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Brain CT Image Processing Using U-Net Model with Data Augmentation for Detection of Ischemic and Haemorrhage Strokes

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Abstract: Brain stroke has been causing deaths and disabilities across the globe in alarming rate. With the emergence of Artificial Intelligence (AI), there has been increased efforts in usage of it in healthcare domain. However, it is observed that deep learning models are more suitable to process medical images. Nevertheless, deep learning models cannot give same level of performance for each application in medical domain. For this reason, in this paper, we proposed a framework where U-Net model is configured appropriate and data augmentation is carried out to solve the problem of brain CT scan based automatic detection of stroke. We proposed an algorithm known as Learning based Medical Image Processing for Brain Stroke Detection (LbMIP-BSD). This algorithm exploits supervised learning using U-Net based model with data augmentation for leveraging brain stroke detection performance. Our empirical study revealed that the proposed model outperformed existing deep learning models such as baseline CNN, VGG16 and ResNet50 with highest accuracy 94.57%.

Keywords: *Brain CT Image, Image Processing, U-Net Model, Data Augmentation, Haemorrhage Strokes*

1. Introduction

Cerebral circulation or cerebrovascular abnormalities lead to death of brain cells which results in a disease known as brain stroke. According to World Health Organization (WHO), stroke is the second leading cause of death across the globe. It occurs predominantly in the adults and elderly. Each year there are more than 5.5 million deaths worldwide. Out of which 40% of the subjects were aged less than 70 years and two-thirds of the deaths occurred in developing countries. In addition to causing more deaths, stroke also left many surviving patients to be disables and need assistance in their daily living. In USA, each year approximately 795,000 people have either new or recurrent stroke. It does mean that in every 40 seconds there is a stroke incidence and in every 4 minutes there is a death. If this continues in this alarming pace, there will be severe crisis pertaining to healthcare unless there comes a technology driven approach to detect stroke early [1].

Stroke has its symptoms besides modifiable and non-modifiable risk factors. Once stroke occurs there are ways to identify it using F.A.S.T features and there is treatment procedure established in the healthcare community. However, the problem is prevention of stroke rather than giving treatment afterwards. This is the challenging aspect with respect to stroke disease as it is clinically defined disease. Nevertheless, an important advantage is that majority of the strokes are preventable if it is smelled early and treated leading to significantly improved outcomes. In addition to the tertiary prevention of stroke which focuses on reducing damage and consequences in stroke patients, it is indispensable to have plans for primary and secondary prevention strategies [2]. Initiatives to increase physical activity and legislation to get rid of or control tobacco smoking come under primary prevention.

The secondary prevention is aimed at reducing the risk of stroke occurrence in people suffering from diabetics and hypertension besides smokers. There are brain imaging technologies such as CT and MRI for diagnosis of stroke. However, there are many cases in which the diagnosis depends on the intelligence of doctors as the CT image, for example, may not distinctly provide location of ischemic stroke. The dependency on the doctor's diagnostic experience may lead to issues when there are less experienced doctors who need to assess the situation. Therefore, a technology driven approach can provide much better alternative that complements the

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doctor's knowledge besides becoming a part of Clinical Decision Support System for stroke.

There are many risk factors associated with brain stroke [2]. In fact, brain stroke has become one of the major causes of death of late [3], [4]. Stroke, in other words, is an accident of cerebrovascular kind pertaining to neurological disease leading to either haemorrhage or ischemia of brain arteries and then result in compromised functionality and heterogeneous cognitive motor impairments [9]. Therefore, the aim of this research to build a deep learning based solution for stroke diagnosis.Our contribution in this paper is a framework based on deep learning for brain CT scan based stroke detection. The remainder of the paper covers prior works in Section 2, proposed methodology in Section 3, experimental results in Section 5 and conclusion and future scope in Section 5.

2. Related Work

In fact, brain stroke has become one of the major causes of death of late [3], [4]. Stroke, in other words, is an accident of cerebrovascular kind pertaining to neurological disease leading to either haemorrhage or ischemia of brain arteries and then result in compromised functionality and heterogeneous cognitive motor impairments [9]. Pradeepa *et al*. [10] proposed a methodology known as Detecting Risk Factor of Stroke Disease (DRFS) which makes use of social media content to detect symptoms of the diseases and explore preventing methods. Initially data is clustered and then data is subjected to Probability Neural Network (PNN) for generating class labels. The overall process includes dataset acquisition from Twitter, pre-processing, spectral clustering, creation of TF-IDF vectors, feature extraction, PNN, clustering, frequent item set mining using Apriori and arriving at risk factors of stroke. Pathanjali *et al*. [12] investigated on ischemic stroke using ML techniques. They proposed a methodology based on supervised learning with techniques such as SVM and RF. Manikandan *et al*. [14] proposed a methodology based on ML for stroke image classification. Kamal *et al*. [16] investigated on the cases of Acute Ischemic Stroke (AIS) using ML and opined that with ML, the diagnosis became easier. As there is increasingly complex data available, it is essential to have further research on the collaborative approaches across many service providers in the real world.

