Intracranial Hemorrhage Detection using Deep Learning

[1]G Naga Sujini, [2]Videsh Loya

[1,2]Department of CSE, MGIT, India. [1]gnagasujini_cse@mgit.ac.in, [2]videshloya24@gmail.com

Abstract - Advances in image recognition using machine learning, has increased the applicability of ML models such as neural networks for medical image processing. Utilizing machine learning to infer and perform complex cognitive tasks such as analyzing CT scans that normally requires an expert radiologist. Using deep learning algorithms we can easily analyze and extract substantial data from these electronic documents. They are not only aiding in detecting a major abnormality in most of the organs but also help doctors in making effective decisions. Minute discrepancies which can be neglected by a human eye can be captured by these machine learning algorithms.

Fast detection of ICH and differentiating it from types of strokes and other brain disease can prompt appropriate treatment and mitigate lasting brain damage and mortality. Using Machine learning algorithms we intend to create a model that can detect such types of acute brain hemorrhages and further classify them into subtypes. Knowing where exactly the hemorrhage is located can be very helpful in directly operating that area of the brain which can result in quick responses. Using Machine learning algorithms we intend to create a model that can detect such types of acute brain hemorrhages and further classify them into subtypes. Knowing where exactly the hemorrhage is located can be very helpful in directly operating that area of the brain which can result in quick responses. In addition to detection and classification, a different model is created to conduct segmentation on these CT scan images to identify the affected area.

Keywords: Intracranial Hemorrhage, Convolutional neural networks, Deep Learning, VGG- 16 model.

I. Introduction

Advances in image recognition using machine learning, has increased the applicability of ML models such as neural networks for medical image processing. Utilizing machine learning to infer and perform complex cognitive tasks such as analyzing CT scans that normally requires an expert, radiologist. Understanding that applying these techniques can help immensely in gaining meaningful insights into medical area which were difficult to decipher with put an expert, many medical personnel are taking aid from this. With successful experiments been conducted and new application been released, Deep Learning has the potential of changing the future of healthcare. Using deep learning algorithms we can easily analyze and extract substantial data from these electronic documents. They are not only aiding in detecting a major abnormality in most of the organs but also help doctors in making effective decisions. Minute discrepancies which can be neglected by a human eye can be captured by these machine learning algorithms. Brain imaging is one of the application which makes use of such algorithm to detect and recognize many major injuries to the head which in turn can cause damage to the brain if not treated correctly.

Here, we use a deep convolution neural network for detection and classification of different ICH on unenhanced CT scans. Fast detection of ICH and differentiating it from types of strokes and other brain disease can prompt appropriate treatment and mitigate lasting brain damage and mortality. Using Machine learning algorithms we intend to create a model that can detect such types of acute brain hemorrhages and further classify them into subtypes. Knowing where exactly the hemorrhage is located can be very helpful in directly operating that area of the brain which can result in quick responses.

II. Literature Survey

"Intracranial Hemorrhage Detection in CT Scans uses Deep Learning" In this study intracranial hemorrhage treatment patient mortality depends on prompt diagnosis based on a radiologist's assessment of CT scans. In this paper, we investigate the intracranial hemorrhage detection problem and built a deep learning model to accelerate the time used to identify the hemorrhages. To assist with this process, a deep learning model can be used to accelerate the time it takes to identify them. In particular, we built a

 DOI : 10.35291/2454-9150.2021.0313

convolutional neural network based on ResNet for the classification. Using 752,803 DICOM files collected from four international universities by the Radiological Society of North America (RSNA) [1], we trained and tested a ResNet- 50 based model for predicting the hemorrhage type. Our model has an accuracy of 93.3% in making the correct multiclass prediction and an average per-class recall score of 76%. We show it is possible to achieve an average recall of 86% while maintaining70% precision via tuning the prediction thresholds [1].

"Intracranial Hemorrhage Segmentation Using A Deep Convolutional Model" In this study, the Traumatic brain injuries may cause intra-cranial hemorrhages (ICH). The current clinical protocol to diagnose ICH is by examining Computerized Tomography (CT) scans by radiologists to detect ICH and localize its regions. However, this process relies heavily on the availability of an experienced radiologist. In this paper, we designed a study protocol to collect a dataset of 82 CT scans of subjects with a traumatic brain injury. The dataset is publicly available online at the PhysioNet repository for future analysis and comparisons. In addition to publishing the dataset, which is the main purpose of this manuscript, we implemented a deep Fully Convolution Networks (FCNs), known as U-Net, to segment the ICH regions from the CT scans in a fully-automated manner. The method as a proof of concept achieved a Dice coefficient of 0.31 for the ICH segmentation based on 5-fold cross-validation [2].

