ISSN: 0974-5823 Vol. 7 No. 1 January, 2022

International Journal of Mechanical Engineering

AN EXTENSIVE STUDY OF BRAIN TUMOR DETECTION AND SEGMENTATION IN COMPUTED TOMOGRAPHIC IMAGING USING DEEP LEARNING TECHNIQUE

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1.0 Introduction

Brain tumors are the second most common cause of cancer death among men and the fifth most common cause of cancer among women. Every year nearly about 19,000 people in the United States of America are diagnosed with primary brain tumor. Ashby et al (2006) pointed out that based on World Health Organization (WHO), the brain tumor is one of the major causes leading to higher incidence of death in human both in developed and developing countries. Recent statistical report published by the Central Brain Tumor Registry, CBTRUS (2013) stated that around 2,95,986 patients in United States of America were diagnosed with primary benign and primary malignant brain tumors in year 2004 -2008. Among these, only 34.4% of the tumors were diagnosed as malignant and 65.5% were diagnosed as benign tumors.

Brain Tumor Segmentation and Classification

Deep learning techniques have been extensively used in various areas and have reached cutting-edge performance. However, segmentation of the brain tumour presents many distinct difficulties. Firstly, picture quality affects segmentation performance critically. Blurred pictures, for example, lead to poor results. Secondly, picture pre-processing procedures have a performance effect as well. For example, for tumour segmentation, intensity standardisation between instances is essential. Third, the development of an effective technique may provide a significant problem for tumour tissue heterogeneity.

U-net Architecture

The contracting route is the first component, and it employs a standard CNN architecture. The upsampled feature map is then cropped and concatenated with the featured map from the appropriate layer in the constricting path. Then there are two 3x3 convolutions in a row, followed by ReLU activation. To decrease the feature map to the necessary number of channels and create the segmented picture, an extra 1x1 convolution is performed at the end.

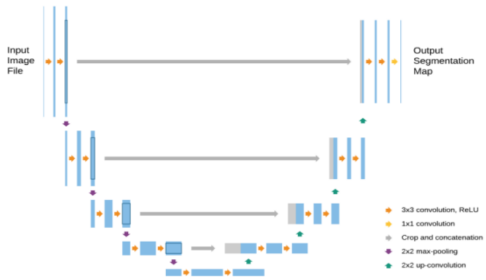


Figure 1: Basic U-net architecture

The energy function for the network is given by the following equation:

$$E = \sum w(x) \log \left(p_{k(x)}(x)\right),$$

$$p_k(x) = \frac{e^{a_k(x)}}{\sum_{k'=1}^{K} e^{a_{k'}(x)}},$$

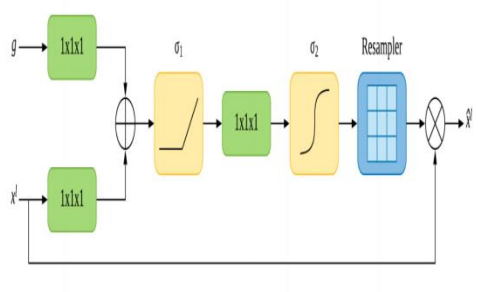


Figure 2: Preservative consideration gate schematic

Because it may offer localised categorization information rather than global classification, the attention unit is helpful in encoder-decoder architectures like the U-net. This enables various sections of the network in U-net to concentrate on segmenting distinct items. The network may also attune to specific items in a picture if the training data is correctly tagged. The following is a description of the additive attention gate:

$$q_{att}^{l} = \psi^{T}\left(\sigma_1\left(W_x^T x_i^l + W_g^T g_i + b_g\right)\right) + b_{\psi},$$

$$\alpha_i^l = \sigma_2(q_{att}^l(x_i^l, g_i; \Theta_{att})),$$

$$\sigma_2\left(x_{i,c}\right) = \frac{1}{1+\exp\left(-x_{i,c}\right)},$$

Recurrent neural networks are a kind of neural network that was originally created to evaluate sequential input like text or audio. This feedback loop generates an internal state or memory for the node, allowing it to alter its output in discrete time steps.