Qiu *et al*. [17] also studied on AIS for early detection purposes. They used non-contrast enhanced CT images to deal with the detection of disease. Their methodology includes U-net transfer learning, feature extraction, mapping and RF based classification. Priyanka and Meera [19] used a hybrid feature selection method before the application of classification techniques such as RF, SVM, NB and logistic regression. SVM is found to have better performance over other classification methods. Pouyanfar *et al*. [20] investigated on different deep learning techniques and identified applications of the same. Different deep learning techniques such as Variational Autoencoder (VAE), Generative Adversarial Network (GAN), DBM, DBN, CNN, RNN, and RvNN. They also compared different deep learning frameworks available. They include CNTK in C++, TensorFlow in Python and C++, MXNet in C++, Theano in Python, Neon in Python, Torch in C and Lua, DL4j in Java and Caffe in C++. They found different kinds of deep learning applications as well. They include autonomous driving, sentiment classification, computer vision applications, speech recognition and information retrieval.

Gupta *et al*. [22] studied the issues caused by ischemic stroke to human lives. They employed AI based framework for its diagnosis. They investigated on different applications based on AI to diagnose ischemic stroke. The application is pertaining to imaging, disease diagnosis, disease analysis, lesion segmentation and neuroimaging in stroke. The tools and applications mostly used MRI, functional MRI and CT images. Lunderwold *et al*. [23] investigated on medical imaging technology such as MRI using deep learning. They discussed different ML and deep learning methods that are used for stroke detection. Different deep learning methods are explicitly provided with their importance in AI methods. They include V-net, U-net, Siamese nets, GANs, YOLO, NASNet, SENets, RESNet, GoogLeNet, VGG and AlexNet. Experiments are made with different deep learning methods. They found different challenges with respect to data, interpretability, workflow integration, perspectives and the expectations in the future. From the review of [1-34], it is understood that there is need for developing a reusable AI based framework for early detection of stroke that considers both data driven approach and also image processing approach to have an integrated solution.

3. Proposed System

This section presents the proposed framework, the deep learning architecture used, algorithm proposed and evaluation procedure.

3.1 Our Framework

We proposed a deep learning based framework for detection of brain stroke. As shown in Figure 1, the framework takes input CT brain images and starts an iterative process to detect probability of brain stroke early. Prior to this, the dataset is divided into training set and test set. A deep learning model is used to extract features from training set using convolutional layers and then features are optimized using pooling layers. Then the region of interest (ROI) in the brain image is identified and the region is recognized as image patch that needs further investigation. Then the patch image is given to U-Net model that is configured to have better performance of image based stroke detection especially early detection of stroke probability.

