Pre-thesis-I Report

Brain Stroke Detection using CT Scan Images and Artificial Intelligence

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Abstract

Stroke is a leading cause of permanent motor disability and death worldwide. It is a serious life-threatening medical condition that occurs when blood supply to part of the brain is restricted or cut off. Brain damage is minimized if stroke is diagnosed immediately, and the patient may regain mobility. Deploying applications of AI in clinical medicine to accelerate the accuracy of stroke-diagnosis aims to minimize the severity of stroke, therefore, enhancing medical care. Adequate analysis of stroke imaging is integral for stroke diagnosis and management. Machine Learning, which is a subset of AI, is widely used in interpreting medical images and has shown promising advancements in distinguishing an ischemic stroke from a hemorrhagic one. With time playing a crucial factor, automatic lesion identification is one of the most important factors in precision medicine dealing with huge datasets of neuroimaging compared to manual lesion segmentation. This paper will look into a machine learning method on neuroimaging to assist in the diagnosis of stroke.

I. Introduction

With the advent of technology surging through all spheres of life, Artificial Intelligence has undoubtedly revolutionized many domains, with its largest impact in the healthcare industry. Integrating AI in the healthcare ecosystem has paved way for continual growth and improvement in the medicine field and an increased revenue potential.

The healthcare industry continues to evolve as the applications of AI becomes more prevalent and allows for a multitude of benefits, from analyzing big patient data sets to automating tasks so as to deliver better healthcare faster. Machine Learning, a subset of AI, has shown potential to provide data-driven clinical decision support by using data and algorithms to give invaluable automated insights to the physicians and healthcare specialists.

The brain is the most complex organ in the human body. A stroke occurs when the blood supply to part of the brain is interrupted or cut off, hence preventing brain tissues from getting nutrients and oxygen. Stroke is a medical emergency because brain cells begin to die within minutes and prompt treatment is crucial to minimize the damage and save lives.

Computed Tomography (CT) of the head is the preferred procedure as the first step to assess a stroke patient so as to determine whether the individual is experiencing an ischemic or hemorrhaging stroke. Currently the standard approach is manual lesion delineation which is both operator-dependent and time-consuming.

Deep learning is a subfield of machine learning based on artificial neural networks with representation learning. The medical field has greatly benefited from the use of deep learning models which saves time and produces accurate results. Our research is mainly focusing on how to automate the detection of brain stroke using CT scan images. We aim to present a method that uses deep learning models that can automatically delineate infarct and bleeding in stroke CT images.

A) Problem Statement

As of today, stroke is a leading cause of serious long-term disability in adults. With a globally ageing population estimated to triple by the year 2050, neurophysiological investigation of patients suffering from stroke with advances of AI in cognitive neuroscience will evolve our understanding of the most complex human organ.

The typology of stroke is classified into two categories: Ischemic and Hemorrhagic. Ischemic stroke is the most common type of stroke which is caused by a blood clot that blocks the brain's blood vessel. Nearly 87 percent of all strokes are ischemic stroke [1]. Hemorrhagic stroke is another major type of stroke in which the blood vessel of a brain ruptures and causes bleeding.

The two modalities regularly used for stroke lesion mapping are computed tomography (CT) and magnetic resonance imaging (MRI). With time playing a crucial factor, CT is the preferred procedure with the advantages of speed, cost and reduced exclusion criteria relative to MR imaging. The current method for lesion identification is still manual that puts forward a number of disadvantages [2]. Even though hemorrhagic stroke appears more clearly on a CT scan image, lesion identification of the more common ischemic stroke takes nearly over a day using the manual delineation approach. Ischemic stroke is difficult or nearly impossible to see in CT images, especially during the first few hours after the stroke occurs, which is the period when treatment decisions are most vital. This means that by the time the region of the abnormal brain tissue is localized, delay of treatment propels the brain damage thus likely to worsen the individual's chances to regain mobility.

With the availability of big medical data sets and development of complex algorithms, AI has made an immense impact in the healthcare industry by recognizing the need for personalized care and earliest definitive diagnosis. Related research and extensive workings in this specific direction have been mostly done using MRI [5]. This is because of MRI producing clearer and detailed images compared to CT [3] and the relative limitations posed by CT images as mentioned by [4].

However, taking into consideration the advantages of CT images that outweighed that of MRI in case of quick stroke-diagnosis as we have mentioned earlier has directed us to work on the problem based on CT images. Our intent is to deploy the deep learning frameworks that have shown great accuracy results and integrate that architecture to CT images and eventually figure out promising results.

