International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. IV, No. 01, pp. 1-4, January

An Automated Detection of Cerebral Infarction in Computed Tomography (CT) Brain Images Using 3D U-Net Model of Convolutional Neural Networks (CNN)

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ABSTRACT: Cerebral infarction is a leading cause of mortality worldwide, resulting from the blockage of an artery that restricts blood flow and oxygen to brain tissues. Computed Tomography (CT) is a widely used imaging tool for early stroke assessment. This study proposes an automated detection model for cerebral infarction in CT brain images using a 3D U-Net model based on Convolutional Neural Networks (CNN). To improve and segment the impacted brain tissues, the system uses preprocessing techniques such slice selection, picture averaging, band-pass filtering, and variation model decomposition. The Medical Image Segmentation framework with CNN (MIS CNN) is used for efficient and accurate detection. The proposed model enhances diagnosis accuracy, assists radiologists in early stroke identification, and contributes to reducing the mortality rate by enabling timely medical intervention.

Keywords: Cerebral Infarction, Computed Tomography (CT), 3D U-Net, Convolutional Neural Networks (CNN), Medical Image Segmentation (MIScnn), Stroke Detection, Deep Learning.

1. Introduction

Cerebral Infarction represents an area of died brain tissues resulting from an inadequate supply of blood and oxygen to the brain due to blockage of an artery as shown in Figure 1. Cerebral Infraction is one of the highest causes of the death worldwide. In 2019, stroke was responsible for 7.4% of the total deaths in India. Computed Tomography (CT) has been popular Imaging tool for emergency assessment of stroke. In this project, the Automated Model for rapid detection and classification of Cerebral Infarction using 3d U-Net Model of Convolutional Neural Network (CNN) is proposed. This model will be very useful to find the affected tissues in brain where the blood is clotted and hence the part which is affected by Cerebral Infarction. Firstly, CT Brain Image Data Base with Cerebral Infarction will be created using an International Standard DICOM. Then, the Images will be subjected with Slice Selection, Band Pass Filtering (BPF), Image Averaging, Variation Model (VM) Decomposition and Segmentation using CNN in order to visualize, enhance and identify the brain tissues that are affected by Cerebral Infarction. The Cross Validation of Medical Image Segmentation with Convolutional Neural Networks (MIScnn) on Cerebral Infarction segmentation will result a powerful and an efficient prediction on earlier and accurate diagnosis of strokes.

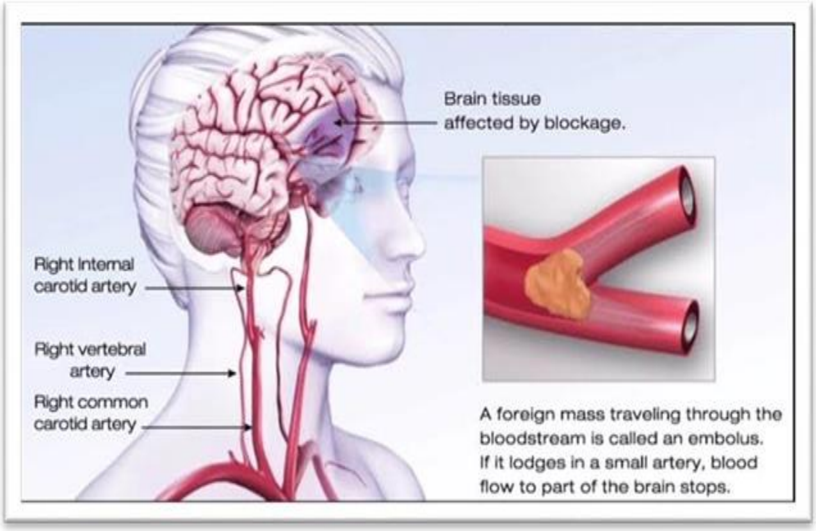

Figure 1: *Cerebral Infarction Illustration*

2. Objectives

To design an automatic segmentation model for earlier detection of cerebral infarction in Computed tomography (CT) scanned brain images. To visualize and to improve the accuracy of diagnosis of Cerebral Infarction by using Medical image segmentation with a 3D UNET Model of Convolutional Neural Networks (MISCNN). To reduce the death rate which is caused by Cerebral infarction. To help the Physicians with the accurate identification of the areas affected by Cerebral Infarction

3. Methodology

A database Computed Tomography (CT) brain images with cerebral infarction will be created firstly. Then they are subjected with basic image processing steps followed by Convolutional Neural Network (CNN) based segmentation. The framework of the proposed model is presented in Figure 2. The detailed description of each and every stage is as follows**.**