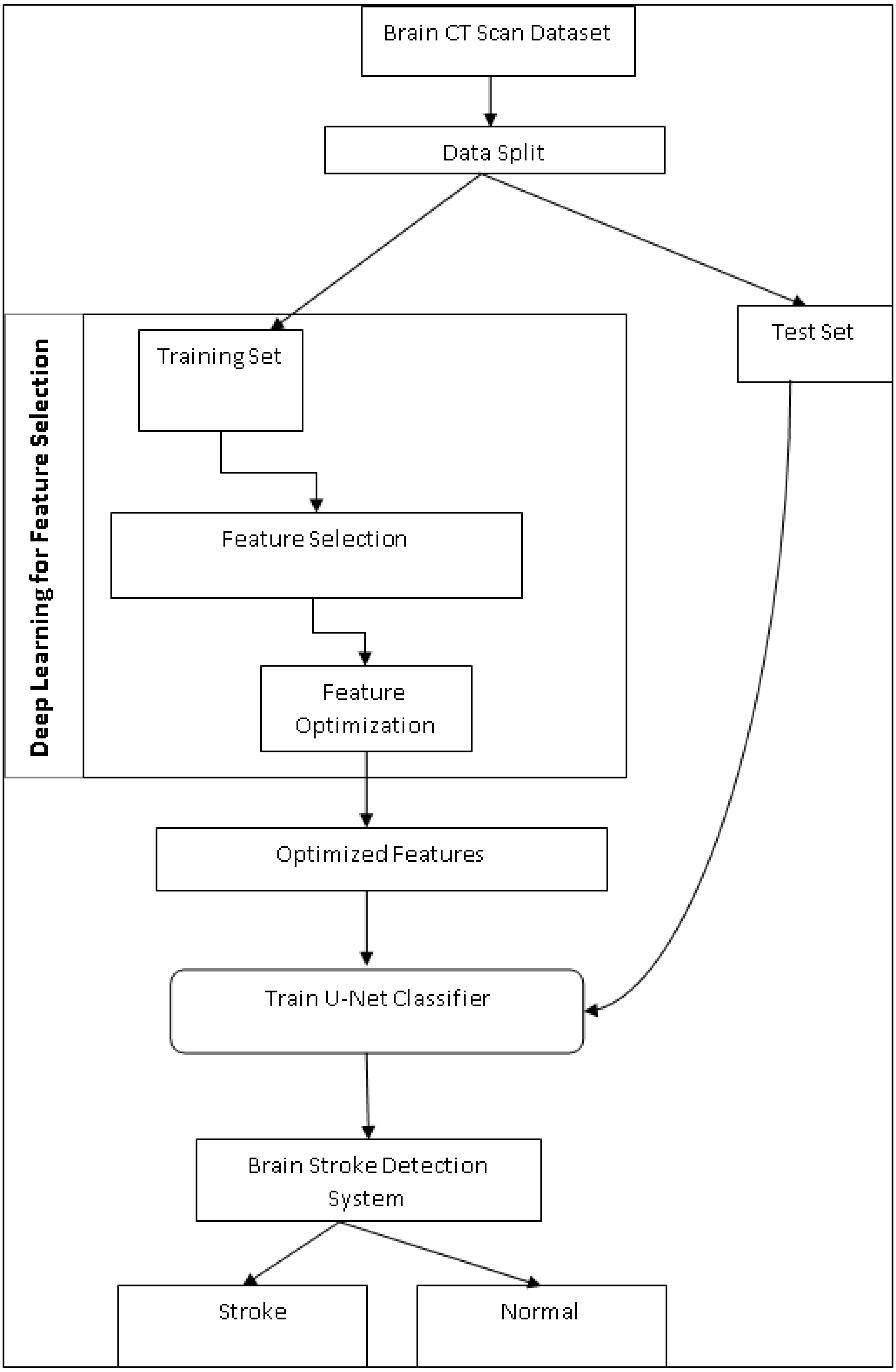

Fig 1: Overview of the proposed system

The proposed system is based on U-Net model which is one of the deep learning models. Architecture of this model is provided in Figure 2. This model is made up of two patches namely contracting and expansive patches (left & right respectively). The former is modelled after convolutional network. It has iterative application of convolutions of 3x3 followed by ReLU and 2x2 pooling layers. The feature channels are doubled with each down sampling. In the latter, up sampling is made with 2x2 convolutions, concatenation, 3x3 convolutions followed by ReLU. Cropping is involved in the architecture because loss of border pixels involved in the convolutions. Finally, 1x1 convolution maps feature vector to class labels.