"Intracranial Hemorrhage Detection and Segmentation" In this study, the proposed problem aims to solve the issue of hemorrhages in the brain especially when the symptoms are acute like headaches or loss of consciousness. Using Deep learning algorithms we intend to create a model that can detect such types of acute brain hemorrhages and further classify them into subtypes. Knowing where exactly the hemorrhage is located can be very helpful in directly operating that area of the brain which can result in quick responses. In addition to detection and classification, a different model is created to conduct segmentation on these CT scan images to identify the affected area. The final resultant of these applied models will be a list of probabilities for detection and classifying tasks, predicted masks will the result obtained from the segmentation task [3].

"Detection and classification of intracranial hemorrhage on CT images use a novel deep-learning algorithm" In this study, A novel deep-learning algorithm for artificial neural networks (ANNs), completely different from the back-propagation method, was developed in a previous study. The purpose of this study was to assess the feasibility of using the algorithm for the detection of intracranial hemorrhage (ICH) and the classification of its subtypes, without employing the convolutional neural network (CNN). For the detection of ICH with the summation of all the computed tomography (CT) images for each case, the area under the ROC curve (AUC) was 0.859, and the sensitivity and the specificity were 78.0% and 80.0%, respectively. Regarding ICH localization, CT images were divided into 10 subdivisions based on the intracranial height. With the subdivision of 41–50%, the best diagnostic performance for detecting ICH was obtained with AUC of 0.903, the sensitivity of 82.5%, and the specificity of 84.1%. For the classification of the ICH to subtypes, the accuracy rate for subarachnoid hemorrhage (SAH) was considerably excellent at 91.7%. This study revealed that our approach can greatly reduce the ICH diagnosis time in an actual emergency situation with a fairly good diagnostic performance [4].

III. DESIGN METHODOLOGY

A. System Architecture:

As shown, Fig 3.1 describes the steps required in constructing a model for Intracranial Hemorrhage Detection. The figure shows a simple block diagram of how the 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.. Can be done. 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 Resnet 18 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 is covid affected or not. In the preprocessing step itself we divide the image data set into training and testing data sets.

During training, the model is given labeled data from a training data set. In this study , the labeled

Training data are a large set of CT scans that are labeled brain hemorrhage and Non brain hemorrhage. During the training process, the classifier (the part of the machine learning system that actually predicts labels of future CT scan Images) learns from the training data by determining the connection between the features of a CT scan Images and its label.

During testing, the deep learning system is given un-labeled data. In our case, these data are CT scan

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Images without the label. Depending on the features of a cell image, the classifier predicts whether the CT scan Images are brain hemorrhage and Non brain hemorrhage. This classification is compared to the true value of brain hemorrhage and Non brain hemorrhage to measure performance.

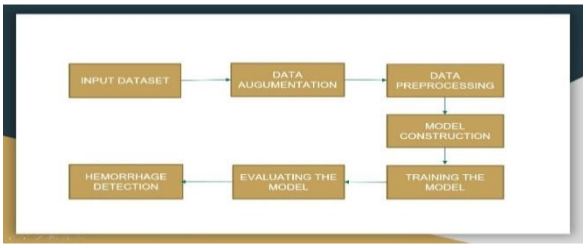

Fig 1: System Architecture

B. Data Preprocessing:

Data pre-processing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and/or lacking in certain behavior or trends, and is likely to contain many errors. Data pre-processing is a proven method of resolving such issues. The dataset contained a lot of noise, and a lot of repetitions were present in the images of this dataset. Since a good dataset dictates the accuracy of the model trained on it, so the data from the above-specified datasets were taken. They were then processed, and also all the repetitions were removed manually. The data cleaning was done manually to remove the corrupt images which were found in the said dataset. Finding these images was a vital part. As it is well known, the corrupt image was a tricky task, but due to valid efforts, we divided the work and cleaned the dataset with mask images and without mask images.

A function pre-processing is defined, which takes the folder to the dataset as input, then loads all the files from the folder and resizes the images according to the CNN model. Then the list is sorted using sorted alphanumerically, and then the images are converted into tensors. Then the list is converted to NumPy array for faster calculation. After this, the process of data augmentation is applied to increase the accuracy after training the model.

C. Data Augmentation:

For the training of CNN model, an enormous quantity of data is necessary to perform training effectively since due to the non-availability of an adequate amount of data for training the proposed model. The amount of data required for the accurate training of a Convolutional Neural Network is generally too large and hence, the dataset present must be augmented in a manner such that the images can be duplicated by creating small changes to the attributes of the image but not changing the overall image itself. The method of data augmentation is used to solve this issue. In this technique, methods like rotation, zooming, shifting, shearing, and flipping the picture are used for generating numerous versions of a similar picture. In the proposed model, image augmentation is used for the data augmentation process. A function image data generation is created for image augmentation, which returns test and train batches of data.

