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ADL-BSDF: A Deep Learning Framework for Brain Stroke Detection from MRI Scans towards an Automated Clinical Decision Support System

Mrs. Anitha Patil[1], Dr. Suresh Kumar Govindaraj[2]
[1]Research Scholar, Department of Computer Science,
Pondicherry University,
Karaikal, Pondicherry UT, India. pin: 609605.
anithapatil243@gmail.com
[2]Assistant Professor, Department of Computer Science,
Pondicherry University,
Karaikal, Pondicherry UT, India, pin: 609605.
mgsureshkumar@gmail.com

Abstract: Deep learning has emerged to be efficient Artificial Intelligence (AI) phenomena to solve problems in healthcare industry. Particularly Convolutional Neural Network (CNN) models have attracted researchers due to their efficiency in medical image analysis. According to World Health Organization (WHO), rapidly developing cerebral malfunction, brain stroke, is the second leading cause of death across the globe. Brain MRI scans, when analysed quantitatively, play vital role in diagnosis and treatment of stroke. There are many existing methods built on deep learning for stroke diagnosis. However, an automatic, reliable and faster method that not only helps in stroke diagnosis but also demarcate affected regions as part of Clinical Decision Support System (CDSS) is much desired. Towards this objective, we proposed an Automated Deep Learning based Brain Stroke Detection Framework (ADL-BSDF). It does not rely on expertise of healthcare professional in diagnosis and know the extent of damage enabling physician to make quick decisions. The framework is realized by two algorithms proposed. The first algorithm known as CNN-based Deep Learning for Brain Stroke Detection (CNNDL-BSD) focuses on accurate detection of stroke. The second algorithm, Deep Auto encoder for Stroke Severity Detection (DA-SSD), focuses on revealing extent of damage or severity of the stroke. The framework is evaluated against state of the art deep learning models such as EfficientNet, ResNet50 and VGG16.

Keywords – Artificial Intelligence, Brain Stroke Diagnosis, Deep Learning, Convolutional Neural Network, Deep Auto encoder.

I. INTRODUCTION

Brain stroke is second leading cause of death and disability across the globe. It has potential to damage human brain, health and wellbeing. Stroke is actually characterized by high rate of occurrence, mortality, disability and morbidity. It is rapidly spreading among younger generation also besides low-income families [1]. In this context, different imaging techniques came into existence for medical image analysis. They include Magnetic Resonance Imaging (MRI), Computed Axial Tomography (CAT), Positron emission tomography (PET) and Computed Tomography (CT). Among these MRI and CT are widely used techniques. Cerebrovascular accident (CVA) is the brain disorder and also considered as stroke has become very common cause of disability and death in the world [8]. With the invent of machine learning and deep learning methods it is found that they play crucial role in computer vision applications.

Many researchers contributed towards brain stroke detection. CNN is most widely used deep learning model. Lundervold *et al*. [3] discussed about deep learning models and their suitability for medical image analysis. Their research found that Convolutional Neural Network (CNN) and its variants have potential for efficient medical image analysis. Basak *et al*. [5] proposed a novel method, named DFENet, based on deep learning for segmentation of brain MRI. It is made up of 3D CNN networks and guided by fusion edge. They exploited a dimension transfer block for improving detection performance. Shah *et al*. [9] focused on ischemic stroke diagnosis using CNN model. Their methodology is based on deep learning considering ISLES dataset. Talo *et al*. [14] focused on the investigation of brain abnormalities. They used CNN and other CNN variants such as ResNet34 for automatic discovery of brain discrepancies using MRI images. In the process they exploited deep transfer learning for improving performance. Chauhan *et al*. [16] investigated on machine learning and deep CNN models to detect

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cognitive performance of patients diagnosed with stroke. From lesion image of patient, their method could extract features and use regression methods for detecting cognitive performance.

Generative Adversarial Network (GAN) models are also found in the literature for data augmentation and stroke detection. Wu *et al*. [6] proposed a methodology based on conditional Generative Adversarial Network (GAN) architecture for neuroimaging segmentation. In the process, they investigated data augmentation strategy based on GAN which is characterized by Generator and Discriminator phenomenon. CNN and feature similarity models are used as part of the model towards improving quality in segmentation. Sathish *et al*. [8] combined CNN model and GAN architecture for improving quality of training MRI brain samples towards stroke lesion detection. MRI imagery is used for empirical study. Adversarial learning is the important feature in their work. Li *et al*. [15] combined pre-trained U-Net model and GAN architecture for lesion detection pertaining to haemorrhagic stroke using brain CT scans. Both generator and discriminator use ground truth to improve the process of data augmentation. From the literature, it is ascertained that there is need for a Clinical Decision Support System (CDSS) for not only accurate stroke diagnosis but also detect severity region in the stroke MRI sample. Towards this end, we proposed a comprehensive framework. Our contributions in this paper are as follows.

1. We proposed an Automated Deep Learning based Brain Stroke Detection Framework (ADL-BSDF). It does not relay on expertise of healthcare professional in diagnosis and know the extent of damage enabling physician to make quick decisions.
2. We proposed two algorithms to realize the framework. The first algorithm known as CNN-based Deep Learning for Brain Stroke Detection (CNNDL-BSD) focuses on accurate detection of stroke. The second algorithm, Deep Autoencoder for Stroke Severity Detection (DA-SSD), focuses on revealing extent of damage or severity of the stroke.
3. A prototype is built and the framework is evaluated against state of the art deep learning models such as EfficientNet, ResNet50 and VGG16. Our model achieved 98.12% accuracy in stroke diagnosis and 86% accuracy in stroke severity region prediction.

