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DEEP CONVOLUTIONAL NEURAL NETWORK IMPLEMENTATIONS FOR EFFICIENT BRAIN STROKE DETECTION USING MRI SCANS

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ABSTRACT

Advancements in Artificial Intelligence (AI) has paved way for solving the problems in different domains. In healthcare industry, brain stroke incidence is in alarming rate across the globe. According to WHO, it is one of the leading causes of disability and depth which needs sustainable research effort. It is believed that bringing AI into Clinical Decision Support System (CDSS) has potential to have unprecedented strides in healthcare units for improving Quality of Service (QoS). The existing MRI scans based research with deep learning has limitations as it uses pre-defined CNN based models. The CNN models such as VGG16, ResNet50 and DenseNet121 have their built in functionalities. However, for a given problem, their performance may not be adequate and they are to be optimized to meet requirements of the problem in hand. To overcome this problem, in this paper, we proposed a framework and underlying mechanisms to optimize and exploit the deep CNN models aforementioned for efficient brain stroke detection. Apart from the improving the models, an algorithm named Optimized Deep Learning for Brain Stroke Detection (ODL-BSD) is proposed. MRI scans are used to evaluate the proposed framework. The empirical results revealed that the proposed methodology has caused improvement in the performance of the deep CNN models significantly.

Keywords:– *Brain Stroke Detection, Deep Learning, Convolutional Neural Network, Densenet121, Vgg16, Resnet50*

1. INTRODUCTION

Machine learning and deep learning techniques are widely used to train machines and provide them needed intelligence. Advancements in Artificial Intelligence (AI) has paved way for solving the problems in different domains. In healthcare industry, brain stroke incidence is in alarming rate across the globe. According to WHO, it is one of the leading causes of disability and depth which needs sustainable research effort. There are different image technologies such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). These imaging techniques are widely used for capturing radiology based imaging of brain and other parts of the body. Since this paper focuses on the brain image analysis with deep learning models, brain MRI is preferred for the empirical study in this paper. The rationale behind this is that MRI scans are found to have more robust data that is better than CT images. It is also found in the literature and MRI based approach is preferred by most of the researchers. There are plenty of datasets available to have supervised learning approach for brain stroke detection automatically.

Different existing methods are found in the literature for medical image analysis. They catered to the ischemic stroke and haemorrhage stroke, feature selection and general medical image analysis using MRI scans. Cerebral microbleeds (CMBs) that can cause haemorrhage are investigated in [2] and [20]. In [4], [11] and [18] there is specific research on the detection of ischemic stroke. These two important categories of brain stroke are investigated using deep learning methods. Stier *et al*. [4] investigated on

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the acute ischemic stroke using MRI imagery by constructing a deep learning model that considers tissue fate features. Wang *et al*. [11] proposed a methodology for automatic selection of ischemic stroke patients for endovascular treatment. Their method a hybrid one that includes deep learning and traditional cohort method to arrive at the final decisions. There is subject level evaluation procedure voxel-level evaluation. They also used ML models for the purpose of automatic selection of patients. They found that their method was useful for selection of patients for aforementioned treatment. Acharya *et al*. [18] used MRI scans for automatic detection of ischemic stroke. Their method exploits the higher order spectra features from the given dataset. It could identify blocked arteries in human brain. Importance of Brain Machine Interface (BMI) is also found in the literature. Ramos-Murguialday *et al*. [10] investigated on chronic stroke rehabilitation using Brain-Machine-Interface (BMI). They found that BMI has its role in understanding latent information of brain stroke patients. Soekadar *et al*. [14] focused on neurorehabilitation of brain stroke using brain-machine interfaces. Their proposed method has provision for inferring human brain using stimulation electrodes and MEG sensors to achieve bio signal recording, feature extraction, signal processing and finally to arrive at useful feedback. They found that multiple kinds of BMIs are required for reaping benefits in this kind of research. Caria *et al*. [22] studied the utility of BMI induced approach for modelling of "Morpho-Functional Remodeling of the Neural Motor System" in stroke patients. From the literature, it is understood that deep learning models and the usage of MRI scans are useful for brain stroke detection. It is found that different CNN models are able to provide better performance in medical image analysis. However, they need to be improved further at architecture level to have more optimized means of brain stroke detection. Our contributions in this paper are as follows.

