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IDENTIFICATION AND DETECTION OF INTRACRANIAL HEMORRHAGE USING DEEP LEARNING

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Abstract: Intracranial hemorrhage (ICH) is a serious medical emergency that requires quick and accurate assessment and treatment. Mortality rate due to brain hemorrhage is very high (approximately 40%) as per reports. Hence early detection and classification on non-contrast computed tomography (CT) is essential for a proper prediction and limiting the occurrence of neurologic problems. However, in present scenario, there is a delay in the early detection of ICHs due to a lack of number of radiologists who can read the scans. Therefore, an automatic notification system using the deep-learning artificial intelligence (AI) method has been introduced for the detection of ICH. Recently, deep-learning methods are tried for the detection of ICH on CT images. Deep-learning methods are ML algorithms that use multiple processing layers to learn representations of data with multiple levels of abstraction. This work builds a convolutional neural network based on ResNet for the identification and classification of ICH. Using dataset collected from four international universities by the Radiological Society of North America (RSNA), training and testing a ResNet-50 based CNN model is done for predicting the hemorrhage and its type. Analysis shows that accuracy of up to 94% can be achieved in identifying the correct type of ICH.

Index: Intracranial Hemorrhage, CT scans, Deep learning, CNN, ResNet-50

INTRODUCTION

The brain is a vital organ in the human body which controls the whole functionality of organs and aids in decision making. It is primarily the control center of the essential nervous system and is accountable for performing the daily voluntary and involuntary activities in the human body. Brain bleeds can cause different problems and there are different types in it. Intracranial hemorrhage (ICH) is a type of brain bleed which letdowns various patients who suffer from trauma, stroke, aneurysm, vascular malformations, high blood pressure, illicit drugs and blood clotting disorders. ICH can be identified and classified by their distinct shape, location, and size. Early diagnosis of ICH, preferably within 24 hours, is important in decreasing patient mortality. Diagnosis time comprises of taking a head computerized tomography (CT) and a radiologist making a diagnosis based on CT elucidation. CT scans consist of a series of X-ray images taken in different angles, combined to form 3D cross-sectional images of the blood, bone, and soft tissue within the body. Advances in image recognition using machine learning, has increased the applicability of ML models such as neural networks for medical image processing. Deep learning systems recognize meaningful patterns and features within large datasets without explicit directions. In this paper, CNN with ResNet-50 model is used in the classification of normal and hemorrhage brain. A model is trained based on the activation function applied on the input features and on the hidden layers where more learning happens to achieve the expected output. In CNN (convolutional neural network), convolution is the name of mathematical linear operation. The dimension of the image is reduced at each layers of CNN without the loss of information needed for training. Different processing like convolve, max pooling, dropout, flatten and dense are applied for creating the model. This work focuses on creating a self-defined architecture of CNN model and tries to identify and classify ICH. Finally the performance of CNN is measured with accuracy test when applied on brain hemorrhage dataset.

LITERATURE REVIEW:

Brain Hemorrhage Detection and Classification System is one of the areas of research which is been considered by many of the researchers today. This section reviews the work done in this area recently. Reference [1] is the source of data and the data required for our work is taken from Kaggle website. Paper[2] deals with Rectified activation units which are state-of-the-art neural networks used to classify images. Paper [3] is a survey paper which deals with deep learning methods for medical imaging. Brain Hemorrhage The image processing techniques such as histogram equalization, image segmentation, image enhancement, and feature extraction have been used. In Paper [4, 9], to prevent and to cure the hemorrhage, magnetic resonance imaging (MRI) is used. CNNs are used to identify ICH which are capable of surpassing human level performance in image classification. Paper

[5,6] elaborate on usage of deep learning algorithms for brain problems with CT scans. ResNet-50 has been used in a few brain image analysis projects, namely for Alzheimer's disease [8] with nearly perfect multi-class prediction accuracy. Another study compared various DL models to detect brain abnormalities and showed RestNet-50 resulted in the best classification accuracy [9]. With this study, brain hemorrhage, its causes and types along with different ways with which involuntary identification of brain hemorrhage can be done is understood. Mainly convolutional neural networks are used in classification.ConvolutionalneuralnetworkmodelbasedonResNetfortheclassificationofthe type of hemorrhage is considered in this paper to reduce the time for identification of the hemorrhage type.

Brain Hemorrhage:

There are two main areas where bleeding can occur in brain –within the skull but outside of the brain tissue, or inside the brain tissue. Based on bleeding happening outside the brain tissue, 3 types are recognized:

Epidural hemorrhage: This bleed happens between the skull bone and the membrane layer, the dura mater.

Subdural hemorrhage: This bleed happens between the dura mater and the arachnoid membrane.