The remainder of the paper is structured as follows. Section 2 reviews literature on different deep learning models for stroke detection. Section 3 presents our methodology that includes materials and methods besides algorithms proposed. Section 4 presents results of experiments that include stroke diagnosis and severity prediction besides comparison with existing deep models. Section 5 concludes our work and throws light on possible future scope of the research.

II. RELATED WORK

This section reviews related works on medical image analysis for brain stroke detection focusing on deep learning models. Zhang *et al*. [1] investigated on deep learning models with MRI imagery for stroke detection. They proposed a methodology multiple deep learning models such as Faster R-CNN for automatic lesion detection. They intend to improve their method with more samples collected for training. Lundervold *et al*. [3] discussed about deep learning models and their suitability for medical image analysis. Their research found that Convolutional Neural Network (CNN) and its variants have potential for efficient medical image analysis. Zhou *et al*. [4] focused on multi-modality in medical image analysis. Particularly, they explored different deep learning models along with hybrid approaches for medical image analysis. Their work encapsulates different imaging techniques such as MRI, CT and PET. Their empirical study was based on the clinical utility of the models in disease diagnosis. Basak *et al*. [5] proposed a novel method, named DFENet, based on deep learning for segmentation of brain MRI. It is made up of 3D CNN networks and guided by fusion edge. They exploited a dimension transfer block for improving detection performance. They used ATLAS dataset [67].

Wu *et al*. [6] proposed a methodology based on conditional Generative Adversarial Network (GAN) architecture for neuroimaging segmentation. In the process, they investigated data augmentation strategy based on GAN which is characterized by Generator and Discriminator phenomenon. CNN and feature similarity models are used as part of the model towards improving quality in segmentation. In future, they intended to incorporate generated samples for more diversity in especial study. Nazari-Farsani *et al*. [7] used diffusion weighted MRI for data-driven approach in acute stroke lesion detection. It is an anomaly detection based approach. They intended to improve their performance further with optimization in their methodology. Sathish *et al*. [8] combined CNN model and GAN architecture for improving quality of training MRI brain samples towards stroke lesion detection. MRI imagery is used for empirical study. Adversarial learning is the important feature in their work. Shah *et al*. [9] focused on ischemic stroke diagnosis using CNN model. Their methodology is based on deep learning considering ISLES dataset. They did experiments with different layers and changes in dropout for better performance. Zhou *et al*. [10] proposed a variant of U-Net model based on the notion of dimension fusion. In the encoding stage they combine 2D and 3D convolutions for

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efficient segmentation of medical images. They also proposed novel loss function known as Enhance Mixing Loss (EML) to evaluate performance. They intend to extend their work with combinations of dimension fusion blocks.

Raghavendra *et al*. [11] used CT brain scans to detect haemorrhagic stroke. They exploited deep machine learning models to obtain non-linear feature maps. Their methodology includes feature rearrangement concept for efficient classification of stroke. They intend to improve with deep models in future. Wood *et al.* [12] exploited deep learning models in order to perform labelling to head MRI data. It is the approach useful for automatic dataset labelling in computer vision applications. Acharya *et al*. [13] extracted features of higher order spectra from MRI imagery for automation of ischemic stroke detection. It makes use of feature extraction and feature ranking based approach for stroke detection. Talo *et al*. [14] focused on the investigation of brain abnormalities. They used CNN and other CNN variants such as ResNet34 for automatic discovery of brain discrepancies using MRI images. In the process they exploited deep transfer learning for improving performance. It has potential to reveal different brain abnormalities like stroke, autism and Alzheimer's disease. Li *et al*. [15] combined pre-trained U-Net model and GAN architecture for lesion detection pertaining to haemorrhagic stroke using brain CT scans. Both generator and discriminator use ground truth to improve the process of data augmentation.

Chauhan *et al*. [16] investigated on machine learning and deep CNN models to detect cognitive performance of patients diagnosed with stroke. From lesion image of patient, their method could extract features and use regression methods for detecting cognitive performance. They have used Principal Component Analysis (PCA) based approach for pre-processing. Anupama *et al*. [17] focused on finding brain abnormalities automatically using CT scans. Their methodology is based on synergic deep learning. It has provision for image segmentation and classification for finding samples that reflect abnormalities. They intend to use more advanced deep learning models with hyperparameter tuning in future for improving their methodology. Choi *et al*. [18] explored real time bio-signals and deep learning for stroke diagnosis. It is a sensor based approach that captures vitals of patient live and perform pre-processing and stroke prediction. Long Short Term Memory (LSTM) is the model used for diagnosis. They intend to improve it to support clinically interpretable and usable system. Havaei *et al*. [19] explored deep learning models for segmentation linked brain pathology using MRI scans. Their approach is based on CNN model towards automatic segmentation. They also explored UNet model for the same purpose. They found issues like imbalance in datasets and also insufficient training samples. In future, they intend to continue research with more training samples. Akkus *et al*. [20] investigated on different deep learning models and imaging techniques for segmentation of brain MRI images. Their research includes different variants of CNN and the role of transfer learning in medical image analysis.