1. We proposed a deep learning based framework for efficient detection of brain stroke using MRI scans.
2. We proposed an algorithm known as Optimized Deep Learning for Brain Stroke Detection (ODL-BSD). This algorithm exploits three optimized CNN models such as VGG16, DenseNet121 and ResNet50.
3. A prototype is built to evaluate and compare the performance of the three deep learning models.

The remainder of the paper is structured as follows. Section 2 reviews literature on MRI based ML approaches covering deep learning models for brain stroke detection. Section 3 presents the proposed methodology, models and algorithm. Section 4 presents experimental results of three optimized deep learning models. Section 5 concludes the work of this paper and gives future scope as well.

2. RELATED WORK

This section reviews literature on deep learning models that are based on MRI scans for detection of brain stroke. Karthik *et al*. [1] proposed a method based on deep learning and neuroimaging for lesion detection and segmentation. They discussed about the breakthroughs achieved deep learning in the field of medial image analysis. Liu *et al*. [2] investigated on cerebral microbleeds (CMBs) and proposed a method for detection of CMB with a two-stage framework. It has stages such as candidate detection and false positive reduction. The former is based on "3D radial symmetry transforms of the composite images from Susceptibility Weighted Imaging (SWI)" and the latter is based on "deep residual neural networks using both the SWI and the high-pass filtered phase images". Their study helped to understand the importance of deep learning with MR images. Kadam [3] used ensemble based approach for detection and classification of brain stroke samples. Stier *et al*. [4] investigated on the acute ischemic stroke using MRI imagery by constructing a deep learning model that considers tissue fate features. They used CNN based architecture for prediction of stroke. They opined that their model can be improved to be useful by healthcare units. Suk *et al*. [5] proposed ML models based on sparse regression and deep learning for diagnosis of brain diseases. Thustheir method is a hybrid approach in automatic detection of diseases. They still desired improvements in their work to have an optimal framework.

Akkus *et al*. [6] studied many existing deep learning models for MRI segmentation. They found that every deep model has its commonality in terms of feature extraction, learning and output predictions. They found that there are different approaches for medical image analysis

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based on the input images. They found lack of a generic framework that can cater to all the needs of medical image analysis. Subudhi *et al*. [7] proposed an approach for automating the detection of brain stroke using MRI scans. They exploited Delaunay Triangulation in MRI scans for improving performance. Their method involves pre-processing, segmentation and classification. They have mechanism to distinguish between stroke lesion in DWI sequences. Havaei *et al*. [8] explored the CNN based deep models for medical image analysis. They explored different architecture of CNN along with their merits and demerits. Open problems they identified are pre-processing and balancing data, global information, structured prediction and training on insufficient data. Kim *et al*. [9] studied the ML algorithms to detect brain stroke detection from MRI reports. Their methodology includes usage of Natural Language Processing (NLP), statistical analysis and model based analysis. They found that NLP is useful to have labelled data required for deep learning. Ramos-Murguialday *et al*. [10] investigated on chronic stroke rehabilitation using Brain-Machine-Interface (BMI). They found that BMI has its role in understanding latent information of brain stroke patients.

Wang *et al*. [11] proposed a methodology for automatic selection of ischemic stroke patients for endovascular treatment. Their method a hybrid one that includes deep learning and traditional cohort method to arrive at the final decisions. There is subject level evaluation procedure voxel-level evaluation. They also used ML models for the purpose of automatic selection of patients. They found that their method was useful for selection of patients for aforementioned treatment. Anupama *et al*. [12] focused on wearable networks in healthcare industry for automatic detection of intracranial haemorrhage cases. Their architecture is based on synergic deep learning model. It has pre-processing, feature extraction with the help of synergic deep learning and classification. They used deep CNN mode as part of their methodology. They intended to improve it with a method for hyper parameter tuning. Chauhan *et al*. [13] investigated on the stroke detection using MRI images. They compared with methods in ML and deep learning. Their study includes pre-processing, regression models, feature selection and prediction. Soekadar *et al*. [14] focused on neurorehabilitation of brain stroke using brain-machine interfaces. Their proposed method has provision for inferring human brain using stimulation electrodes and MEG sensors to achieve bio signal recording, feature extraction, signal processing and finally to arrive at useful feedback. They found that multiple kinds of BMIs are required for reaping benefits in this kind of research. Lundervolda and Arvid Lundervolda [15] explored MRI scan based research with deep learning for medical image analysis. They discussed different deep models for the same including their architecture, inputs and outputs. They found that MRI scans are suitable for medical image analysis. However, it is ascertained that there are challenges pertaining to "data, trust, interpretability, workflow integration, and regulations".