Subarachnoid hemorrhage: This bleed happens between the arachnoid membrane and the pia mater.

Based on bleeding inside the brain tissue, two types of brain bleeds are recognized – intracerebral hemorrhage and intraventicular hemorrhage

Intra ventricular hemorrhage: This bleeding occurs in the brain's ventricles, which are specific areas of the brain (cavities) where cerebrospinal fluid is produced.

MATERIALS AND METHODOLOGY:

The agenda for today's researchers is to enable machines to view the world as humans do, perceive it in an analogous manner and use the knowledge for a number of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. Convolutional Neural Network, is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre- processing required in a CNN is much lower as compared to other classification algorithms. The architecture is analogous to that of the connectivity pattern of Neurons in the Brain and is motivated by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. The goal of the Convolution Operation is to extract the high-level features such as edges, from the input image. Convolutional networks need not be limited to only one Convolutional Layer. The first Layer is used for capturing the Low-Level features such as edges, colour, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features.

ResNet is a type of CNN, which makes the way easier for the gradients to propagate to deeper layers of the network before they are attenuated to small or zero values. This was first introduced by Kaiming He and others in their 2015 computer vision research paper titled 'Deep Residual Learning for Image Recognition'. There are different types of ResNet like ResNet-50, ResNet-101 etc. This work uses ResNet50 which is 50 layers deep in structure.

Dataset:

Dataset used in this work is from Radiological Society of North America (RSNA)[1] –available in kaggle website, with a total of 752,803 labeled DCM files that contain cross-sectional images of brain which are 512x512 in size. For this work, around 500 images are considered among which 10% of examples are selected randomly and are set aside to make a test set. Each file is labeled separately which mentions one or more than one type of hemorrhage present or the absence of hemorrhage. Type of hemorrhages that is present in the dataset used in our work is shown in Fig.1. Labels are in the form of CSV file which contains 5 lines for each patient ID, where each line correspond the type of hemorrhage present, followed by boolean value referring if that type of hemorrhage is present in the considered image.

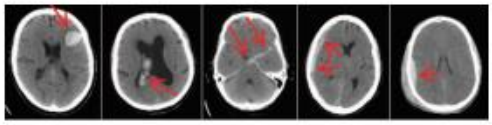

Fig1. Intraparenchymal, Intraventricular, Subarachnoid, Subdural, Epidural (from left to right)

Methodology:

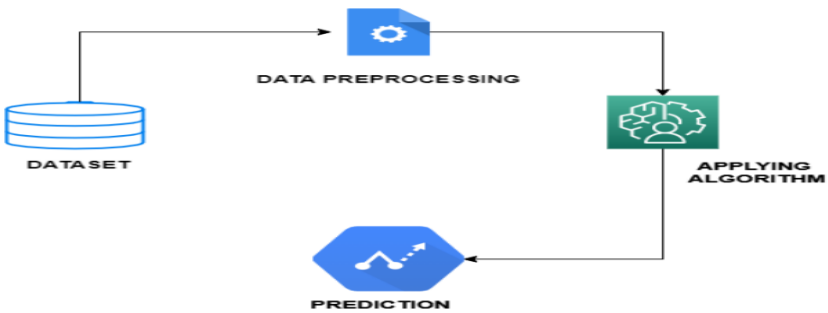

Fig2: Flow diagram

The above figure shows the steps requisite in building a model for Intracranial Hemorrhage identification process takes place. First Image Data Set needs to be read from Storage/Database, different image sizes are not accepted for Model Training, So, all images need to be transferred to some fixed size which is done by Image Pre-processing. In Image Preprocessing, we have reshaping the image, rotation, normalization, etc. The images given to the training dataset are used for training the model and when an input image is given, it is initially scaled to predefined size for easy computations and then ResNet50 model is used to

classify the Brain Hemorrhage. Initially various images consisting of Brain Hemorrhage CT scan images are collected. In this all the images are resized to the dimensions 224 x 224. After scaling, we get the images of the same size which helps in analyzing and testing the system easily. The images are converted into Numpy arrays in which all of its fields consist of the pixel values. All these arrays are grouped together as a Numpy array and then they are labeled across each image indicating whether the CT scan image has symptoms of blood leakage. In this study, the labeled Training data are a large set of CT scans that are labeled brain hemorrhage and Non brain hemorrhage. Convolutional base from ResNet50 is used as a feature extractor onto which 2 layer fully connected classifier is stacked. Parameters of the convolutional base are initialized with weights pre-trained on ImageNet dataset. Adam optimizer is used. Training is done for 25 epochs. 10% of the entire dataset is chosen as test set for model evaluation. On completing 25 epochs the model is able to yield an accuracy of 94% which is taken as a key metric for the project.