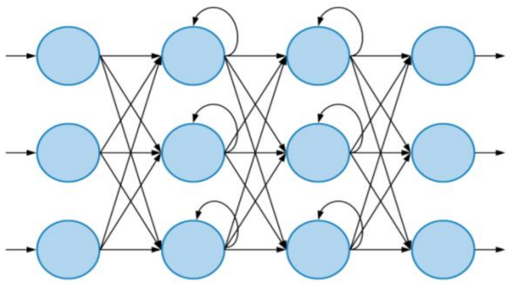


Figure 3: Recurrent Neural Network

The feedback attribute enables parts to update their feature maps depending on context from neighboring units, resulting in improved exactness and swiftness. The recurrent convolution neural network's output y may be represented as follows:

$$y^l_{ijk}(t) = \left(w^f_k\right)^T x_l^{f(i,j)}(t) + (w^r_k)^T x_l^{r(i,j)}(t-1) + b_{k'}$$

The goal of overall survival prediction is to estimate a patient's remaining life span after being diagnosed with a brain tumour. The majority of current research relies on conventional machine learning and linear regression techniques. T1, T1ce, T2, and FLAIR are the four modalities in A. Following that, as illustrated in C, the suggested CANet is applied to a segment tumour. In D, you can see the segmentation results. In E, the segmented aberrant tissues are used to categorise the tumour using a 3D CNN. In F, we use the front-end of CANet to extract high-dimensional characteristics, and then use a linear regression to predict overall survival. It's worth noting that the best tumour segmentation model may also be the best at classifying tumour subtypes and predicting overall survival.

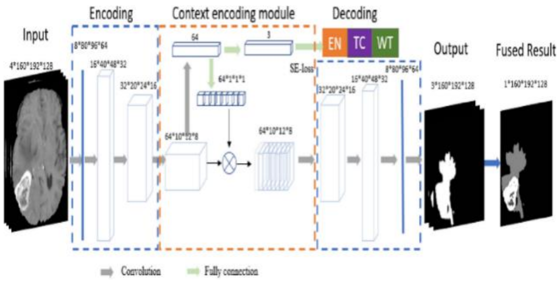


Figure 4: Overview of the proposed CANet architecture for tumour segmentation

2.0 Literature Review

The literature review focuses on all the aspects of survey and other aspects regarding the brain tumor and CT scan where all the areas of the authors' related expertise and knowledge in a particular field and their respective journals are discussed thoroughly. Literature review forms an important component of the proposed work. The books and journals based on a given particular topic are discussed here which helps in proper understanding and methodology of this particular topic on brain tumors and CT scan. Many opinions and views are shared by different authors and their respective journals on a particular topic where the brain tumor research and the importance of CT scan is clearly mentioned which helps in the proper completion of this work in a proper and an efficient manner.

In this chapter, computer vision based and image processing methods for brain tumour detection can be surveyed, and several brain tumour segmentation methods, feature extraction, tumour classification and deep learning algorithm can also be examined. An effort can be made to survey and analyze the current knowledge in the automatic brain tumour detection using effective segmentation method. The importance of accuracy and tumour classification has been extensively discussed in this literature. Different research works are obtainable on brain tumour detection utilizing an effective image classifier in this survey. Only some of the present works are assessed for brain tumour segmentation methods.

Data mining techniques such as classification and clustering are often employed. The goal of clustering techniques is to extract information from a data collection in order to locate groups or clusters and explain the data set **[1].** In machine learning, classification, also known as supervised learning, seeks to categories new circumstances by learning existing patterns and categories from the data set and then predict future scenarios. In classification tasks, the training set, which is used to build the classifying structure, and the test set, which is used to evaluate the classifier, are frequently mentioned. This study is primarily concerned with the classification and prognosis of brain tumours. This section reviews related research on supervised learning methods and their use in brain tumour diagnosis.

BRAIN TUMOUR Segmentation Methods

Demirhan *et al.* (2015) introduced a new tissue segmentation approach for brain images, which segmented tumour, WM, GM, CSF, and edoema. Since the rise of tumour on healthy brain tissues, the identification of healthy brain tissues has been carried out simultaneously with the detection of malignant tissues. It has the potential to be the most important for treatment planning. T1, T2, and Fluid-attenuated inversion recovery images of 20 participants suffering from glial tumour were used in this study. An algorithm for striped skull has been improved before the segmentation procedure. The picture segmentation was done using the unsupervised learning method and a self-organizing map that has been finetuned using learning vector quantization approach. An algorithm was improved in this way to cluster the SOM replacement of an extra network. The features obtained from the coefficients of stationary wavelet transform were used to measure the input feature vector.