Table 1 Summary of literature findings on deep learning models with MRI and CT scans for stroke detection

IMAGE DATA	REFERENCES	METHODS	DATASETS
MRI scans	Zhang *et al.* [1]	R-CNN, SSD, and YOLOv3	Dataset obtained from two local hospitals of Grade III A
	Lundervold *et al*. [3]	Deep CNN models and variants.	Dataset collected from hospitals in NIFTI format
	Lundervold *et al*. [3]	CNN variants	[61, 62, 63]
	Zhou *et al*. [4]	VAE	[64]
	Basak *et al*. [5]	CNN variants	ATLAS dataset
	Wenshan *et al*. [6]	GAN (cGAN) model	ATLAS dataset
	Farsania *et al*. [7]	Automated lesion segmentation	Dataset collected from 106 patients
	Sathish *et al*. [8]	DWI and PWI	SPES dataset from the challenge
	Shah *et al*. [9]	CNN architecture	benchmark ISLES 2015 challenge dataset
	Zhou *et al*. [10]	D-UNet framework	Lesions-After-Stroke (ATLAS) dataset
	Wood *et al*. [12]	Natural language processing (NLP)	PACS

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	Acharya *et al*. [13]	SVM Poly, SVM Poly, k-NN and PNN.	LACS, PACS, TACS
	Chauhan *et al*. [16]	CNN, Ridge Regression Method and SVR	Dataset collected from local hospital
CT scans	Raghavendra *et al*. [11]	k-NN, PNN and SVM	Dataset obtained from hospitals
	Lu *et al*. [15]	U-net	[65, 66]
	Anupama *et al*. [17]	GC-SDL model	ICH dataset

Tandel *et al*. [21] focused on cancer classification based on deep learning. Stier *et al*. [22] explored tissue fate features using deep learning for stroke detection. Many other research contributions [23-60] have covered a variety of deep learning and swallow methods towards brain stroke detection. From the literature, it is found that plenty of deep learning models and their variants are in use for brain stroke prediction research. As summarized in Table 1, there are shallow and deep models used for stroke detection. Another important observation is that MRI and CT scans based deep learning approaches are found and various datasets are also available. It is observed from the literature that stroke diagnosis is given importance. However, there is need for more comprehensive framework for not only efficient stroke diagnosis but also severity region detection. In this paper, we proposed such framework and evaluated with MRI scans dataset.

III. MATERIALS AND METHODS

The ATLAS MRI dataset is obtained from [67] for empirical study. It is widely used dataset for brain stroke research. It has 955 T1-weighted MRI scans along with metadata. Out of the 955 samples, it has 655 samples for training and 300 samples for testing. *A. The Framework*

We proposed a framework known as Automated Deep Learning based Brain Stroke Detection Framework (ADL-BSDF) as illustrated in Fig. 1. It has provision for brain stroke detection and also finding the region of severity. The stroke detection is achieved by using LeNet architecture which is a CNN variant. The detection of abnormal region with severity is done using deep autoencoder based approach. The given dataset is subjected to pre-processing which includes denoising using Median filter for improving quality of images. Each pixel value is replaced by median of its neighbouring pixels. Afterwards normalization is performed considering pixel range between 0 and 1. Normalization computation is done as in Eq. 1.

$$I(new) = \frac{I-I(min)}{I(max)-I(min)} \quad (1)$$

Once pre-processing is done, a CNN model known as LeNet is built as part of brain stroke detection process. Then the model is compiled and fit to obtain a trained model. The trained model is saved to reuse it as required. This comes under training phase. As part of testing phase, the test data samples and saved CNN model are loaded. The loaded trained model is used to predict stroke from given test samples. Then the performance of the model is evaluated with metrics such as accuracy.

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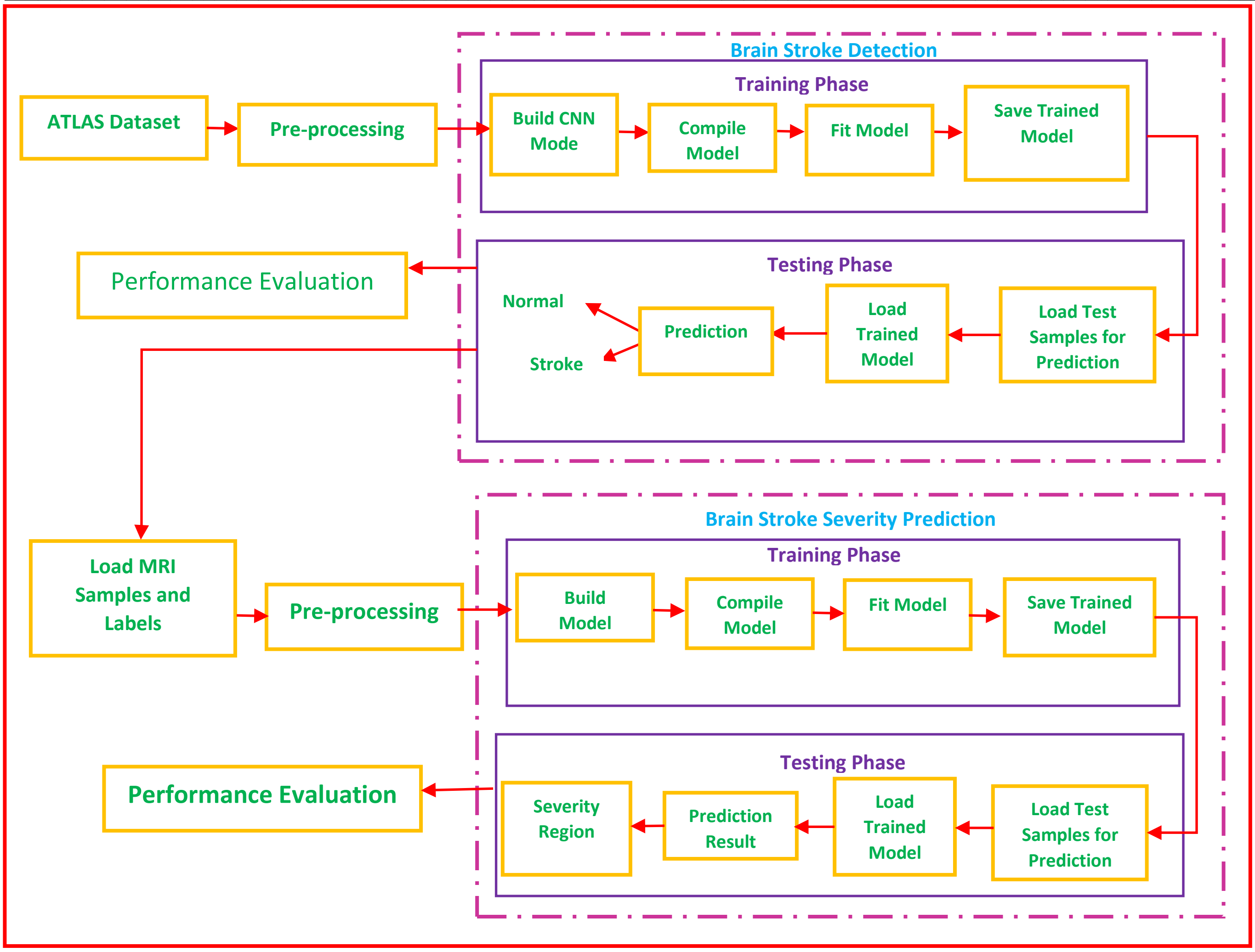