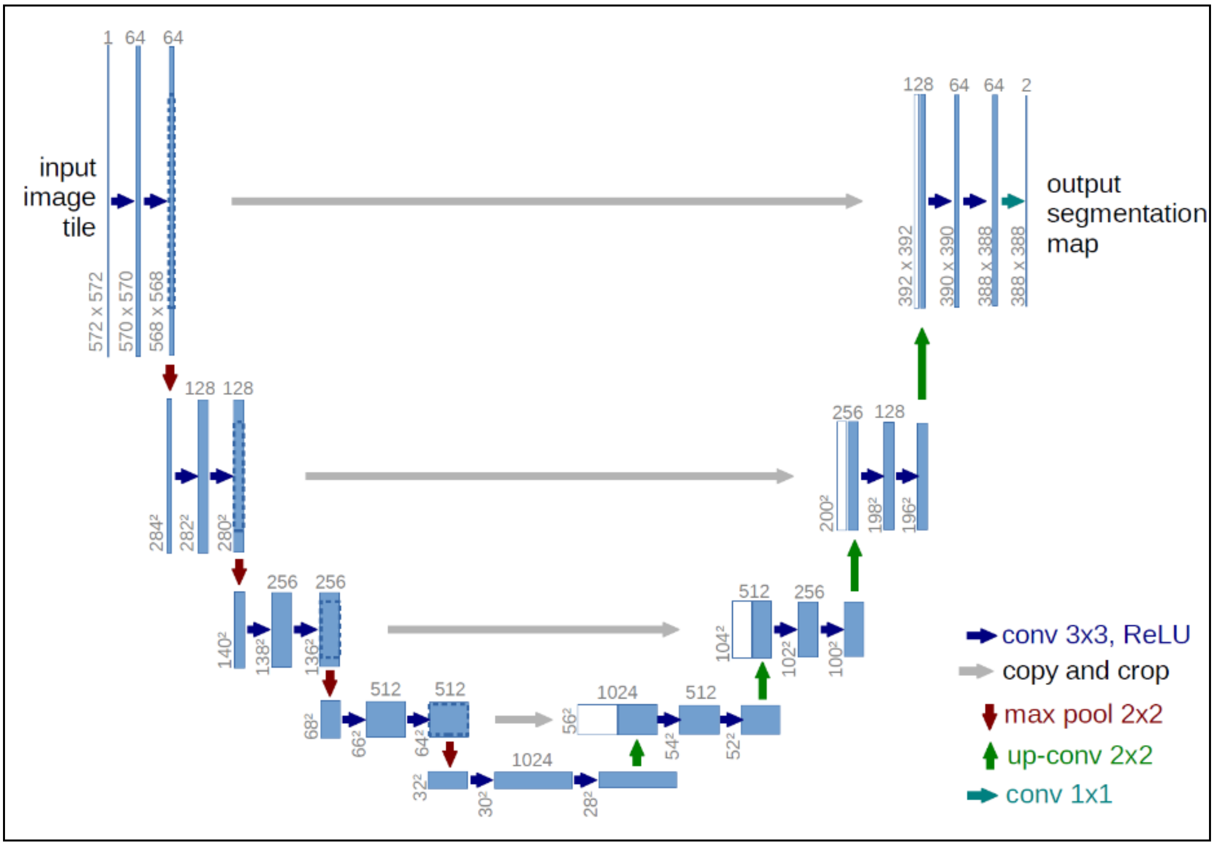

Fig 2: Architecture of U-Net Model used for brain stroke detection

In the training process, the given CT images are subjected to segmentation and network is trained with the help of SGD. In order to support large number of inputs, large size of batches is used. Therefore, 0.99 is used as momentum for better optimization. Once the feature maps are generated and optimized, soft-max is applied pixel wise in order to compute energy function and loss function. Soft-max involved in the U-Net architecture is defined as in Eq. 1.

$$p_k(X) = \exp\left(a_k(X)\right) / \left(\sum_{k'=1}^{K} \exp\left(a_{k'}(X)\right)\right) \quad (1)$$

where k denotes feature channel while its activation function is denoted as $a_k(X)$ at given pixel represented as $x \in \Omega$ in such a way that $\Omega \subset \mathbb{Z}^2$. Number of class labels is denoted by K while $p_k(X)$ denotes max function. Then crop entropy is computed as in Eq. 2 to compute penalty at each position based on the deviation such as $p_{\ell(X)}(X)$ from 1.

$$E = \sum_{X \in \Omega} w(X) \log(p_{\ell(X)}(X)) \quad (2)$$

where the true label is ℓ such that $\{1, \dots, K\}$ while the weight map is $w : \Omega \rightarrow R$ which is used to give importance to some pixels in the training process. For every ground truth, a weight map is pre-computed to take care of pixels with various frequencies in the training. This will lead to the network learning small borders also between cells. Morphological operations are involved in the computation of separation border and eventually computation of weight map as expressed in Eq. 3.

$$w(X) = w_c(X) + w_0 \cdot \exp\left(-\frac{(d_1(X)+d_2(X))^2}{2\sigma^2}\right) \quad (3)$$

where there is need to balance classes using $w_c : \Omega \rightarrow \mathbb{R}$ as desired weight map and the distance with respect to nearest cell border is $d_1 : \Omega \rightarrow \mathbb{R}$ and distance with respect to second nearest cell is $d_2 : \Omega \rightarrow \mathbb{R}$. In our experiments $\sigma \approx 5$ pixels and $w_0 = 10$ are set. Table 1 shows notations used in the proposed model.

Notation	Meaning
$a_k(X)$	Activation function
$\ell : \Omega \rightarrow \{1, \ldots, K\}$	Denotes pixel wise true label
$w : \Omega \rightarrow R$	Denotes weigh map used to give significance to some pixels
$w_c : \Omega \rightarrow \mathbb{R}$	Denotes weight map for class frequency balance
$d_1 : \Omega \rightarrow \mathbb{R}$	Distance related to first nearest cell
$d_2 : \Omega \rightarrow \mathbb{R}$	Distance related to second nearest cell

Table 1: Notations used in the proposed deep learning model

In deep learning, it is essential to have initialization of weights to avoid excessive activations and certain paths unable to contribute. With the empirical study, we understood that it is important to initialize weights to ensure that each feature map has unit variance approximation. In the U-Net architecture, initial weighs are provided using Gaussian distribution considering deviation $\sqrt{2/N}$ based on nodes of given neural. In other words, N is set to 9x64 for a 3x3 convolutional layer with 64 feature channels present in the preceding layer.In the proposed system, data augmentation is employed to ensure that there is no overfitting problem. It is important to train network with more robust properties especially if the number of training samples is less. Robustness to different deformations, rotation and shift invariance and gray value variations is to be achieved. With respect to CT scan images in this research, it is important to have elastic deformations.

3.2 Proposed Algorithm

We proposed an algorithm known as Learning based Medical Image Processing for Brain Stroke Detection (LbMIP-BSD). This algorithm exploits supervised learning using U-Net based model with data augmentation for leveraging brain stroke detection performance.

Algorithm: Learning based Medical Image Processing for Brain Stroke Detection (LbMIP-BSD)

Input: Brain CT scan dataset D

Output: Stroke detection results R, performance statistics P

1. Begin
2. D’←DataAugmentation(D)
3. (T1, T2)←Pre-process(D’)
4. M←CreateU-NetModel()
5. M←CompileModel()
6. M←TrainModel(T1)
7. Save model M
8. (R,P)←TestData(M, T2)
9. Display R
10. Display P
11. End

Algorithm 1: Learning based Medical Image Processing for Brain Stroke Detection

As presented in Algorithm 1, it takes brain CT scan dataset as input, performs pre-processing to generate train and test datasets. Then the algorithm proceeds with U-Net based deep learning model including model creation, model compilation and model training. Once the model is trained with T1, it is subjected to persisting to reuse in future. In testing phase, the model M is reused to test unlabelled data (T2). Then the algorithm computes result and also performance statistics and display the same.