Therefore, this research will attempt to employ deep learning algorithms such as Convolutional Neural Network (CNN) on CT scan images to automate the stroke lesion segmentation and thus enhancing an effective clinical diagnosis.

B) Research Objectives

As today's medical industry continues to evolve, the notion of computer-based clinical decision support has accelerated as a dominant topic in informatics research so as to improve the quality of decision-making in healthcare. AI has the potential to optimize personalized care by facilitating diagnosis and therapeutic decisions. Hence, we aim to find a way to develop an understanding of how incorporating the applications of AI accelerates the diagnosis of stroke and create a solution that leverages on data accuracy for improved decision-making. Our goal is to develop a solution using Image Processing with Deep Learning models that will assist healthcare specialists to make an improved diagnosis.

The objectives of our research are:

- To thoroughly understand the applications of AI and how it works in our interested domain
- To deeply understand Deep Learning models and contrast their usage in different scenarios of our solution
- To develop a model for automatic lesion delineation using CT scan images
- To evaluate the model
- To offer recommendations on improving the model

II. Literature Review

Currently, stroke is one of the costliest diseases from human, family and societal perspectives. Starting from human costs, stroke is also a leading cause of death and disability. About 16 million first-ever strokes occur in the world, that causes a total of 5.7 million deaths throughout a year [6]. Higashida and Chair (2003) gave definitions for two types of stroke. They are : ischemic stroke and hemorrhagic stroke. An ischemic stroke is ANY damage to the brain which is caused by lack of blood flow in brain blood vessels or in major arteries that lead to the brain. This stroke usually results in temporary or permanent loss of one or more normal functions of the body [7]. On the other hand, A hemorrhagic stroke is a damage to the brain caused due to the bleeding into the brain [7]. The ischemic stroke accounts for nearly 80 percent of all strokes [b] and Hemorrhagic strokes account for about 20 percent of strokes [7].

Computed tomography scan or CT scan has proven to be a great and efficient technique in detecting strokes especially with hemorrhage strokes. In a study, it is said that for the hemorrhage type classification, more than 92% accuracy is achieved in identifying hemorrhage strokes by CT scans [8]. CT Scan is considered to be very efficient and useful in detecting the internal bleeding of a brain that occurs in hemorrhagic brain stroke. However, in cases in which the patient is having an ischemic stroke it may be quite difficult or may even be impossible to track the bleeding in the brain with the help of CT scan. In such times when the CT scan fails show an ischemic stroke and the neuroradiologists are strongly suspecting that the patient is having a brain stroke whereas in the reports of CT scan, no signs of hemorrhagic stroke was detected, they often use IV TPA to the patient [11]. IV TPA - Tissue plasminogen activator helps to dissolve the stroke-causing clot [11]. In other ways, a patient who might be reckoned to be having an ischemic brain stroke undergoes a different type of CT scan, called CT perfusion imaging, or CTP. [11] . This CTP involves a second injection of a type of dye called a contrast agent. CTP helps to estimate the flow of blood through the microscopic blood vessels that are small enough for the brain to extract oxygen and other nutrients found from them. Doctors or neuroradiologists can make use of this CTP in order to measure the overall amount of the blood that has been flowing through a particular part of the brain, or they can even calculate the speed with which the blood has been flowing through the brain. This information can be useful for the neuroradiologists to figure out and make decisions about the best possible way to give treatment to the patients who are having ischemic brain stroke[11].

According to Baird et al. (2009), Computed tomography Scan-CT Scan is considered to be gold standard e CT is the gold standard for the clear-cut exclusion of brain hemorrhage. But When it comes to the remaining acute ischemic signs, it is slightly more open to debate [9]. Over the years there has been notable progress in scanner hardware, and these new CT units now allow to scan the entire human brain in just a few seconds [10].

However, another tool has been introduced to improve the performance of CT scan for ischemic stroke called multiphase CT angiography which is an imaging tool that provides three time-resolved images of pial arterial filling in the whole brain, unlike conventional single-phase CT angiography [10]. It has shown great promise in predicting the clinical outcomes in patients with acute ischemic stroke [10]. The results of multiphase CT angiography were quite promising.

In a study of 147 patients, for multiphase CT angiography the inter-rater reliability is excellent (n = 30, k = 0.81, P , .001) [10]. Clinical outcome predictability is quite modest at the receiving operating characteristic curve analysis (C statistic = 0.56, 95% confidence interval [CI]: 0.52, 0.63 for 50% decrease in NIHSS over 24 hours; C statistic = 0.6, 95% CI: 0.53, 0.68 for 90-day mRS score of 0–2) hence it is better than that of models using single-phase CT angiography and perfusion CT (P , .05 overall). With AIC and BIC, models that are using multiphase CT angiography are better than models using single-phase CT angiography and perfusion CT with a decrease of 50% or more in NIHSS over 24 hours (AIC = 166, BIC = 171.7; values were lowest for multiphase CT angiography) and a 90-day mRS score of 0–2 (AIC = 132.1, BIC = 137.4; values were lowest for multiphase CT angiography) [10].