D. Algorithm:

A. Convolutional Neural Networks:

In neural networks, Convolutional neural networks (CNNs) are one of the main categories to perform Image recognition, Image classifications, Objects detections, Face recognition etc. These are some of the areas where CNNs are widely used. CNN image classification stakes an input image, processes it and classifies it under certain categories (Eg: Dog, Cat, Lion).

Computers see an input image as an array of pixels and it depends on the image resolution. Based on the image resolution, CNN will see h x w x d (h = Height, w = Width, d = Dimension). An image of 6x6x3 array of matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of matrix of grayscale image.

The key technology of CNN is the local receptive field, sharing of weights, sub sampling by time or space, so as to extract feature and reduce the size of the training parameters.

Same neuron weights on the surface of the feature mapping, thus network can learn parallel, and reduce the complexity of the network Adopting sub sampling structure by time robustness, scale and deformation displacement. Input information and network topology can be a very good match; it has unique advantages in image processing and object detection.

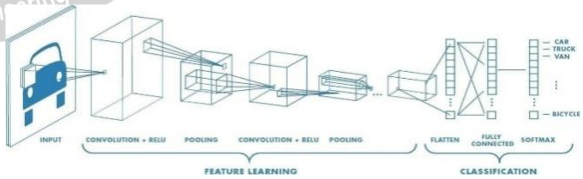

Fig 2: CNN Architecture

The above Fig 3.2 is a complete flow of CNN to process an input image and classifies the objects based on values. Technically, Deep Learning CNN models in order to train and test, each input image will pass it through a series of convolution layers with filters (Kernels), Pooling, fully connected layers(FC) and apply Softmax function to classify an object with probabilistic values between 0 and 1. The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any supervision.

A typical CNN consists of convolutional layers and pooling layers followed by a fully connected neural

 DOI : 10.35291/2454-9150.2021.0313

ISSN : 2454-9150 Vol-07, Issue-03, JUNE 2021

network. The convolutional layers and the pooling layers are supposed to learn how to extract relevant, locally distortion invariant, features from the input, and the fully connected neural network is supposed to learn how to classify these features and output layer predicts the output.

B. VGG-16 Model:

VGG-16 is convolution neural network architecture and its name VGG-16 comes from the fact that it has 16 layers. Its layers consist of Convolutional layers, Max Pooling layers, Activation layers, fully connected layers. VGG-16 network is trained on ImageNet dataset which has over 14 million images and 1000 classes, and achieves 92.7% top-5 accuracy. It surpasses AlexNet network by replacing large filters of size 11 and 5 in the first and second convolution layers with small size 3x3 filters.

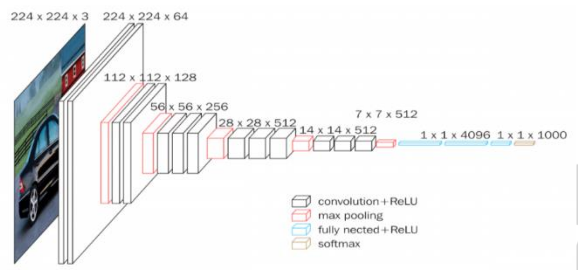

Fig 3.3 VGG-16 Architecture

As shown in the Fig 3.3, the input to conv1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2.

Three Fully-Connected (FC) layers follow a stack of convolutional layers .The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalization (LRN), such normalization does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time.

There are 13 convolutional layers, 5 Max Pooling layers and 3 Dense layers which sums up to 21 layers but only 16 weight layers. Conv 1 has number of filters as 64 while Conv 2 has 128 filters, Conv 3 has 256 filters while Conv 4 and Conv 5 has 512 filters. This model is finished by two fully connected hidden layers and one output layer. The two fully connected layers have the same neuron numbers which are 4096. The output layer consists of 1000 neurons corresponding to the number of categories of the Imagenet dataset. As the number of filters increases following the model depth, hence the number of parameters increases significantly in the later layers. Especially, the parameter number in the two fully connected hidden layers is very large, with 102, 764, 544, and 16, 781, 312 parameters, respectively. It accounts for 86.4% parameters of the whole model.

IV. RESULTS

We will evaluate the model we built in the training phase by making predictions with them on the data from our test dataset because just validation is not enough. We have also built a nifty utility module called model evaluation utils, which we can use to evaluate the performance of our deep learning models with relevant classification metrics. In the below Figures 4.1 and 4.2, we have plotted the accuracy and loss obtained by the model after training on 30 epochs and validating the model on validation data.