3.3 Evaluation Method

Since we employed a supervised learning based methodology, confusion matrix as shown in Figure 3 is used to achieve performance evaluation.

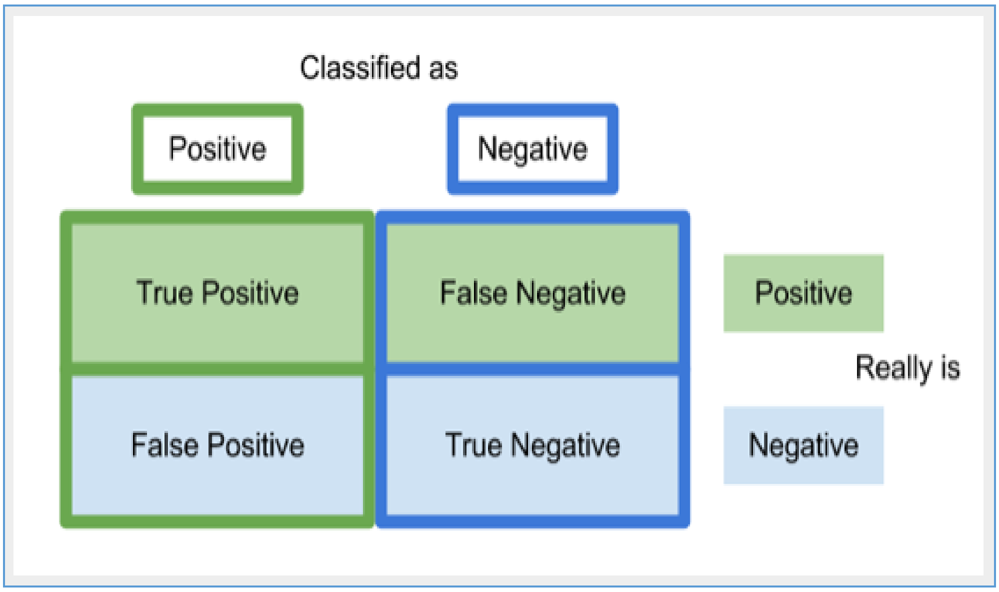

Fig 3: Confusion matrix

By comparing ground truth with respect to given test CT scan samples with the actual classification results of the proposed system, performance is estimated.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Accuracy is the metric used to know the performance of the proposed system. It helps in evaluating the proposed algorithm and compare its performance with the state of the art models.

4. Experimental Results

We implemented the proposed system using Python language. With empirical study, we observed the ability of the proposed system in stroke detection given brain CT images as input. The proposed system, based on U-Net, is compared against existing deep learning models such as VGG16, ResNet50 and CNN baseline model. We used CT scan dataset collected from [34] for experiments.

4.1 Stroke Detection Results

This section presents the brain stroke detection results of the proposed system when tested with brain CT scans that are unlabelled.

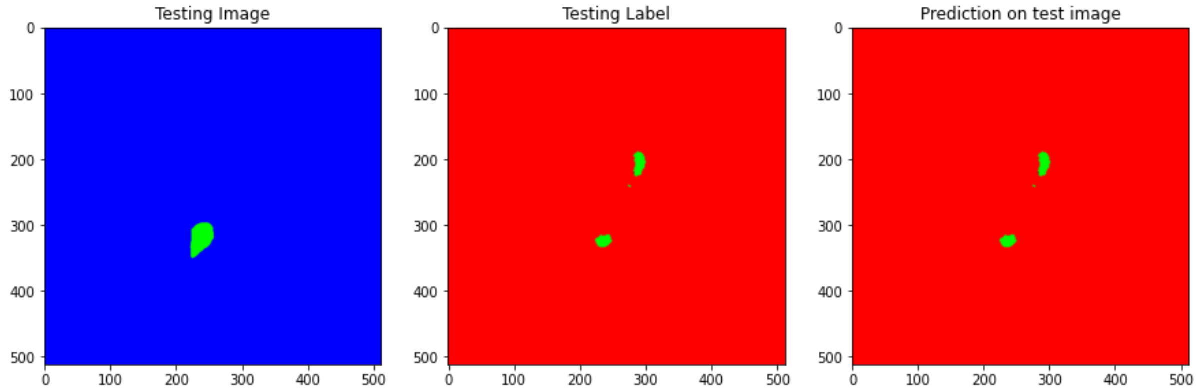

Fig 4: Shows the prediction results along with testing image and its ground truth

As presented in Figure 4, it shows the test testing image, its true label and also predicted label reflecting the ability of the proposed system in diagnosis of brain stroke.