Takahashi et al. (2014) designed a method called MCA dot sign which was used for classifying images using an SVM with four features. 297 CT images from seven patients with an MCA dot sign were used in the process. This study was able to gain a maximum sensitivity of 97.5% which had a false positive rate of 1.28 per image and 0.5 per hemisphere while assessing the MCA dot sign on CT scan images which were unenhanced [12]. However, their use of unenhanced images can be problematic as they might create distortion in the results.

Forkert et al. (2015) used 12 SVM classification models for predicting the mRS score of ischemic stroke patients with parameters such as lesions in different brain regions, NIHSS at admission, and patient age. An mRS prediction was obtained which had a multi-value accuracy of 56%, and another dichotomized mRS was obtained with a prediction accuracy of 85% [13]. However, they selected patients with a balanced distribution of mRS scores which is not the same as a real-life distribution of mRS scores. Using CT scan images, early detection of ischemic strokes was done by Rajni and Bhavani (2013) with segmentation, midline shift and image feature characteristics. They used SVM, k-NN, ANN and decision tree with accuracy scores respectively 98%, 97%, 96% and 92% [14]. Though their accuracy scores were good, they used a small sample size which consisted of 15 stroke cases and 6 normal case.

Hemispheric ischemic stroke happens due to the blockage of a blood vessel and the patient’s outcome is directly related to the final size of the ischemic infarct i.e. the severity of damage to the brain parenchyma. Generally, MRI T2-weighted imaging (T2WI MRI) at 3 months post-ictus is considered the gold standard for the measure of tissue recovery and the patient outcome [15]. Although, unsupervised clustering technique such as ISODATA (Iterative Self-Organizing Data Analysis) can be used to combine MRI data sets from the acute phase and the sub-acute phase post-stroke to predict final infarct volume and produce a time-independent surrogate MRI outcome predictor [15]. However, ISODATA has some significant drawbacks. Maps produced by ISODATA are not approximately continuous and does not produce an easily visualized association between the map and the outcome measure. [15] Furthermore, ISODATA is instable in the presence of image artifacts and noise. However, Artificial Neural Network (ANN) model is useful to predict the stroke outcome [15]. An ANN model was used to combine the clinical and imaging variables National Institutes of Health Stroke Scale (NIHSS) and DWI images to determine the final infarct volume of patients treated with IV rt-PA (recombinant Tissue Plasminogen Activator), and the ANN was completely able to predict the tissue fate. The ANN technique provides a very fast (essentially real-time), approximately continuous, and intuitive mapping of the predicted outcome, while preserving the time-independent and multi-parametric strengths of clustering approaches.

III. Work Plan

For our research, the data sets we will be using are the CT scan images we have collected from the source [16]. Computed Tomography (CT) Scan will show the image of the part of brain with stroke. CT scan of head is that the first step to work out whether the person is suffering from ischemic or hemorrhaging stroke. CT scan combines a series of X-ray images taken from various angles across the body and uses computer imaging to create cross-section images of bones, blood vessels and soft tissues within the body. Initially, the images produced by the CT scans were in the transverse (axial) anatomical plane, perpendicular to the long axis of the body. Modern scanners allow scan data to be formatted as images on other planes. Digital geometry analysis can produce a three-dimensional image of an object within the body from a collection of two-dimensional radiographic images taken by rotating around a fixed object. The features of the stroke lesion vary depending on the type of imaging modality. In order to establish an accurate method for identifying stroke lesions, the features must be carefully extracted from the input images. This study aims to categorize and analyze the various deep architectures used to diagnose stroke and segmentation depending on the underlying imaging modality. This also helps to explain the importance of two deep neural network elements to the medical image processing, namely the Convolutional Neural Network (CNN) and the fully Convolutional Network (FCN). It proposes other potential deep architectures that can be suggested for improve outcomes in the identification of stroke lesions. The emerging developments and breakthroughs in stroke identification have also been detailed in this evaluation.