RESULT:

The model is trained on around 650 images and it is tested for the unseen data. Upon analysis of the image, the model is able classify four hemorrhage types as shown in the following diagrams; Fig3.classified as subdural hemorrhage where the scan is revealing blood on the surface of the brain under the skull. Epidural hemorrhage in Fig4.where the bleeding occurs between skull and the outermost layer of meninges, the dura mater. Image in Fig5 is intraventricular hemorrhage, here the bleeding is into cavities in the brain called the ventricles. A rupture or tear causes blood to flow into one or both ventricles which is usually filled with cerebrospinal fluid (CSF). In this scan the blood has accumulated one ventricle. Image in Fig6.is subarachnoid hemorrhage, the blood leaked into the subarachnoid space. Fig7.depicts any class indicating the presence of hemorrhage say of any type.

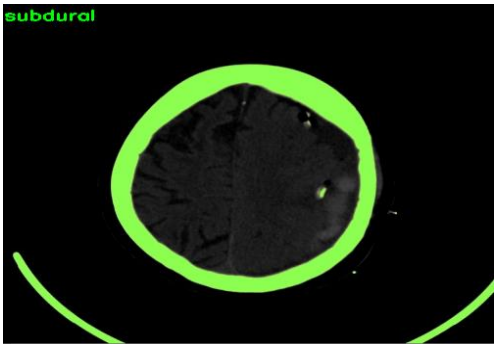

Fig3.subdural hemorrhage

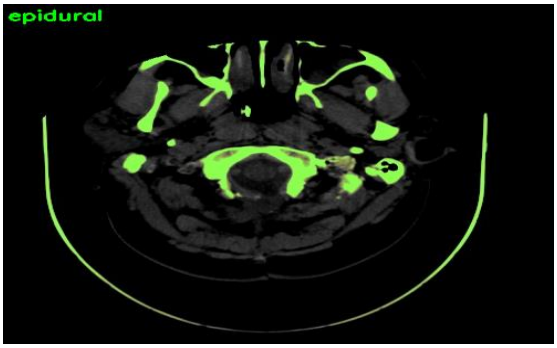

Fig4.epidural hemorrhage

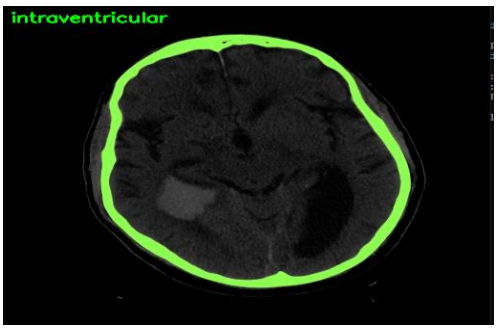

Fig5.intraventricular hemorrhage

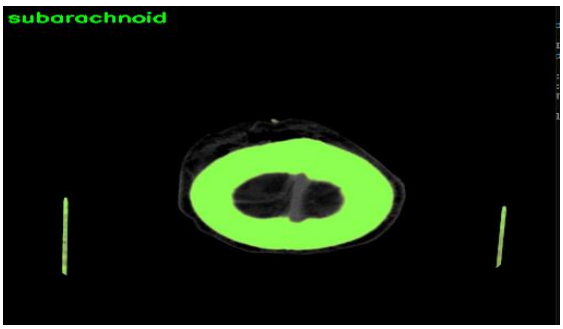

Fig6.subarachnoid hemorrhage

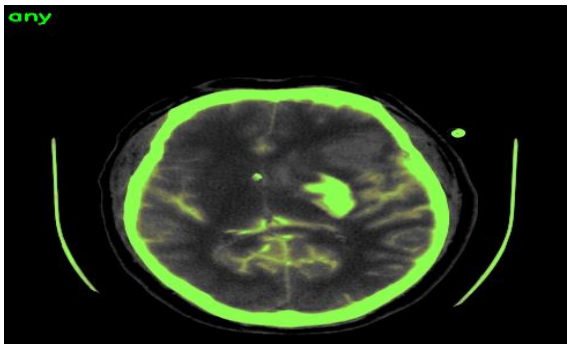

Fig7.any class

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CONCLUSION:

A model has been built using CNN based on ResNet50 that can detect and classify four different types of hemorrhages with a comparative accuracy to radiologists. The model is trained on around 650 images, all taken from RSNA dataset. Dicom images are converted Jpeg for building the model. Windowing is the preprocessing method used for contrast enhancements. Binary accuracy is the key metric used for the evaluation of the model. Upon training, the model reached an accuracy of 94.5% in 11th epoch. As further improvement, deeper versions of ResNet can be considered.

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