Fig. 1 Automated Deep Learning based Brain Stroke Detection Framework (ADL-BSDF)

In the brain stroke severity prediction part of the framework, a deep auto encoder is implemented with provision for encoding and decoding. It has training and testing phases to learn from given samples and predict the severity region from given test samples. More details pertaining to brain stroke detection and severity region prediction are provided in the following sub sections.

B. Stroke Prediction

A CNN variant known as LeNet explored in [2] is used for automatic brain stroke detection. Its architecture is as shown in Fig. 2. It has 7 layers consisting of 3 convolution layers, 2 max-pooling layers, 1 fully connected layer and 1 output layer. Input image considered is of 197x233x1. The feature map generated by the layers are feature map with 66x78x6, feature map with 22x26x6, feature map with 6x8x16 and feature map with 66x78x6. Number of neurons used in fully connected layer is 128 while 2 output nodes are used in softmax layer.

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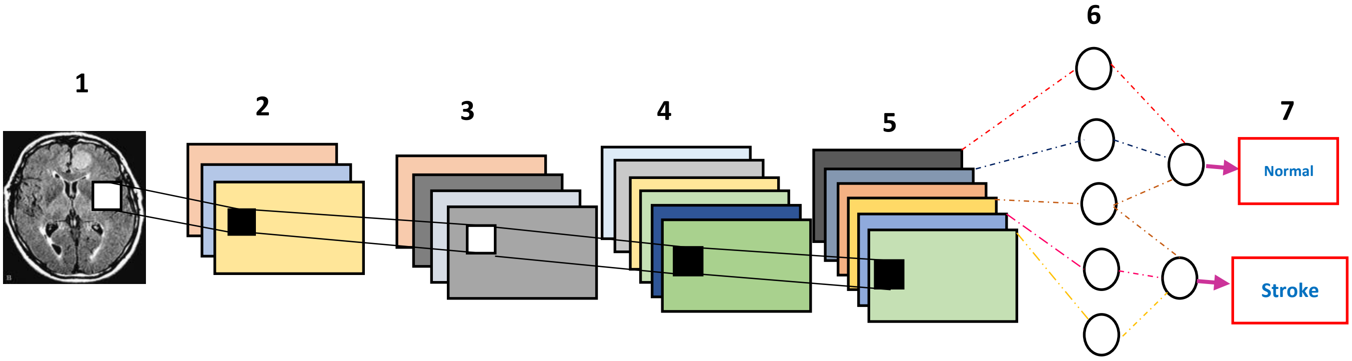

Fig. 2 Architectural overview of LeNet

Feature extraction from given medical image is carried out by convolutional layers. Filters involved in convolutional layers perform convolutions, learn relationships among pixels to acquire feature map. Outcome of convolutional layer is given as input to ReLU activation and dropout layers to get rid of overfitting. ReLU activate positive value neurons and convert negative value neurons to zero. This activation function is computed as in Eq. 2.

$$f(x) = \begin{cases} 0 \; for, & x < 0 \\ X \; for, & x \geq 0 \end{cases} \qquad (2)$$

Output of this convolutional layer is passed to the ReLU activation followed by dropout layer for avoiding over fitting. The ReLU activation function convert negative value neuron into zero and only activate positive value neuron. ReLU activation function is calculated based on equation (2). The positive value neurons are given as input to the max-pooling layer. The max-pooling layer performs dimensionality reduction to optimize feature map. Finally, the optimized feature map is given to fully connected layer. This layer flattens output into a vector and send it to softmax function where probability of two classes is computed as expressed in Eq. 3.

$$F(xi) = \frac{e^{xi}}{\sum_{j=0}^{k} xj} \qquad (3)$$

Where input image probability is denoted by x and k denotes number of classes. The software function computes probability for two classes. After creating the model, it is compiled an optimizer known as Stochastic Gradient Descent (SGD). This optimizer evaluates model with a random sample with given learning rate between 0.0 and 1.0. A binary cross entropy function is used to compute loss. The usage of loss function and SGD as optimizer result in optimizing weights of given samples to facilitate model performance evaluation. For each epoch, this process is continued. The cross entropy is computed as in Eq. 4.