Atiq Islam *et al.* (2013) proposed a novel Multi-Fractal (MultiFD) feature extraction and supervised classifiers for improved brain segmentation of tumour and identification of cancer tumour, as well as a modified AdaBoost algorithm to account for extensive unpredictability in features of surface diagonally hundreds of multiple patients for expanded tumour and non-tumour tissue categorization.

Analysis of Survey and Problem Statement

Radiologists may confront difficulties in determining the nuclei of brain cells from the content of scanned picture on the medical side. Due to the shape and location of tumours in the human brain, tumour segmentation is currently a tough task when combining multi-modal imaging data. The primary obstacles in detecting brain tumours are the lack of precision in detecting tumour areas and segmenting the tumour region. As a result, picture segmentation may be the most difficult aspect of tumour detection. However, the work of tumour segmentation and separation may be critical in identifying a brain tumour and making an accurate diagnosis. The right segmentation procedure may provide quantitative and qualitative data on a benign tumour or a malignant tumour, which can be used to determine what the best therapies are for the patient and to help the doctor who serves the patient, develop a better strategy. When picture analysis is simple to grasp and segment, effective tumour identification may be achieved. As a result of the difficult tumour segmentation process, several algorithms and approaches for manual, semi-automatic, and fully automated tumour segmentation have been developed. Many of them were only performed on limited datasets.

3.0 Methodology

This Chapter includes the proposed and description of an enhanced clustering model for the identification and prediction of brain tumour disease.

Pre-processing

Unlike many other current deep learning algorithms that utilize the whole picture to extract essential characteristics, we just use a small portion of it to extract critical features. The genuine negative outcomes are considerably reduced by deleting these needless uninformative sections. We also don't need to utilize a particularly deep convolution model if we adopt such a method.

Distributions that are similar

We employ four brain modalities to increase final segmentation accuracy: T1, FLAIR, T1C, and T226,27. When this method is used to a medical brain picture, the result is an image with a zero mean and unit variance24. In just the brain area, we did this step by removing the mean and dividing by the standard deviation (not the background).

CNN cascade model

Figure shows the flowchart of our cascade mode. We employ four modalities to collect as many rich tumour characteristics as possible: fluid attenuated inversion recovery (Flair), T1-contrasted (T1C), T1-weighted (T1), and T2-weighted (T2) (T2). In addition, we add four Z-Score normalised pictures of the four input modalities to boost the dice score of segmentation results without adding additional difficult layers to our structure.

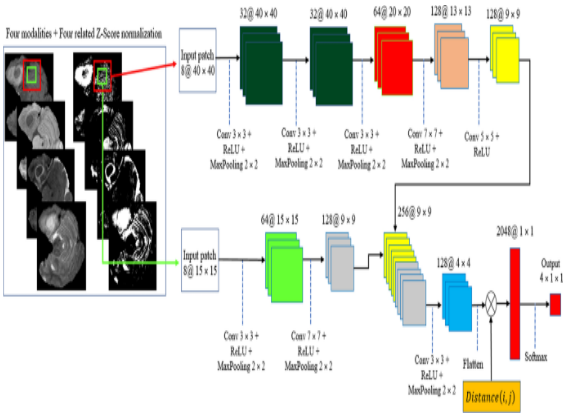


Figure 5: CNN cascade model

Our cascade structure has been implemented. The local and global patches are represented by the green and red windows in the input pictures, respectively. Before the FC layer, the DWA module is represented at the end of the structure.