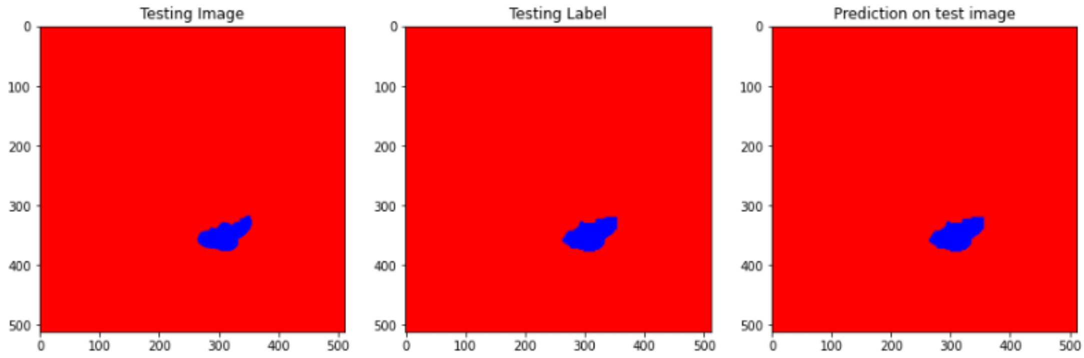

Fig 5: Shows the prediction results along with testing image and its ground truth in another experiment

As presented in Figure 5, it shows the test testing image, its true label and also predicted label reflecting the ability of the proposed system in diagnosis of brain stroke in another experiment.

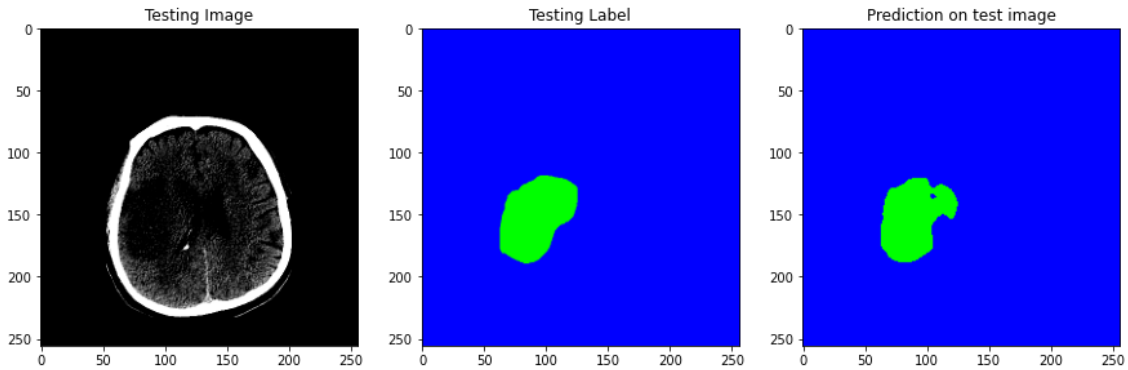

Figure 6: Shows the prediction results along with testing image and its ground truth

As presented in Figure 6, it shows the test testing image, its true label and also predicted label reflecting the ability of the proposed system in diagnosis of brain stroke with different test sample.

4.2 Discriminating Ischemic and Haemorrhage Stroke

The proposed system is capable of discrimination between two kinds of brain strokes that prevail. They are known as ischemic stroke and haemorrhage stroke

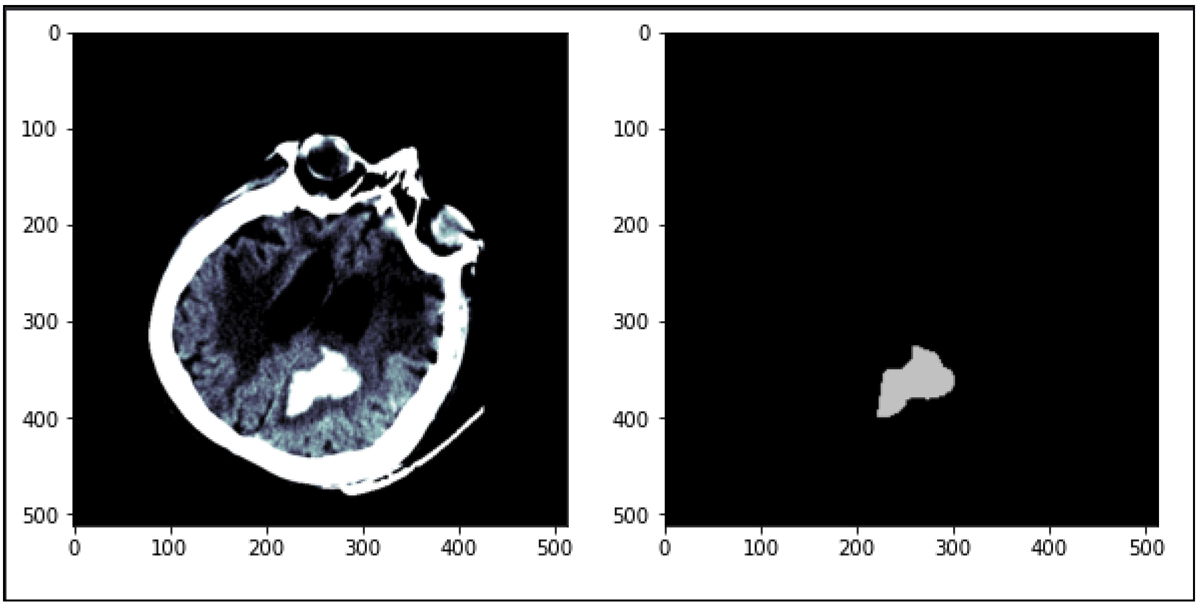

Fig 7: Detection of haemorrhage stroke

As presented in Figure 7, the testing image containing haemorrhage stroke is given as input and the systems is able to detect it correctly.