$$\text{Cross entropy} = -\sum_{i}^{c} yi \; \log xi \qquad (4)$$

As the problem is related to binary classification, the value for c is given as 2. The cross entropy loss on the other hand is computed as in Eq. 5.

$$\text{Cross entropy} = -y1 \log(x1) \; - (1 - y1) \log(1 - x1) \qquad (5)$$

Where label of one hot encoder with a value range between 0 and 1 is denoted as yi while the outcome of fully connected layer is denoted as xi. The CNN model is trained using given size and number of epochs. Batch size refers to number of training samples in a batch while epoch refers to, for all training samples, one forward pass and one backward pass. Considering overfitting and underfitting problems, number of epochs is determined. With the LeNet model, 25 epochs with 64 as batch size are used in the training process. Once training is completed, the trained model is saved to reuse it later. In order to predict class labels for unseen test samples, the trained model is used. It results in prediction of two class labels such as Normal and Stroke.

Algorithm: CNN-based Deep Learning for Brain Stroke Detection (CNNDL-BSD)
Inputs: ATLAS MRI dataset D
Output: Classification results R, Performance statistics P

1. Begin
2. D'←PreProcess(D)
3. (T1, T2)←SplitDataset(D')
4. Build LeNet model m
5. Compile m
6. m←FitModel(T1)
7. Persist m
8. Load test data T2
9. Load trained mode m
10. R←TestModel(m, T2)
11. P←EvaluateModel(R, ground truth)
12. Display R
13. Display P
14. End

Algorithm 1: CNN-based Deep Learning for Brain Stroke Detection (CNNDL-BSD)

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As presented in Algorithm 1, it takes ATLAS MRI dataset D as input and performs prediction of brain stroke. The given dataset is subjected to pre-processing which includes denoising using Median filter for improving quality of images. Pre-processing results in an improved dataset D'. In Step 3, the dataset is split into training and testing sets denoted as T1 and T2 respectively. Afterwards LetNet based CNN architecture with different layers as illustrated in Figure 2 is built in Step 4. In Step 5, the model is compiled. Than the model is trained with T1. The training results in useful knowledge model which is saved for future usage. This is the end of training process. In the testing phase, the test dataset T2 and the saved model m are loaded. Then the model is subjected to testing with T2 as set of test samples. The test results are assigned to R while performance statistics are assigned to P. Finally, the algorithm returns outputs in terms of prediction results for each test sample (Normal or Stroke) and performance of the proposed model in terms of precision, recall, F1-score and accuracy.

C. Severity Region Detection

Detection of severity and the abnormal region in the brain plays crucial role in medical image analysis. Towards this end we proposed a deep autoencoder architecture as presented in Fig. 3. It has encoder and decoder components in order to achieve desired results. Then it has provision for pixel wise classification in order to detect severity region. Encoder is made up of 4 convolutional layers with 64, 128, 256 and 512 filters respectively. Each filter is of size 2x2. The convolutional layers produce a set of feature maps which are subjected to normalization. In the process ReLU is used to get rid of negative values and replace with zero padding in order to preserve image dimensions. The encoder also has 3 max pooling layers considering 2x2 window size. Thus encoder feature map holds pooling indices.

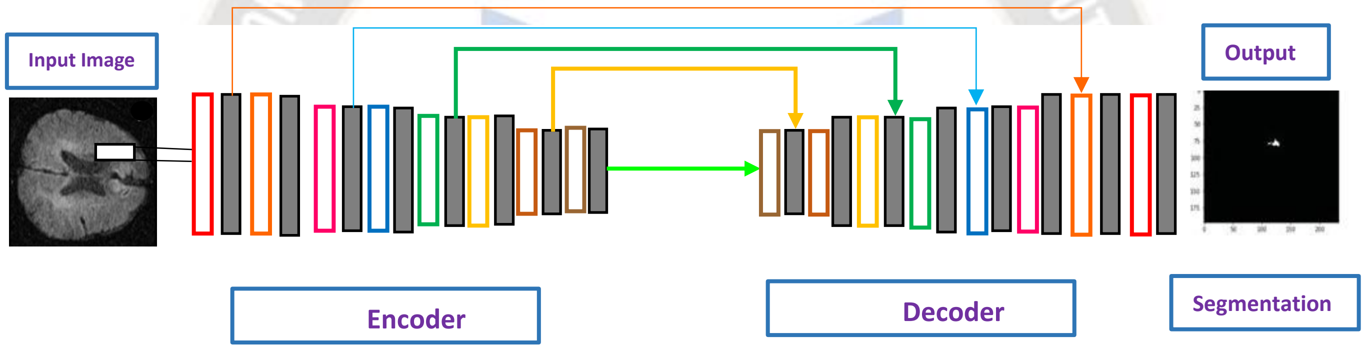

Fig. 3 Deep auto encoder for severity region detection

Decoder is made up of 4 convolutional layers with different sized filters such as 512, 256, 128 and 64 respectively. The decoding process also involves in batch normalization and 3 upsampling layers instead of max pooling layers. The pooling indices of the encoding process are used in decoder. It makes use of the convolutional layers to reconstruct feature maps with same number of channels, size and features. Afterwards, the result of decoder is given to softmax function that performs severity region detection corresponding to the two class labels. Once the model is created, it is compiled using SGD optimizer. SGD takes samples and chooses mini-batches to reduce noise and testing loss. Loss is computed in the form of Mean Square Error (MSE) as expressed in Eq. 6.

$$\text{Mean Squared error} = \frac{1}{N}\sum_{i=1}^{N}(yi - \overline{y1}) \qquad (6)$$

Where array of pixels is denoted as N, probability is denoted by yi and predicted probability is denoted as $y1$. With batch size 5 and number of epochs 35, the model is trained. After training, the resultant model is saved for further usage. In order to test the model, unseen brain MRI (abnormal) images are given as input. With the underlying procedure, the proposed autoencoder based model is able to predict severity region in the abnormal images.