MODELS

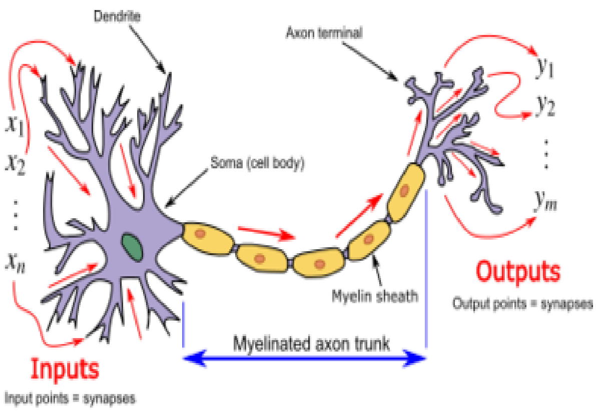


Figure 6: Signal flow from dendrite inputs to axon terminal outputs in a neuron and myelinated axon

ANNs began as an effort to leverage the design of the human brain to do jobs that standard algorithms couldn't. They swiftly changed their attention to better empirical results, abandoning most efforts to remain faithful to their biological forefathers. Neurons are connected in a number of ways such that one neuron's output might become the input of another. The network generates a directed, weighted graph. An artificial neural network is made up of a collection of synthetic neurons. Each neuron is a node with connections that correspond to axon-synapse-dendrite connections in biology. The weight of each connection determines the intensity of one node's influence on another

4.0 Analysis, design and Implementation

In the analysis, design and implementation part, the discussion about the deeper analysis of the project on “Brain Tumor and CT scan” is done here in which all the features, areas of “Brain tumor and CT Scan” are discussed in detail, the discussion about the relative designs and the diagrams of this project model is done here and the discussion about the coding that is give some diagrams of coding and implementation that is how it is done and implemented here is discussed briefly and clearly so that all the necessary areas are covered here in this part of the project (Minnema *et al*. 2018). Here, python implementation and coding is done on CT scan of Brain tumor. For validating the algorithm’s performance, two benchmark datasets are used where one dataset is collected from radiologists who are experts, which consists of sample images of 15 patients with slices of 9 for each of the patients. This section gives the proper analysis, design and implementation of this project and plays an important role in this project work and also forms an important basis and foundation of this work. The proper

CT scan of the brain tumor is very important for actual study and detection of the tumor in the brain. A dense layer of 256 neurons which is fully connected is applied along with the layer of “softmax output layer” that estimates the score of probability for every class and classifies the labels of final decision whether the input image contains cancer (Petr *et al.* 2018). All the aspects of analysis, design and implementation are discussed properly and efficiently for the basic structuring and completion of this project and making the project execute and work successfully.

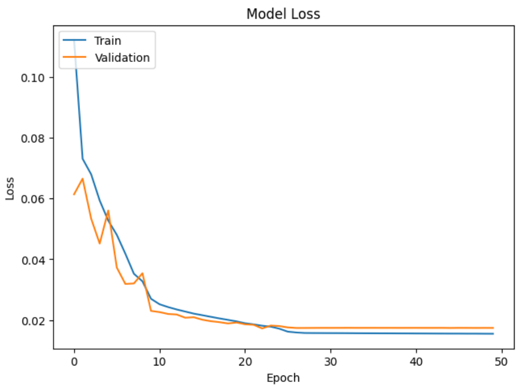
```
def transform_to_hu(medical_image, image):
    intercept = medical_image.RescaleIntercept
    slope = medical_image.RescaleSlope
    hu_image = image * slope + intercept

    return hu_image
```

Figure 7: The Medical Image Code

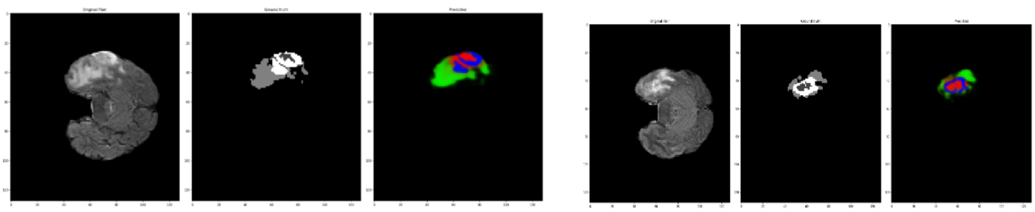
(Source: Self-created in Google Colab)

PERFORMANCE MATRICES



Prediction Results

Predictions generated from the model with UNet.



