pär Salander, A Tommy Bergenheim, Katarina Hamberg, Roger Henriksson

The time between experiencing symptoms and treatment in cancer diseases is a time of insecurity and despair. Brain tumour disease is a severe disease with dramatic manifestations and it is important that this time be kept as short as possible. A consecutive sample of 28 patients with malignant gliomas and their spouses were interviewed about symptom development, help-seeking and experiences of medical care. The cumulative development of their symptoms was described and factors acting as obstacles to medical care were identified. Most spouses witnessed months of global dysfunction preceding the symptom leading to physician consultation. The patient factors 'fewer alien symptoms', 'personality change' and 'avoidance'; the spouse factors 'spouse's passivity' and 'spouse's successive adaptation'; and the physician factors 'reasonable alternative diagnosis', 'physician's inflexibility' and 'physician's personal values' were identified as obstacles on the pathway to appropriate medical care. The importance of acknowledging the power of the spouse as a provider of substantial information from everyday life facilitating differential diagnosis is stressed.

In [3], Brain tumours: incidence, survival, and etiology

AUTHORS: McKinney PA

The term ‘‘brain tumours’’ refers to a mixed group of neoplasms originating from intracranial tissues and the meninges with degrees of malignancy ranging from benign to aggressive. Each type of tumour has its own biology, treatment, and prognosis and each is likely to be caused by different risk factors. Even ‘‘benign’’ tumours can be lethal due to their site in the brain, their ability to infiltrate locally, and their propensity to transform to malignancy. This makes the classification of brain tumours a difficult science and creates problems in describing the epidemiology of these conditions. Public perception generally fails to distinguish between different tumour subtypes and although treatments and prognosis may vary, the functional neurological consequences are frequently similar. This article will give an overview of the burden of brain tumours in the population, looking at the major subtypes where possible, in addition to giving a summary of current views on possible causes

In [4], Impact of brain tumour treatment on quality of life

AUTHORS: Heimans, J., Taphoorn, M

Measurement of Health-Related Quality of Life (HRQL) in brain tumour patients is important because brain tumours and brain tumour treatment usually affect physical, cognitive as well as emotional functioning. Measurement of HRQL is important for the understanding of disease burden and for the impact of specific tumour treatment. Quality of Life is a multidimensional concept consisting of physical, psychological and social phenomena. A large number of Quality-of-Life instruments have been developed. The European Organization for Research and Treatment of Cancer Quality of Life Questionnaire (EORTC QLQ-C30) and the MOS Short-Form Health Survey are two frequently used general HRQL instruments. A specific brain tumour scale is the Brain Cancer Module, which is designed to be used in combination with general questionnaires. HRQL measurement and neuropsychological examination were used to investigate the impact of radiotherapy and surgery in low-grade glioma patients and the influence of tumour volume, tumour localization, performance status and age in both low-grade and high-grade glioma patients.

In [5], Real-Time Hand Gesture Recognition Using Deep Learning

AUTHORS: Malavika Suresh, et al

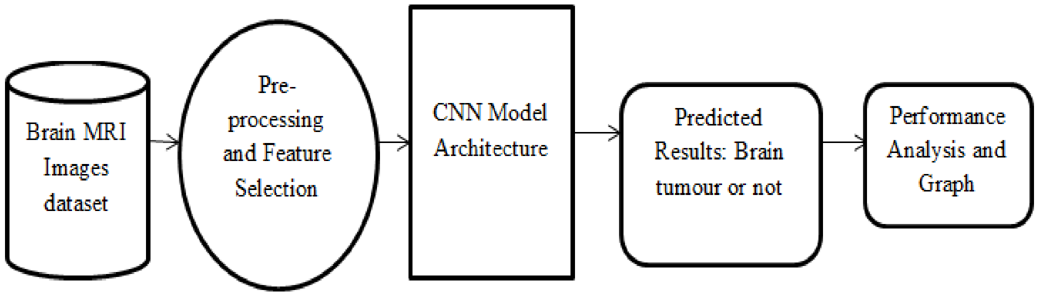
With the impetuous advancement of informatics, human knowledge is unable to bridge the boundaries and human computer interaction is paving the way for new eras. Here, a real-time human gesture recognition using an automated technology called Computer Vision is demonstrated. This is a type of non-cognitive computer user interface, having the endowment to perceive gestures and execute commands based on that. The design is implemented on a Linux system but can be implemented by installing modules for python on a windows system also. OpenCV and KERAS are the platforms used for the identification. Gesture displayed in the screen is recognized by the vision-based algorithms. Using background removal technique, an assortment of skin color masks was trained by Lenet architecture in KERAS for the recognition. The users have tested and produced over 5000 masks with KERAS to generate 96% more accurate results.