Talo *et al*. [16] proposed a deep transfer learning method for automatic detection of brain abnormalities using brain MRI scans. They proposed a 3 stage deep learning framework consisting of ResNet34 configured differently in each stage. With augmented brain MRIs, in each stage, it has provision for classification to detect normal or abnormal brain sample. Bagavathi [17] investigated on interpretation of brain imagery using ML and deep learning methods. They found that feature fusion is one of the approaches that could improve performance in image analysis. Acharya *et al*. [18] used MRI scans for automatic detection of ischemic stroke. Their method exploits the higher order spectra features from the given dataset. It could identify blocked arteries in human brain. Saba *et al*. [19] focused on a hybrid approach in feature selection. It includes a hand crafted approach and deep learning approach. The features obtained in each approach are subjected to fusion for efficient brain tumor detection. They used VGG19 method for obtaining features and they are fused with hand crafted features. Myung *et al*. [20] investigated on CMBs using deep learning models. They built an algorithm with pre-processing, learning and classification for detection of CMBs.

Wood *et al*. [21] proposed a methodology for automatic labelling of brain MRI datasets using deep learning. Their method is useful to computer vision applications. They trained different models in order to achieve this. Caria *et al*. [22] studied the utility of BMI induced approach for modelling of "Morpho-Functional Remodeling of the Neural Motor System" in stroke patients. Al-Galal *et al*. [23] explored different methods used for medical image analysis using MRI images particularly with

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brain tumor cases. Their study encapsulates image registration, detection, segmentation and classification. From the literature, it is understood that deep learning models and the usage of MRI scans are useful for brain stroke detection. It is found that different CNN models are able to provide better performance in medical image analysis. However, they need to be improved further at architecture level to have more optimized means of brain stroke detection. In other words, the main research gap found is that pre-trained models based on CNN cannot directly yield desired optimal performance in brain stroke detection. They are to be optimized with changes at architecture level in order to reap their benefits based on the problem in hand.

3. PROPOSED METHODOLOGY

This section presents the proposed deep learning based framework, the underlying models, algorithms and evaluation procedure.

3.1 Problem Statement

Provided the computer vision problem such as brain stroke detection using MRI scans, the pre-trained CNN models available provide deteriorated performance unless they are enhanced. This is the challenging problem considered and addressed in this paper.

3.2 The Framework

We proposed a framework that exploits optimized deep CNN models for brain stroke detection automatically from MRI images. It is found from the literature that existing deep CNN models have limitations with MRI image analysis. Due to differences in datasets in every domain, just fine tuning the CNN models is not adequate. There is need for an optimization strategy for leveraging such models for brain stroke detection. Our optimization strategy is based on the inspiration gained from the work in [25]. The optimized architectures of deep learning models such as DenseNet121, ResNet50 and VGG16 are provided in the subsequent sections. The strategy is used to configure layers differently in order to have improved performance with brain MRI scans. Thus the models are built in such a way that they work well with large and also small datasets. The drawback of them to work with only large datasets for which they are originally built is overcome with the optimization strategy.