Algorithm: Autoencoder based CNN for Stroke Severity Detection (ACNN-SSD)
Inputs: Test MRI scans with labels T2
Output: Stroke severity detection results R

1. Begin
2. Initialize an image vector T
3. For each sample t2 in T2
4.   IF label of t2 is Stroke Then
5.   Add t2 to T
6.   End If
7. End For
8. encoderLayers←AddLayers(Conv2D, MaxPooling, Zero Padding, Activation)
9. E←CreateEncoderNetwork(encoderLayers)
10. decoderLayers← AddLayers(Conv2D, UpSampling, Zero Padding, Activation)
11. D←CreateDecoderNetwork(decoderLayers)
12. Compile E and D
13. features←Encoder(T)
14. reconstructedFeatures ←Decoder(T,features)

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15. region←findSeverityRegion(T, features, reconstructedFeatures)
16. Update R with detected regions
17. Display R
18. End

Algorithm 2: Autoencoder based CNN for Stroke Severity Detection (ACNN-SSD)

As presented in Algorithm 1, it takes Test MRI scans T2 with labels as inputs and produces stroke severity detection results R. From Step 3 to Step 7 there is an iterative approach in identifying only Stroke diagnosed samples (taken from the results of Algorithm 1) and add them to T. Now T holds only Stroke samples. In Step 8 and Step 10 encoder and decoder layers are constructed based on illustration in Figure 3. Step 9 and Step 11 are meant for creating Encoder E and Decoder D respectively. Then both encoder and decoder are compiled. Encoder performs its functionality to obtain features in Step 13. In the same fashion, Decoder performs its functionality to reconstruct features in Step 14. With the process of encoding and decoding, there is detection of severity Stroke regions as in Step 15. Then severity detection results R is returned by the algorithm.

D. Performance Evaluation

Performance of the proposed framework is evaluated based on the prediction results found in the empirical study. The proposed model in the underlying framework has provided the prediction results along with confusion matrix reflecting number of True Positives (TP), number of True Negatives (TN), number of False Positives (FP) and number of False Negatives (FN). These values are used to compute performance of the model in terms of precision, recall, F1-score and accuracy. These are computed as in Eq. 7, Eq. 8, Eq. 9 and Eq. 10 respectively.

$$\text{Precision } (p) = \frac{TP}{TP+FP} \quad (7)$$

$$\text{Recall } (r) = \frac{TP}{TP+FN} \quad (8)$$

$$\text{F1-score} = 2 * \frac{(p * r)}{(p+r)} \quad (9)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

All these metrics are evaluated to result in a value ranging from 0 to 1 indicating least and highest performance.

IV. RESULTS AND DISCUSSION

The proposed framework known as ADL-BSDF and its underlying algorithms such as CNNDL-BSD and DA-SSD meant for stroke detection and severity prediction respectively are evaluated using dataset collected from [67]. Table 2 shows the execution environment used in the empirical study.

Table 2: Environment details

Item	Description
Coding language	Python
CPU	Intel Xeon (2 GHz)
Environment	Google Colab
GPU	Tesla P100
Operating System	Windows
RAM	16 GB

Results of experiments are compared with state of the art deep learning models such as ResNet50 and DenseNet121. The proposed framework ADL-BSDF has two architectures to achieve stroke detection and severity prediction. The former is LeNet taken from [2] while the latter is deep autoencoder based architecture. Table 3 shows hyper parameters used in the experiments of the two architectures.

Table 3: Shows hyper parameters and values

Hyper parameter	Parameter value	
	LeNet	**Deep Autoencoder**
Learning rate	**0.001**	**0.001**
Optimization	Gradient descent	Stochastic gradient descent
Batch Size	**64**	**128**
Number of epochs	**25**	**20**
Dropout	**0.5**	**0.5**

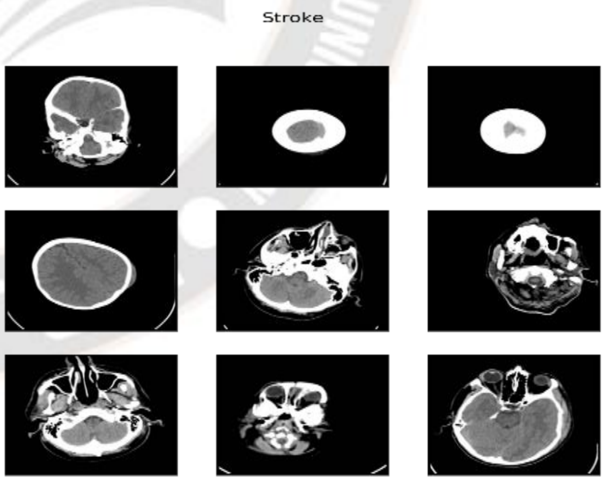

Fig. 4 Brain stroke samples from ATLAS dataset

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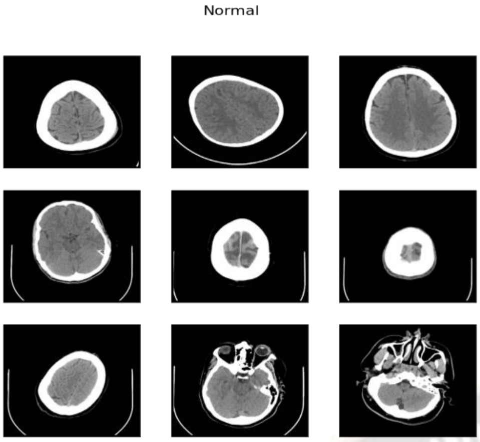