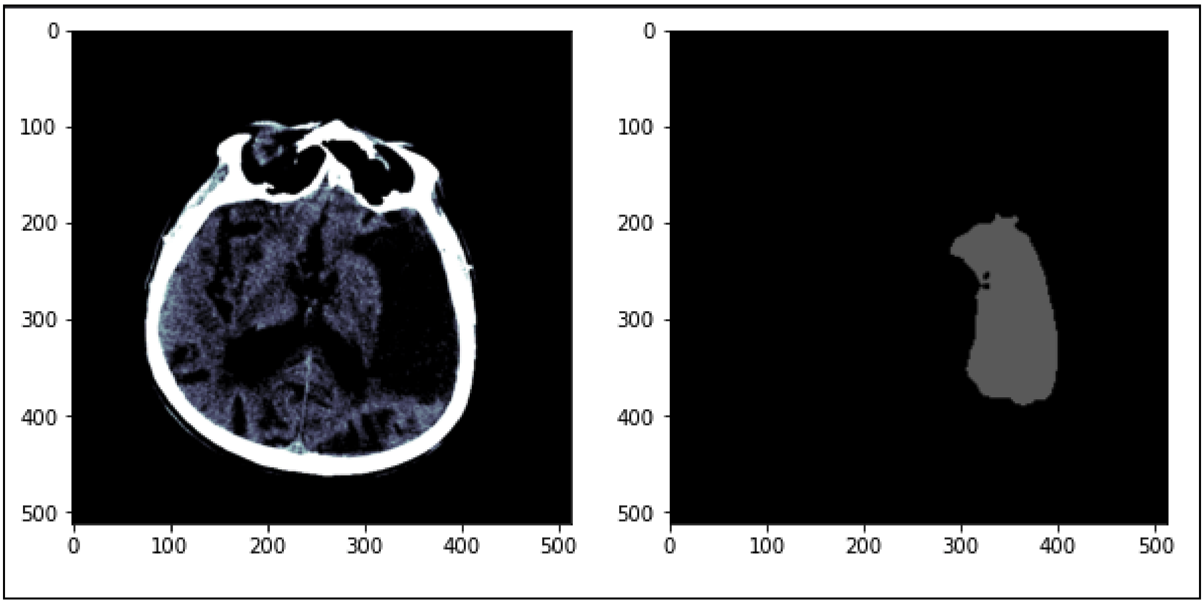

Fig 8: Detection of ischemic stroke

As presented in Figure 8, the testing image containing ischemic stroke is given as input and the systems is able to detect it correctly.

4.3 Model Performance

The proposed model is executed with 250 epochs. Its performance is measured at each epoch in the execution.

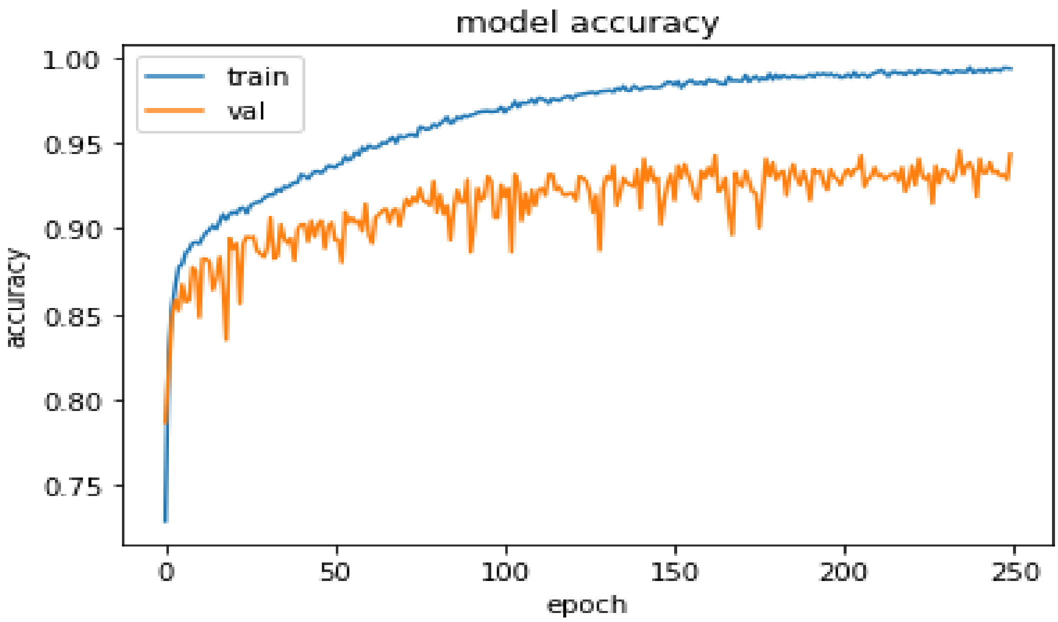

Fig 9: Model performance in terms of accuracy

As presented in Figure 9, accuracy is evaluated. Higher value for accuracy indicates better performance. The validation accuracy is increased as the number of epochs is increased gradually. In the same fashion, training accuracy is improved until convergence as the number of epochs is increased. At the convergence point, highest accuracy is achieved for both the measures.