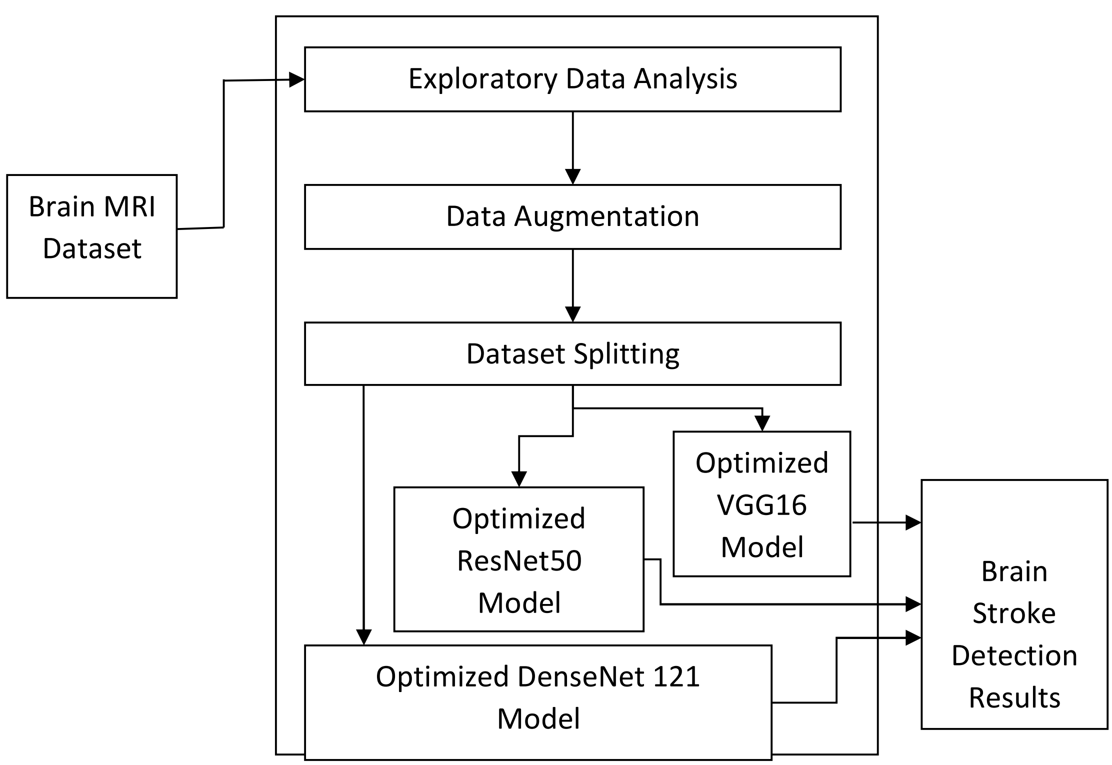

Figure 1: Proposed Deep Learning Based Framework For Efficient Brain Stroke Detection

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As presented in Figure 1, the proposed framework takes brain MRI scans as dataset for the empirical study. Dataset is subjected to exploratory data analysis which results in important findings such as the number of samples for training, testing and validation. It also provides clue for the need of data augmentation techniques so as to improve quality of training. The techniques used for data augmentation include random flip, random rotation and random zoom. The dataset is split into training, validation and testing samples appropriately to avoid overfitting. Then the optimized deep CNN models such as DenseNet121, ResNet50 and VGG16 are used appropriately for improving prediction performance. These models are capable of learning from training samples and predict the probability of brain stroke in given test samples.

Table 1: *Notations used in the mathematics of this paper*

Notation	Description
x and y	Input and output vectors of the layers
$F(x, \{W_i\})$	Residual mapping
W_s	A linear projection
Y	Label
p(y)	Predicted **probability of the point being green** for all **N** points.
Log(p(y))	Log probability of it being green
Log(1-p(y))	Log probability of it being red
N	Points
TP	True positive
FP	False positive
FN	False negative
TN	True negative

As provided in Table 1, there are different mathematical notations that are useful to understand equations used in this paper.

3.3DenseNet121

By modifying standard CNN model DenseNet121 is created to solve the problem of vanishing gradients. Between layers in DenseNet121, the connectivity patterns are simplified. In the case of ResNet, gradients flow directly from layer to layer via identity block. This approach is further improved in DenseNet as it has direct connections from a layer to all the subsequent layers. Thus it allows any layer can receive, from preceding layers, concatenation of feature maps.