Fig. 5 Brain normal samples from ATLAS dataset

As shown in Fig. 4 and Fig. 5, an excerpt from brain MRI dataset [67] is provides with stroke and normal samples.

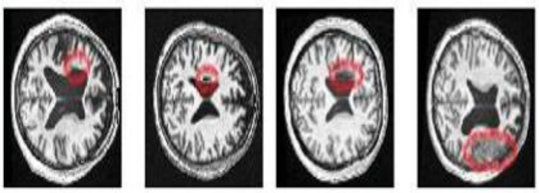

Fig. 6 Brain stroke images

Fig. 7 Brain stroke images with ground truth

As shown in Fig. 6 and Fig. 7, brain stroke images and their corresponding images with ground truth pertaining to affected region respectively.

Table 4 Stroke prediction results for a single image

Input Image	Stroke Probability	Prediction Result
	[[0.72723945, 0.27266246]]	Normal
	[[0.12587873,0.79603426]]	Abnormal

As shown in Table 4, the stroke detection results are provided for a single image. In the first experiment, given brain image is detected to be normal due to its probability distribution between normal and abnormal. In the same fashion, in the second experiment, the given input image is detected to be abnormal. This way, it is observed that the saved model (as per Algorithm 1) is capable of detecting the presence of absence of stroke correctly. When a bulk of test images is given, the performance of the proposed prediction model is evaluated and the results are provided in Table 5.

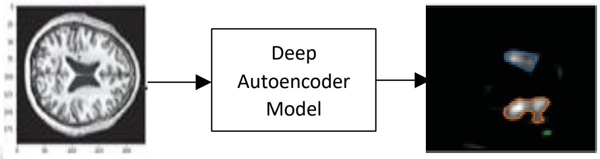

Fig. 8 Result of severity region detection

As shown in Fig. 8, the result of deep autoencoder model is provided. Multiple experiments are made like this and the performance of deep autoencoder model in terms of accuracy is found to be 86%.

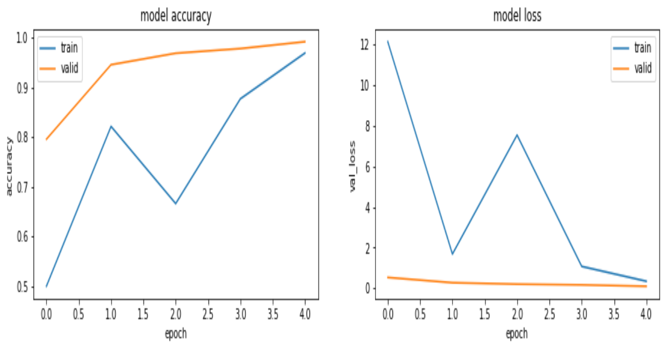

Fig. 9 Model accuracy and model loss exhibited by DenseNet121

As presented in Fig. 9, model accuracy and model loss values against 40 epochs of DenseNet121 are provided. These observations are related to brain stroke detection using MRI images.

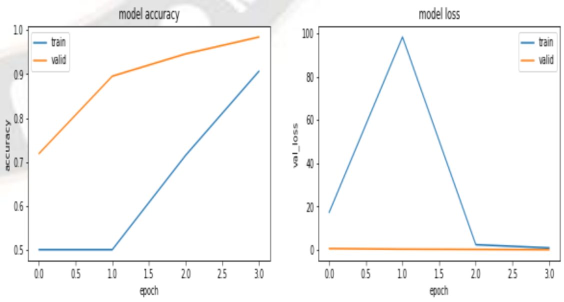

Fig. 10 Model accuracy and model loss exhibited by ResNet50

As presented in Fig. 10, model accuracy and model loss values against 30 epochs of ResNet50 are provided. These observations are related to brain stroke detection using MRI images.

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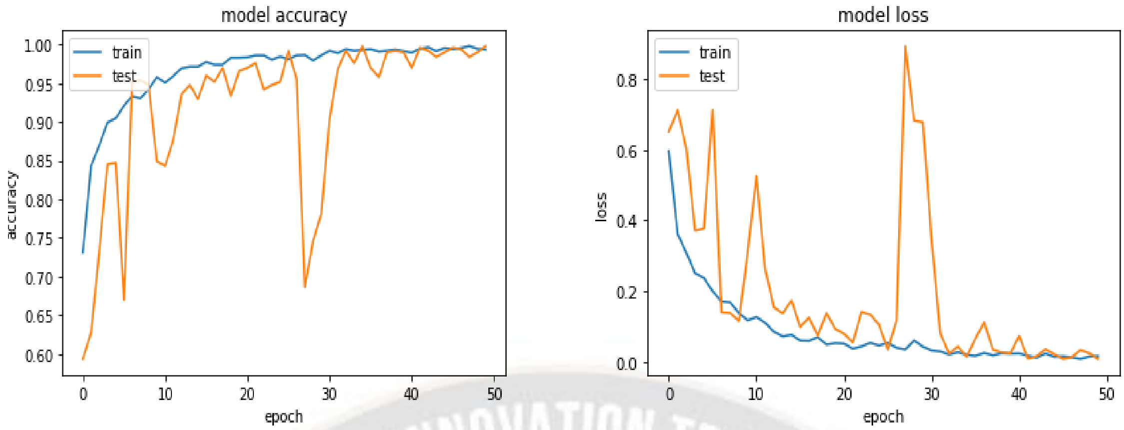