GREEN = Edema

YELLOW = Enhancing Tumour

BLUE = Necrosis and Non-Enhancing

Thefollowing table shows the assignment of CNN and deep neural network .The dataset contains 768 attributes which divides into two clusters which has been shown in the table. The experimental outcome of proposed M-tree based Brain tumour prediction model are as follows:

Table 1: Performance analysis of proposed and existing methods

Parameters	Proposed Method (%)	K-Means (%)	CNN (^{0}0)	SVM
Sensitivity	94.0	85.7	90	83
Specificity	93.2	87.3	92.8	85.1
Accuracy	93.6	86.5	91.6	84.28

From the above comparison table, the proposed method has provided 94 percentages in sensitivity level, 93.2 percentages in specificity level and 93.6 percentages in the accuracy level compared to existing techniques K-means, conventional SVM and Conventional Neural Networks. As a result, this proposed deep learning method for brain tumour segmentation can give high percentage in sensitivity, specificity and accuracy to the tumour recognition and segmentation than the existing methods.

So, in the analysis, design and implementation part all the coding of CT scan on Google Colab is discussed along with their analysis and implementation for clearly making the project work understandable and the final result is the derived result which is required here (Zawish *et al.* 2021). All the codes and their related descriptions along with the block diagram of functioning of CT scan on brain tumor is clearly discussed here and being the most important part of this project work, all the necessary things and points are kept in mind for performing this work. The coding diagram gives an idea about how the code looks and how it's implemented and analyzed properly.

5.0 Interpretation of Results and Discussions

Here, in this part the output of the code will be given and will be discussed accordingly. The results and discussions part is important because here the results of the output are genuine and according to the requirements for making it understandable about what is going to be done which is the main point of discussion here (Shakeel *et al.* 2019). The output results are given properly so that no issue arises while doing and executing the project so that is important while defining the project work properly. The proper interpretation of output results and their discussions are important for giving the project a clear and concrete view of knowledge and expertise in the field of "Brain Tumor and CT scan" and some pictures which are relevant are also added for better understanding of this important work in such a manner so that no problem arises during the thorough completion of this work.

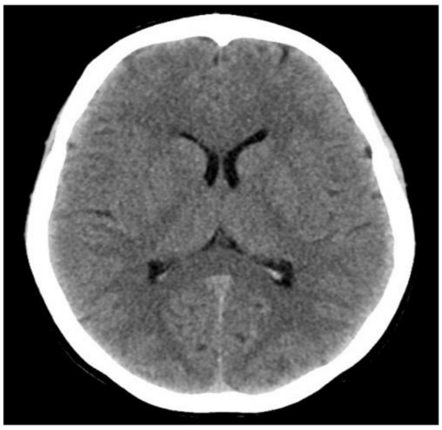


Figure 7: Image of Brain CT-scan

(Source: Self-Created on Google Colab)

This picture shows the CT-scan of the brain and its inner parts also which defines all the aspects of the brain. This is required for the actual work because it shows the tumor in the brain clearly and also the “CT scan” mechanism of the brain for detecting the tumor in the brain clearly (Valindria *et al*. 2018).

This output is relevant in the context of this work and this is valid tool for processing and evaluation of this work because it shows the detailed and minute analysis of the brain tumor by “CT scan” and also making the process of scanning easier and appropriate so that no problems arises in the accurate scan and detection of tumor in the brain by CT scan.

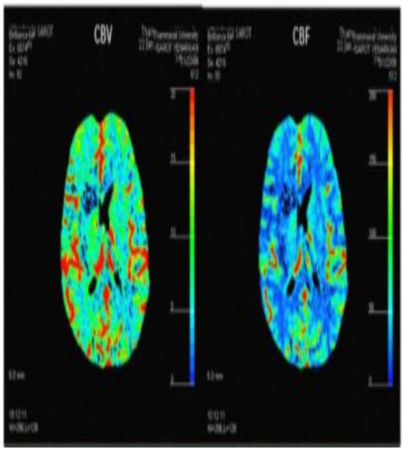


Figure 8: CT scan of the coloured images of the brain for the first two stages

(Source: Self-created on Google Colab)

This picture shows the brain CT scan which is replaced by color images and which clearly shows various sections in the brain in a well-defined manner so that the version of CBV and CBF is clearly shown here and explained properly (Sobhaninia *et al*. 2018). All the parameters are mentioned here in all the sections of this CT scan of the coloured images of the brain. These coloured images of the various sections of the brain are clearly shown here and also discussed properly so that the color images can be effective and appropriate too as compared to the normal image of the CT scan of the brain and making the work fully complete by giving the details which are relevant to this image. The initial two stages of the brain which is the “CBV” and “CBF” is shown and discussed here in such a manner so that all the internal parts of the brain can be shown clearly.