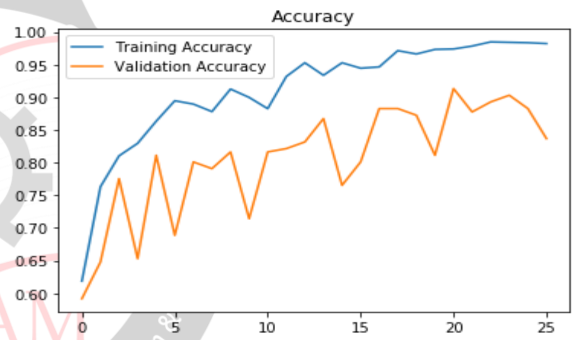

Fig 4.1 Accuracy

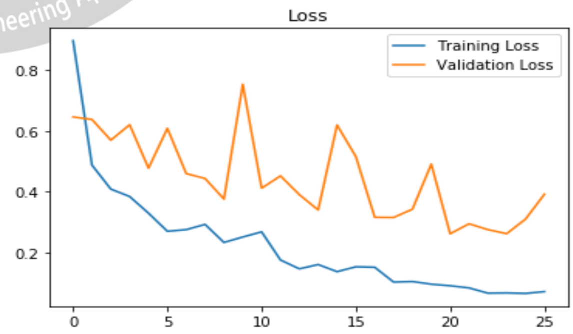

Fig 4.2 Loss

Here, we have obtained the accuracy and loss after training the VGG-16 model over 30 epochs. After 30 epochs, we obtained an accuracy over validations set of 0.8567 and a loss over validation set of 0.0731. . As we validate the model we got a validation accuracy of 85%, we evaluate the model that is built in the training phase by making predictions with them on the data from test metrics dataset.

 DOI : 10.35291/2454-9150.2021.0313

ISSN : 2454-9150 Vol-07, Issue-03, JUNE 2021

Confusion Matrix

A much better way to evaluate the performance of a classifier is to look at the confusion matrix. The Confusion Matrix is a machine learning performance estimation model. Better the adequacy, better the performance of the model. Confusion Matrix is a recital estimate for classification problems with machine learning, where yield can be at least two classes. As shown in the Fig 4.3, it is a table containing 4 distinct mixes of actual and predicted values. Confusion Matrices are extremely useful for measuring Recall, Precision, Specificity, Accuracy which are critical metrics for measuring model performance and most importantly AUC-ROC curves. The metrics are calculated by using true and false positives, true and false negatives. Positive and negative in this case are generic names for the predicted classes. There are four ways to check if the predictions are right or wrong:

1. **TN / True Negative**: when a case was negative and predicted negative
2. **TP / True Positive**: when a case was positive and predicted positive
3. **FN / False Negative**: when a case was positive but predicted negative
4. **FP / False Positive**: when a case was negative but predicted positive

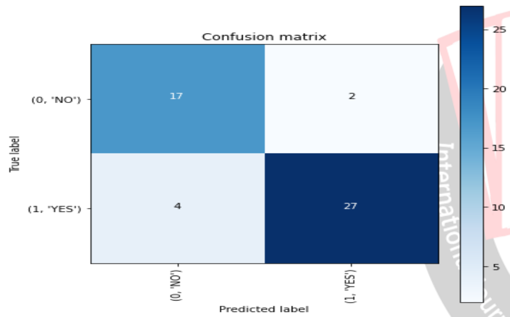

Fig 4.3 Confusion Matrix

V. Conclusion

This Study gives a deep learning model that uses convolution neural networks VGG-16 architecture for Intracranial Hemorrhage detection using CT scan images. Here we review a critique of computer vision and image analysis studies which address the automated diagnosis of Intracranial Hemorrhage on CT scan images. We took the dataset from Kaggle.com website for Biomedical Communication, which are pre-processed to their average dimensions and data is augmented as we have small data set and are divided into test and training sets for further computation, and developed a deep learning model i.e. Convolutional neural networks model VGG-16 with 16 layers - convolutional and pooling layers followed by dense layers, and a dropout layer for regularization. As we validate the model we got a validation accuracy of 85%, evaluate the model that is built in the training phase by making predictions with them on the data from test dataset because just validation is not enough, The final step is to leverage module and check the performance of model with relevant classification metrics that is area under curve. Finally, this model performs accuracy of 85 %.

Future Scope

In the future, the large dataset of Hemorrhage images can be considered to validate our proposed model on it. This study can also be extended in identifying the Brain Hemorrhage. A person can directly take a picture of the Brain CT scan from his mobile and check whether there is presence of Hemorrhage or not. We can get more accuracy if we increase the number of images in the data set. We intend to make this model more robust and accurate by using more such images. The Deep Learning model can be extrapolated for the diagnosis of Brain Hemorrhage, using transfer learning as well, given sufficient amount of data. Thus, this study has immense scope in the field of medicine and health care, and can be continued for other such insightful innovations.

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 DOI : 10.35291/2454-9150.2021.0313