4.4 Performance Comparison

Performance of our model (U-Net based framework) is compared against existing models. CNN is one of the baseline models used for comparison. Other existing deep learning models are VGG16 and ResNet50 that are widely used in the computer vision research.

Models	Accuracy
CNN	89
VGG16	90.89
ResNet50	92.12
Proposed Model	94.57

Table 2: Performance comparison among stroke detection models

A presented in Table 2, accuracy of the proposed model is compared against existing deep learning models in CT scan based brain stroke detection.

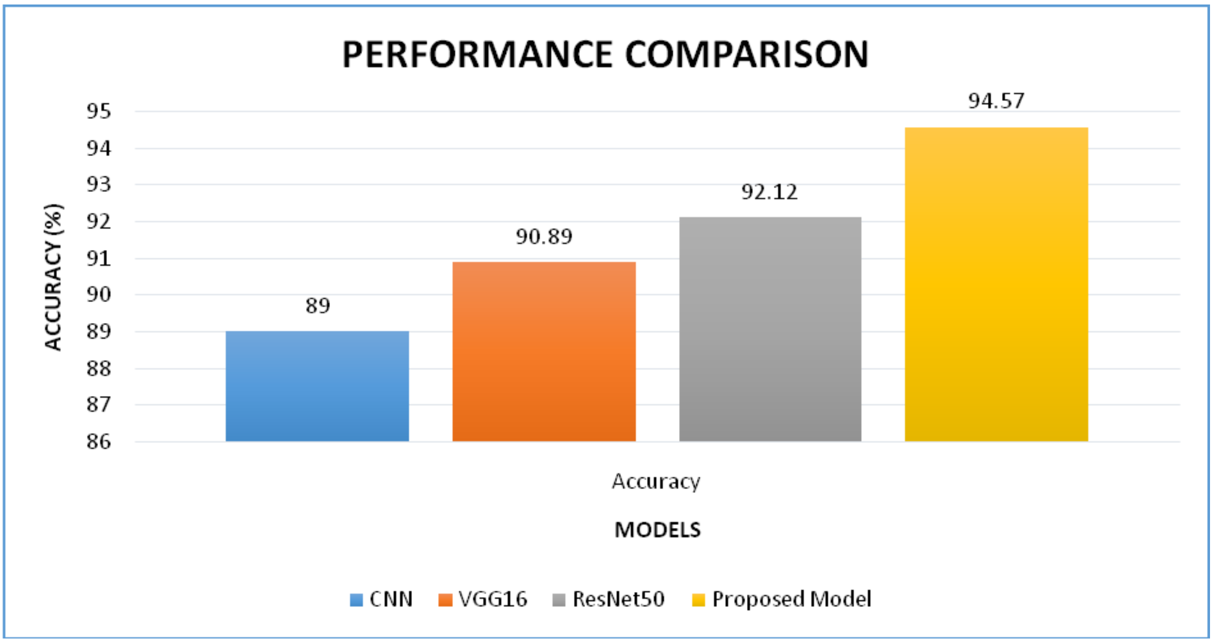

Fig 10: Performance comparison among brain stroke detection models

As presented in Figure 10, accuracy of the proposed model is compared against existing deep learning models in CT scan based brain stroke detection. Existing deep learning models are VGG16 and ResNet50 that are widely used in the computer vision research. Accuracy is the metric used for evaluation. Higher in accuracy reflects better performance. CNN is the baseline model which is used in empirical study showed least performance with 89% accuracy. VGG16 and ResNet50 are pre-trained models widely used in medical image analysis research. They have improved configuration of layers and they are proven to be better models to solve many kinds of problems. In this research, they are found better than CNN model. However, ResNet 50 outperformed VGG16 with 92.12% accuracy while VGG16 achieved 90.89% accuracy. Highest accuracy is exhibited by the proposed model with 94.57%.

5. Conclusion and Future Work

In this paper, we proposed a framework where U-Net model is configured appropriate and data augmentation is carried out to solve the problem of brain CT scan based automatic detection of stroke. In the training process, the given CT images are subjected to segmentation and network is trained with the help of SGD. In order to support large number of inputs, large size of batches is used. We proposed an algorithm known as Learning based Medical Image Processing for Brain Stroke Detection (LbMIP-BSD). This algorithm exploits supervised learning using U-Net based model with data augmentation for leveraging brain stroke detection performance. Our empirical study revealed that the proposed model outperformed existing deep learning models such as baseline CNN, VGG16 and ResNet50 with highest accuracy 94.57%. In our future work, we intend to use brain MRI imagery with our framework and compare the difference between CT scan based and MRI based brain stroke diagnosis.

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