After collecting data set we proceed towards pre-processing. The pre-processing includes (Grayscaling, Scaling, Contrast Limited Adaptive Histogram Equalization). First a part of pre-processing is Grayscaling, which may be a process to convert RGB image into grayscale image. So, first the RGB image has got to be converted into grayscale image. After this we proceed to scaling which is a process to reduce the pixel amount of the image that used as input to neural network. So the computation duration can be shortened. Last part for pre-processing is, CLAHE which is a process to raise contrast in image, so the stroke object looks clearer. Afterward we have to use segmentation. Segmentation is used to distinguish the object and background We use thresholding to segmented image which will create a binary image. For example: Each pixel in the image is used as input to classify stroke for the Convolutional Neural Network. The value of the threshold is set to 170,

- If the pixel color ≤ 170, change the color to black (0).
- If the pixel color ≥ 170, change the color to white (1).

These images are going to be an input for scan line algorithm.

Furthermore, we can classify CT image using convoluted neural network algorithm CNN, a deep learning method without a priori feature definition. There are two process of convolutional neural network to classify stroke. One of them is training process, where CNN being trained with 10 data training of each type classification. In training process, CNN contains two process (feedforward and backpropagation). Feedforward counts all incoming neurons from the input layer in the hidden layer. Weights from Hidden Layer will be sent to Output Layer.

Backpropagation will trace the error by counting all the weight from Output Layer and then sent it back to Hidden Layer so the neural network gets a new weight with least error. Moreover, in testing process, CNN only have feedforward process. Testing process is where CNN is being evaluated with 5 data analyses for each form of classification and Compare the weights of the data experiments with the weights derive from the data preparation to classify stroke.

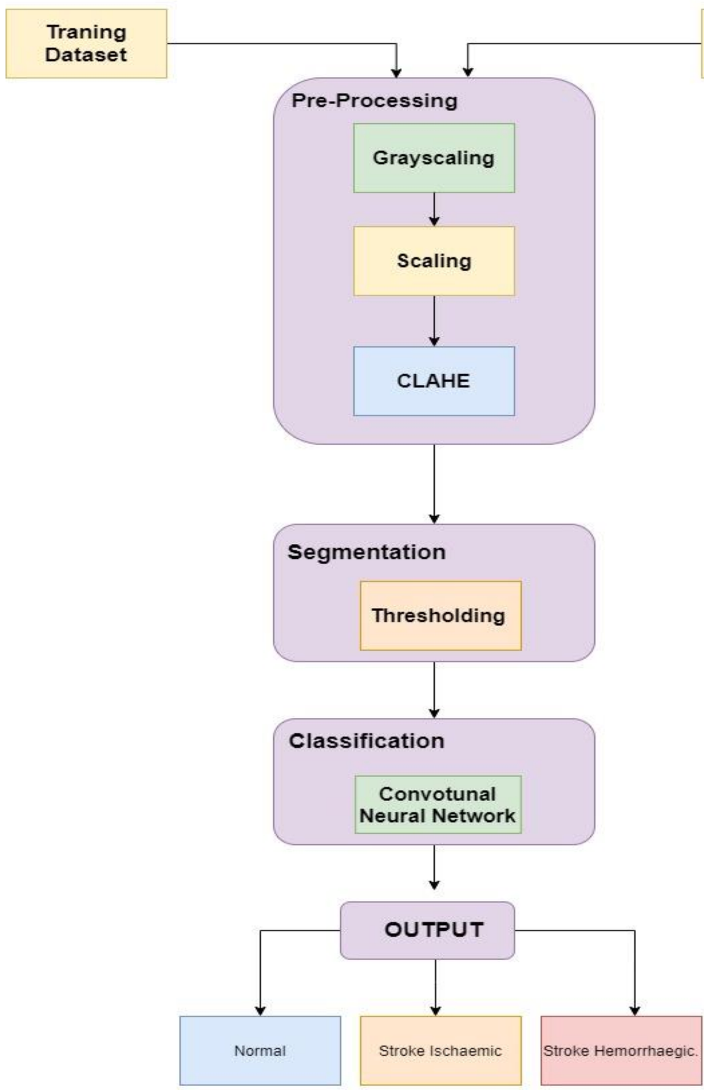

Figure 1. The flow chart of the proposed model

IV. Conclusion

Health is the greatest asset and advances in technology has been profoundly shaping healthcare by opening up more avenues of extensive research and exploration to improve the quality of life. Our research wanted to address the challenge of a leading life-threatening medical emergency and figure out how incorporating AI in this sphere could help to assist healthcare experts for an improved and effective clinical diagnosis. With our work we hope to provide a solution that detects and narrows down the lesion delineation on CT scan images of the more commonly occurring ischemic stroke. It is going to be a challenge to integrate our understanding of machine learning models on a medical domain of clinical neuroscience but we also believe that by accomplishing our goal, not only will be able to use technology to help individuals suffering from stroke but also better our understanding of the most complex organ of the human body.

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