Existing System:

Mircea Gurbin, Mihaela Lascu, and Dan Lascu et al. proposed a method consisting of Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM). It uses different levels of wavelets, and by training, the cancerous and non-cancerous tumours can be identified. The computation time is longer for the proposed method.
Somasundaram S. and Gobinath R. et al. explains the present status of detection and segmentation of tumour through deep learning models. For deeper segmentation, 3D based CNN, ANN and SVM is used.
Damodharan S. and Raghavan D. et al. address segmentation of pathological tissues (Tumor), normal tissues (White Matter (WM) and Gray Matter (GM)) and fluid (Cerebrospinal Fluid (CSF)), extraction of the relevant features from each segmented tissues and classification of the tumor images with Neural Network (NN).

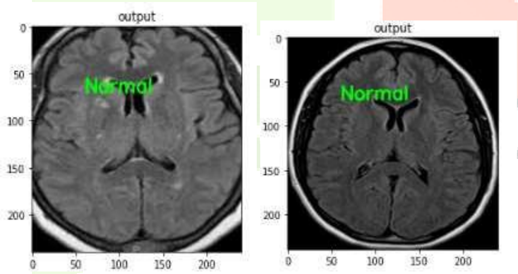
Proposed System:

The proposed system "Brain Tumor Detection Using Deep Learning" aims to develop an automated system for the accurate and efficient detection of brain tumors in MRI images. Traditional methods of brain tumor detection often rely on manual analysis by radiologists, which can be time-consuming and subjective. By leveraging the power of deep learning, specifically Convolutional Neural Network (CNN) model architecture, this project aims to provide a reliable and automated solution to assist healthcare professionals in the early detection and diagnosis of brain tumors. The proposed system utilizes a Brain MRI Images dataset obtained from Kaggle, which contains a diverse collection of brain MRI images, including tumor and non-tumor cases. The dataset is preprocessed to enhance image quality and normalize dimensions. The CNN model architecture is employed, consisting of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. During the training phase, the dataset is split into training and validation sets to evaluate the model's performance and prevent overfitting. Hyperparameters are iteratively adjusted to optimize accuracy and minimize loss. The experimental results demonstrate the effectiveness of the proposed approach, achieving an accuracy of 97% on the test dataset. This high accuracy suggests the potential of the system in aiding healthcare professionals in accurate and efficient brain tumor diagnosis. The automated nature of the system reduces the burden on radiologists and allows for quicker and more objective tumor detection.

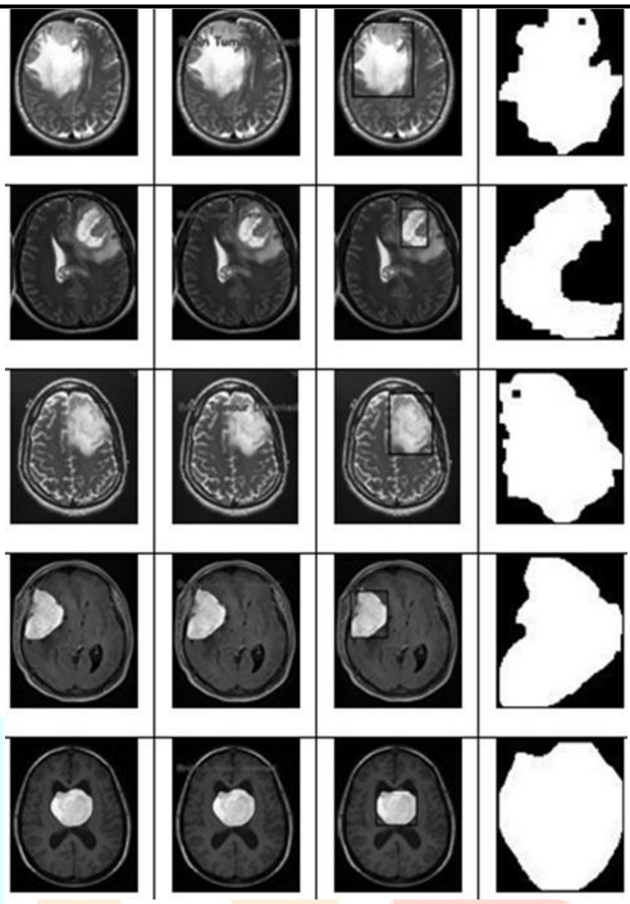


Results and Discussion:

Objective of the proposed system is to classify malignant brain tumour from the MRI images. 253 MRI images were collected from Kaggle dataset. The count of the data is insufficient for modelling a deep neural network. So 2530 images have been created with augmentation technique. The extracted cropped images are then resized to (240, 240) resolution. Keras (with TensorFlow backend) framework is chosen creating the model. Two types of segmentation at different level are implemented to analyze the performance of the system. Segmentation was done before and after classification. From the performance analysis, segmentation after the classification gives better result. This algorithm is faster in execution for normal MRI images. If it identifies the abnormal images, it goes to the next step ,ie : segmentation. ROC curve shows the relation between sensitivity and specificity.



Normal Images Results



Tumour detection results : (a) Input Image (b) Abnormality Detection (c) Tumour region detection (d) tumour mask for density estimation.