Fig. 11 Model accuracy and model loss exhibited by proposed model

As presented in Fig. 11, model accuracy and model loss values against 50 epochs of the proposed model are provided. These observations are related to brain stroke detection using MRI images.

Table 5 Performance comparison of stroke prediction models

Brain Stroke Detection Model	Performance (%)			
	Precision	**Recall**	**F1-Score**	**Accuracy**
ResNet50	0.978	0.368	0.534	0.951
DenseNet121	0.917	0.624	0.742	0.96
Proposed Model	0.9852	0.8784	0.9288	0.9812

As shown in Table 5, brain stroke detection performance of different deep learning models such as ResNet50 and DenseNet121 are compared with the proposed model.

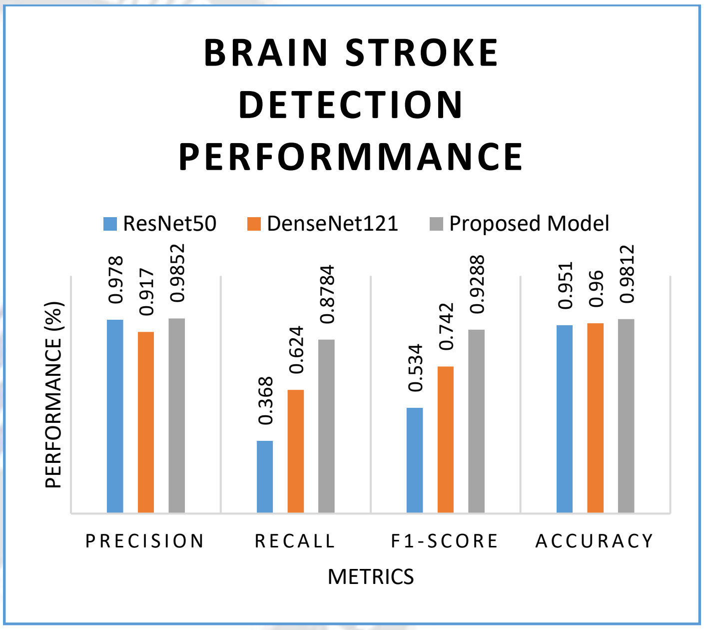

Fig. 10 Performance evaluation of proposed model against state of the art models

As presented in Fig. 10, brain stroke detection performance of the proposed model is compared against existing models such as ResNet50 and DenseNet121. These models showed different level of performance as their architectures are different with varied number of layers and filters. The precision of ResNet50 is 97.8%, DenseNet121 is 91.70% and proposed model is 98.52%. The recall of ResNet50 is 36.80%, DenseNet121 is 62.40% and the proposed model is 87.84%. With respect to accuracy of the models, ResNet50 showed 95.10%, DenseNet121 96% and the proposed model 98.12%. From the results of experiments made with ATLAS dataset [67] it is observed that the proposed model outperforms existing models with highest accuracy 98.12%.

V. CONCLUSION AND FUTURE WORK

In this paper, we investigated on deep learning models and deep autoencoder for automatic detection of brain stroke using MRI scans. A framework known as Automated Deep Learning based Brain Stroke Detection Framework (ADL-BSDF) is proposed and implemented. It is meant for realizing a Clinical Decision Support System (CDSS) to diagnose brain stroke automatically without relying on expertise of doctor. Two distinct functions such as accurate detection of stroke and stroke severity detection are incorporated in the framework. The former is realized by proposing an algorithm known as CNN-based Deep Learning for Brain Stroke Detection (CNNDL-BSD) while the latter is achieved by proposing another algorithm named Autoencoder based CNN for Stroke Severity Detection (ACNN-SSD). The framework is evaluated and found that it could achieve highest accuracy in stroke diagnosis. ADL-BSDF could accomplish highest accuracy with 98.12% when compared with state of the art deep learning models such as ResNet50 and DenseNet121 in terms of stroke diagnosis. ADL-BSDF could achieve 86% accuracy pertaining to stroke severity region detection. The proposed framework is designed to work with MRI scans only. In future, we will improve it to support CT scan images besides further enhancing the stroke severity detection module. We also intend to incorporate the notion of Region of Interest (ROI) in our future endeavour to improve prediction performance by localizing stroke affected region in brain.

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Mrs. Anitha Patil	Research Scholar, Department of Computer Science, Pondicherry University, Karaikal, Puducherry UT, India. PIN: 609605.
Dr. Sureshkumar Govindaraj	Dr.Sureshkumar Govindaraj is working as Assistant Professor in the Department of Computer Science, Pondicherry University, Karaikal, Puducherry UT, India. He earned his Master’s Degree in Computer Science and Engineering from College of Engineering Guindy, Anna University, and Chennai, India. He teaches post graduate degree engineering courses and guiding Ph.D students. His research areas of interest include Knowledge Engineering and Information Retrieval systems. He has published many papers in reputed international journals.