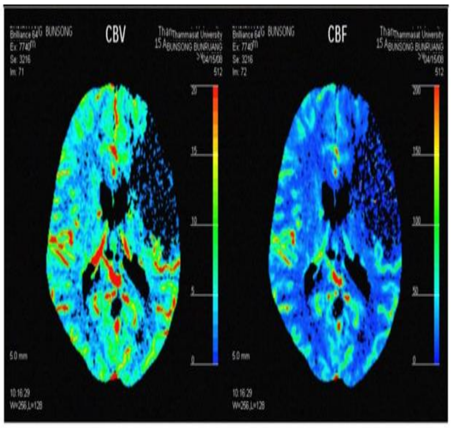


Figure 9: CT scan of the coloured images of the brain for the last two stages

(Source: Self-created on Google Colab)

The above image shows the last two stages of CBV and CBF of the brain. The steps are clearly outlined here and the features and aspects of the brain are shown and discussed here properly and clearly and it also clearly shows the regions which are proper and relevant according to the title of “Brain Tumor and CT scan” (Hussain *et al*. 2020). The internal images are shown here in such a manner so that it is clearly understandable and relevant too without any problems.

According to dataset, CT scan is the sensitive imaging which is used in tumors which are intracranial but are not specific. The predictive value which is highly positive and also lowly negative also made the diagnostic procedures which are reliable when it is very difficult for accessing mass directly. The dataset also displayed that seizure might predict tumors which are malignant but different symptoms such as “hemiparesis”, “headache”, “vomiting”, “diplopia” and “nausea” too may not be shown. In this research and study relation between pathologic findings and CT scan findings concluded by surveying that some of the findings such as “solid lesions or cystic”, “calcification”, “edema”, “shifting” and “enhancement” did not predispose reports which are biopsy, but “hydrocephalus” found as a finding which is predictive in reports of “CT scan” to determine tumors which are malignant. According to this study of dataset and the results obtained here it is concluded that “CT scan” is better for diagnosis and treatment of tumors in the brain and correlation of biopsy (Dey *et al.* 2019). The brain tumors of all the patients are investigated and the values are recorded from them in such a manner such that the record of all the patients are shown and discussed properly with the proper effectiveness and efficiency. This helps in the proper analysis of the tumor in the brain by “CT scan” and also their relevant results with their discussion in this segment.

6.0 Conclusions and Future works

In the preliminary stage, the resolution part of the CT scan will be increased to the administrator intravenous of contrast. While the part of administration is going to be in contrast then the area of the revolution will be concentrating the entire surrounding framework like the part of arteries and others. To enhance the quality of the CT scan, UOC has developed some new methods. CT scan is one of the most effective testing parts in the medical area to analyze the affected part of an illness, included with the Covid 19. The international team of UOC has developed a new quality that will be helping out to enhance the obtained part of the CT scan.

CT scan is the acronym of a Computerized tomography is a one kind of series of x-rays image which is taken from in different angles of one's body. It is a totally technological based process. This medical process is done by computer software. The process can capture the image of various parts of the body such as bones, blood vessels as well as soft tissue of the body. CT scan can provide detailed information which is needed to the doctor to evaluate the disease specifically. In the modern medical field, the use of CT scan is huge. This process occurred with giving any pain to the patient. In the case of Brain Tumor, CT scan is the crucial process which can provide the details of the affected areas. Nowadays new technology arrives in the medical field. CT is constructed with updated software to better performance at a time. The developed technology can enhance the performance of the CT scan which will be able to decrease the radiation. The use of technology in CT is able to provide a clear picture and also it can decrease the time. This study has so far established the importance of CT scan in the medical world through its implementation. The future work here suggested the affordable implications for the particular concern and this study has so far established the overall discussion of the CT scan and Brain tumor.

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