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Alzheimer's Brain Disease Tumor Detection Architectural Model Using Artificial Intelligence

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Abstract

Background: Alzheimer's disease is one of the neurodegenerative disorders. Though the symptoms are benign initially, they become more severe over time.
Objectives: This disease is challenging because there is no treatment for it. The diagnosis of the disease is done, but that too at a later stage.
Methods: This disease is challenging because there is no treatment for it. The diagnosis of the disease is done, but that too at a later stage.
Statistical Analysis: As the brain is confined within the rigid skull, any undue expansion can lead to severe complications, making early and accurate detection vital for effective treatment.
Findings: Detection involved an expert examination of medical images, primarily magnetic resonance imaging (MRI) scans.
Applications and Improvements: Convolutional neural networks (CNNs) have revolutionised image classification and segmentation across various fields.

Keywords: Mild cognitive impairment; Neurodegeneration; Synaptic plasticity.

1. Introduction

Alzheimer's disease is one of the neurodegenerative disorders. Though the symptoms are benign initially, they become more severe over time. This disease is challenging because there is no treatment for it. The diagnosis of the disease is done, but that too at a later stage. This paper uses machine learning algorithms to predict Alzheimer disease using psychological parameters like age, number of visits, MMSE, and education. It demonstrates the untapped potential of the brain tumour architecture model in brain tumour detection and contributes to the growing body of research on applying deep learning in medicine. As the brain is confined within the rigid skull, any undue expansion can lead to severe complications, making early and accurate detection vital for effective treatment. Detection involved an expert examination of medical images, primarily magnetic resonance imaging (MRI) scans. Convolutional neural networks (CNNs) have revolutionised image classification and segmentation across various fields. While designing a custom CNN is intricate due to decisions regarding layers, filter sizes, padding types, and more, pre-trained models like VGG-16 offer a powerful alternative. Despite its extensive use in other domains, its applicability in brain tumour detection remained unexplored, prompting this investigation.

2. Related System

Deep learning techniques have been extensively employed in cancer and tumour detection, with numerous studies aiming to enhance their accuracy and efficiency. Each study, however, has unique aspects related to the type of cancer or tumour investigated, the deep learning techniques employed, the performance metrics used, and the datasets utilized. These variables might influence the generalizability of the models to other datasets. By grouping the studies based on specific cancer or tumour types and the deep learning technique used, we can discern commonalities and differences and understand their implications for our current study. Numerous studies have leveraged convolutional neural networks (CNN) for cancer and tumour detection and segmentation. For instance, Yang et al. used EasyDL and GoogLeNet, achieving impressive detection efficiencies of 96.9% and 92.54%, respectively. Similarly, Cha et al. developed a deep learning CNN (DLCNN) to distinguish the interior and exterior of the bladder. However, these studies are limited by the size and type of datasets used, which might restrict the applicability of the models to more diverse datasets. Some studies employed other deep learning techniques. Lorencin et al. used a multi-layer perceptron (MLP) with a Laplacian edge detector, while Harmon et al. employed a multivariable logistic regression and neural network model for prediction, achieving an accuracy of 95%. Despite these promising results, the potential generalizability of these models to other datasets requires further investigation. In terms of segmentation, Ma et al. utilised deep learning frameworks, specifically fully convolutional residual networks (FCRN) and U-Net-based deep learning techniques (U-DL), respectively. They improved the segmentation of cancerous regions in medical images, illustrating the potential of deep learning for precise tumour localization.

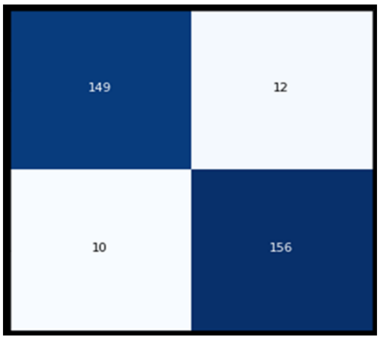

Figure 1. Confusion Matrix Obtained for the Dataset

3. Proposed System

Proposed a model where longitudinal analysis is performed on consecutive MRIs and is essential to design and compute the evolution of disease with time for the purpose of more precise diagnosis. The actual process uses those features of morphological anomalies of the brain and the longitudinal difference in MRI to construct a classifier for distinguishing between the distinct groups. The MRI brain images of six time points, that is, consecutive intervals in a gap of six months, are taken as inputs from the ADNI database. Then feature learning is done with the 3D Convolutional Neural Network. The CNN is followed by a pooling layer and has many ways for pooling, like collecting the mean value, otherwise the maximal or definite sequence of neurons

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in the section. In today's society, medical care problems have become a hot topic, and problems such as the unbalance and insufficient allocation of medical resources has become increasingly apparent. In this situation, the application of ML has become an unavoidable trend in the current development of medical care. As early as 1972, scientists at the University of Leeds in the UK have been trying to use artificial intelligence (ANN) algorithms to judge abdominal pain. Now, more and more researchers are committed to the combination of ML and medical care.