Conclusion and Future Scope:

This paper provides a new method for detecting brain tumour by deep learning method. The early detection of cancer helps timely and effective treatment. Kaggle dataset contains good quality of MRI images for research purposes. Different segmentation algorithms were experimented. From this , multilevel thresholding and OTSU thresholding are the best methods for the dataset. Convolutional Neural Network with modified approach helped to get a result with accuracy 98%. Density estimation method is also proposed using Gaussian kernel distribution. This system can be improved to support with a web interface. Detection of different diseases can be also identified from the MRI images. Apart from the density some other parameters can also estimate for therapeutic purposes.

References:

[1] David N. Louis, Arie Perry, et al., “The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary”, Acta Neuropathology , Springer may 2016.

2] Pär Salander, A Tommy Bergenheim, Katarina Hamberg, Roger Henriksson, Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumour patients, Family Practice, Volume 16, Issue 2, April 1999, Pages 143–148.

[3] McKinney PA,” Brain tumours: incidence, survival, and etiology”, Journal of Neurology, Neurosurgery & Psychiatry 2004;75:ii12-ii17.

[4] Heimans, J., Taphoorn, M. Impact of brain tumour treatment on quality of life. J Neurol 249, 955–960 (2002)

[5] Malavika Suresh, et al. “Real-Time Hand Gesture Recognition Using Deep Learning”, International Journal of Innovations and Implementations in Engineering (ISSN 2454- 3489), 2019, vol 1

[6] M. Gurbină, M. Lascu and D. Lascu, “Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines”, 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 2019

[7] Somasundaram S and Gobinath R, “Early Brain Tumour Prediction using an Enhancement Feature Extraction Technique and Deep Neural Networks”, International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278 3075, Volume-8, Issue-10S, August 2019

[8] Damodharan S and Raghavan D, “Combining Tissue Segmentation and Neural Network for Brain Tumor Detection”, The International Arab Journal of Information Technology, Vol. 12, No.1, January 2015

[9] G. Hemanth, M. Janardhan and L. Sujihelen, “Design and Implementing Brain Tumor Detection Using Machine Learning Approach”, 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019

[10] A. R. Mathew and P. B. Anto, “Tumor detection and classification of MRI brain image using wavelet transform and SVM”, International Conference on Signal Processing and Communication (ICSPC), Coimbatore, 2017

[11] W. Chen, X. Qiao, B. Liu, X. Qi, R. Wang and X. Wang, “Automatic brain tumor segmentation based on features of separated local square”, Chinese Automation Congress (CAC), Jinan, 2017

[12] Navoneel Chakrabarty, “Brain MRI Images for Brain Tumor Detection Dataset”, Kaggle, April 2019

[13] S. Poornachandra and C. Naveena, "Pre-processing of MR Images for Efficient Quantitative Image Analysis Using Deep Learning Techniques," 2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT), Bangalore, 10.1109/ICRAECT.2017.43. 2017, pp. 191-195, Doi:

[14] Mohammed Thanveersha N., et al. “Automatic Brain Hemorrhage Detection Using Artificial Neural Network”, International Journal of Innovations and Implementations in Engineering (ISSN 2454- 3489), 2019, vol 1

[15] Soumya R S, et al. “Advanced Earlier Melanoma Detection Algorithm Using Colour Correlogram”, 2016 International Conference on Communication Systems and Networks (CommNet) | 21-23 July 2016 | Trivandrum

[16] J. A. Akhila, C, Markose, et al. "Feature extraction and classification of Dementia with neural network," 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kerala, India, 2017, pp. 1446-1450

[17] Avigyan Sinha, Aneesh R. P., “Real Time Facial Emotion Recognition using Deep Learning”, International Journal of Innovations and Implementations in Engineering (ISSN 2454- 3489), 2019, vol 1

[18] H. B. Nandpuru, S. S. Salankar, and V. R. Bora, ‘‘MRI brain cancer classification using support vector machine,’’ in Proc. IEEE Students’ Conf. Electr., Electron. Comput. Sci., Mar. 2014, pp. 1–6.
[19] E.-S.-A. El-Dahshan, T. Hosny, and A.-B.-M. Salem, ‘‘Hybrid intelligent techniques for MRI brain images classification,’’ Digit. Signal Process., vol. 20, no. 2, pp. 433 441, Mar. 2010.

[20] W. H. Ibrahim, A. A. A. Osman, and Y. I. Mohamed, ‘‘MRI brain image classification using neural networks,’’ in Proc. Int. Conf. Comput., Electr. Electron. Eng. (ICCEEE), Aug. 2013, pp. 253–258.

[21] N. H. Rajini and R. Bhavani, ‘‘Classification of MRI brain images using k-nearest neighbor and artificial neural network,’’ in Proc. Int. Conf. Recent Trends Inf. Technol. (ICRTIT), Jun. 2011, pp. 563–568