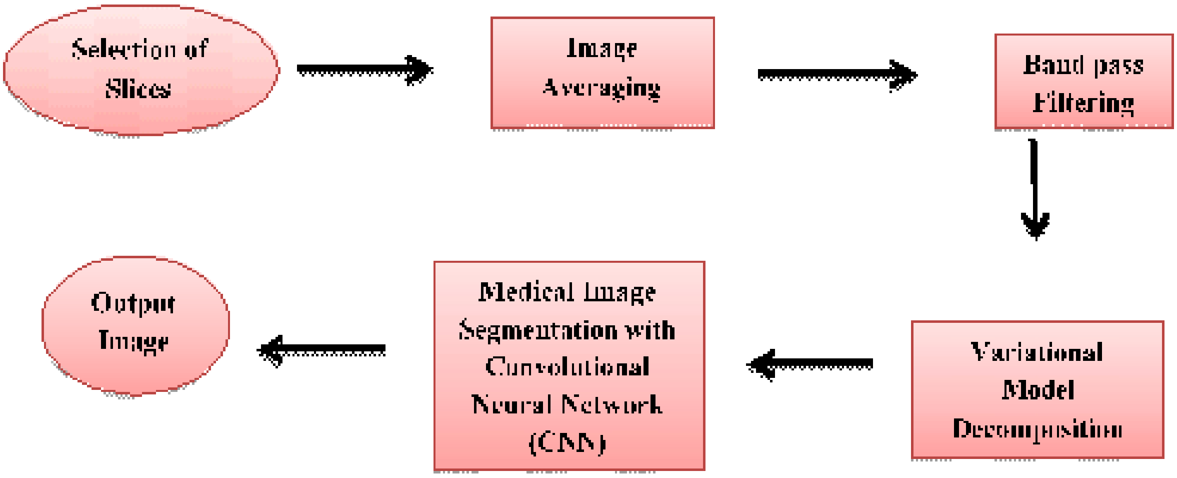

Figure 2: *Framework of Proposed Automated Segmentation Model*

3.1 Selection of Slices

Each patient with a suspected cerebrovascular infarction must have a series of brain photographs chosen as a prelude to image processing. In the same anatomical area that is used for the evaluation, medical image slices will be chosen. Since strokes most frequently damage the middle cerebral artery territory and based ganglia, a sequence of slices in these areas will be chosen, as seen in Figure 3.

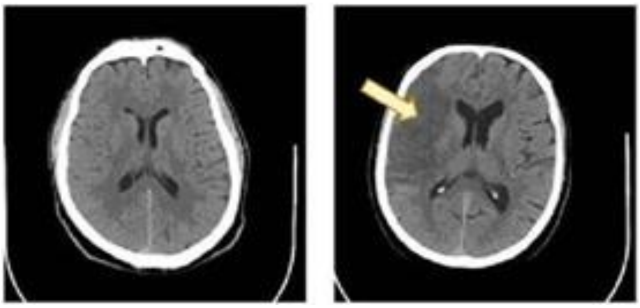

Figure 3: *Normal CT brain slice (Left) and Cerebral Infarction slice (Right)*

3.2 Image Averaging

A typical processing technique is picture averaging, which improves photos by reducing random noise. This technique brings attention to the presence of stroke and lowers the amount of noise in the image. Once slices with sensitive ischemia density changes have been selected, an image averaging will be performed by adding the gray to level in each slice.

An arithmetic mean of the intensity levels for every pixel position in images taken from a subsequent slice is calculated by the image averaging algorithm.

$$P_{(i,j)} = \sum_{n=1} N \frac{S_{n(i,j)}}{N} \qquad (1)$$

Where, $P_{(i,j)}$= A resulting pixel of the averaging

S_n= The sequence of selected slices

(i, j)= Pixel condition for each image

N (4 to 9) slice = The number of slices utilized sequentially

3.3 Band Pass Filtering, Histogram Stretching and Normalization

After, an image averaging, the resultant image is subjected with band pass filtering by thresholding to remove the tissues that are not affected by Infarction Variation Model (VM) Decomposition. The histogram Stretching and Normalization will be used to improve the contrast between adjacent regions. Histogram Stretching will cause the intensity range to shift from [5 to 50], with the intensity range falling between 0 and 255 on the grey scale. This means that the histogram will show all degrees of intracranial gray intensity.

$$P = U+V+W \qquad (2)$$

Where, U = Related to Contours, V = Smooth Second Order Part ,W = linked to fine texture

Since the V component is connected to the image's brightness and contrast, it is of primary interest. Using different values for Y and U will make the cerebral infarction region more visible.

3.4 MIS with CNN

Following variation model (VM) decomposition, picture segmentation will be applied to the V component. In this project, the segmentation will be carried out by using open-source python library MISCNN which includes data I/O pre-processing, data augmentation, training, prediction and automatic evaluation.

4. Conclusion

The proposed 3D-UNET model is promising tool for the detection of cerebral infarction in CT brain images. Image preprocessing on patient and control data highlighted the crucial information for effective cerebral infarction diagnosis for CT images. The convolution neural network structure has been used to produce artificial intelligence capable of extracting image attributes from CT data and identifying image patches of CT pictures as infarcted or not. Data augmentation augmented the limited quality of clinical data available to allow adequate training of convolutional neural network, preventing over fitting and improving detection accuracy. The high accuracy and sensitivity of the model can aid radiologists in the early and accurate diagnosis of cerebral infarction, leading to better patient outcomes.

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