4. System Architecture

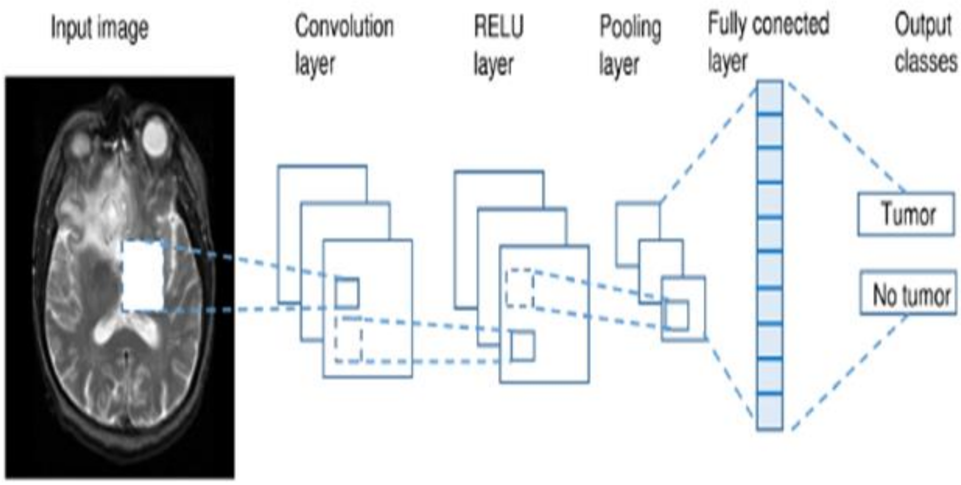
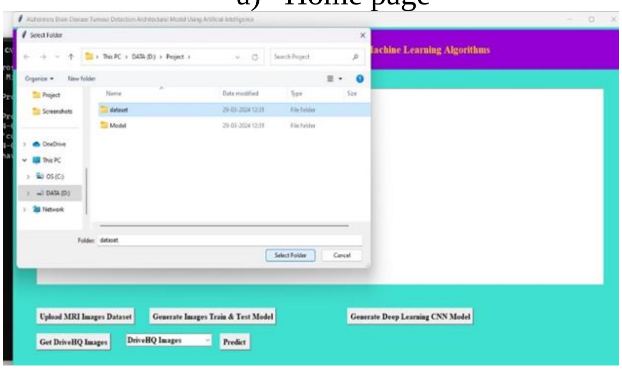


Figure 2. Architecture

5. Results and Analysis

a) Home page

b) MRI Images



c) Select Datasets

d) Trained Datasets

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e) Deep Learning in CNN model

f) Predict Tumour

Figure 3. Results

6. Conclusion

A recurring theme in machine learning is the limit imposed by the lack of labelled datasets, which hampers training and task performance. Conversely, it is acknowledged that more data improves performance, as Sun et al. show using an internal Google dataset of 300 million images. In general computer vision tasks, attempts have been made to circumvent limited data by using smaller filters on deeper layers, with novel CNN architecture combinations, or hyperparameter optimisation. In medical image analysis, the lack of data is two-fold and more acute: there is a general lack of publicly available data, and high-quality labelled data is even more scarce. Most of the datasets presented in this review involve fewer than 100 patients. Yet the situation may not be as dire as it seems, as despite the small training datasets, the papers in this review report relatively satisfactory performance in the various tasks. The question of how many images are necessary for training in medical image analysis was partially answered by Cho et al. He ascertained the accuracy of a CNN with GoogLeNet architecture in classifying individual axial CT images into one of six body regions: the brain, neck, shoulder, chest, abdomen, and pelvis. With 200 training images, accuracies of 88–98% were achieved on a test set of 6,000 images. While categorization into various body regions is not a realistic medical image analysis task, his report does suggest that the problem may be surmountable. Being able to accomplish classification with a small dataset is possibly due to the general intrinsic image homogeneity across different patients, as opposed to the near-infinite variety of natural images, such as a dog in various breeds, colours, and poses. VAEs and GANS, being generative models, may sidestep the data paucity problem by creating synthetic medical data.

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