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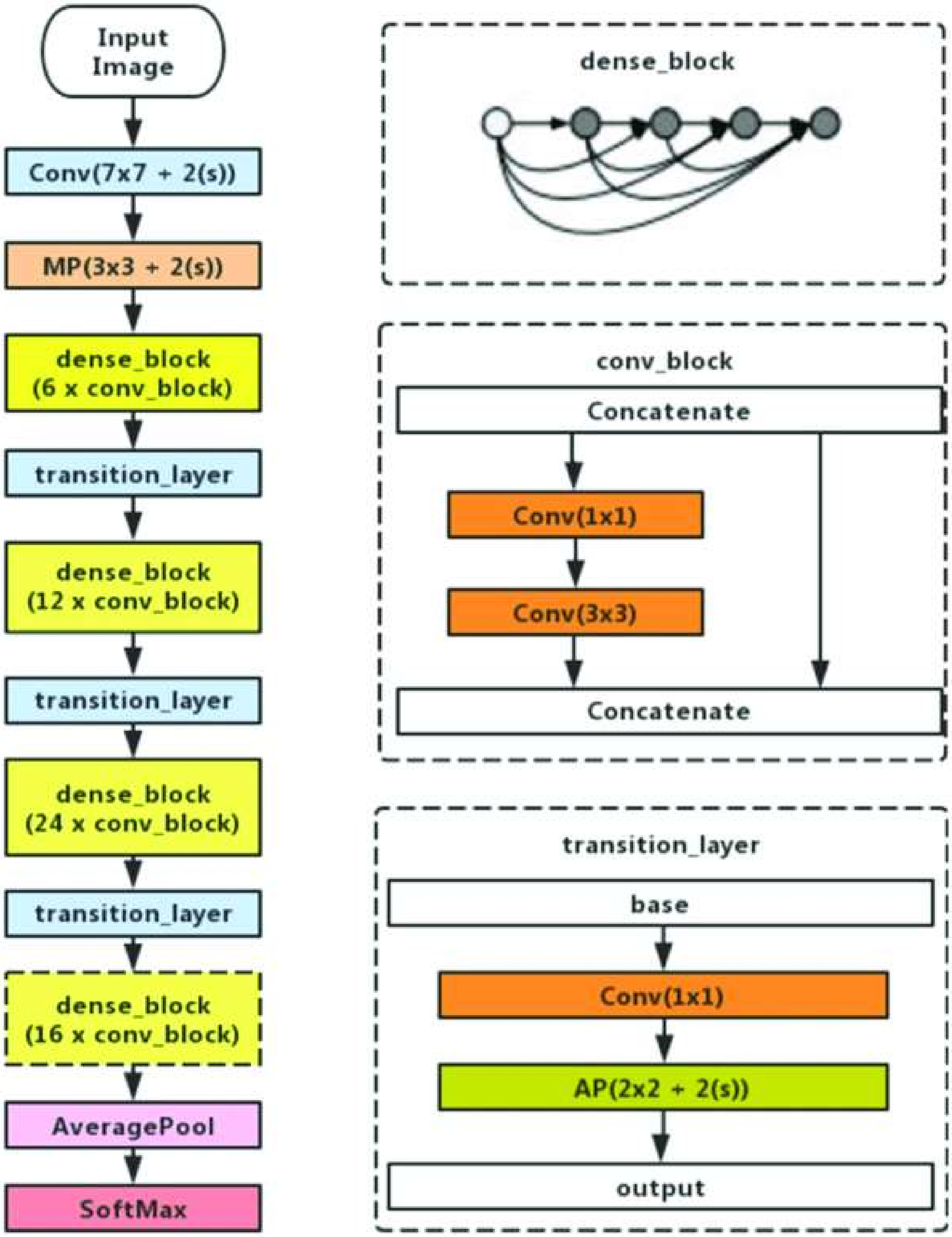

Figure 2: Densenet121 Architecture (Left) And Its Blocks (Right)

As presented in Figure 2, three kinds of blocks are involved in the implementation of DenseNet. They are known as convolution block, dense block and transition layer. The basic block in dense block is known as convolution block. It is similar to the ResNet's identity block. In the dense block, there are convolution blocks are densely connected and concatenated. The main component in the DenseNet is known as Dense block. Any two contiguous dense blocks in DenseNet are connected through transition layer. As the size of feature maps is same in the layers of dense block, the transition layer plays crucial role by reducing dimensions in the given feature

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map. This approach is known as bottleneck design that improves performance of the model.

3.4ResNet50

ResNet50 is a deep residual learning model suitable for medical image analysis. It is of 50 layers deep. It is a kind of CNN which are very deep with its innovative approach with skip connection. In the implementation of ResNet50, there are two kinds of shortcut modules namely convolution block and identity block. The former has convolution layer at shortcut while the latter does not have it. In convolution block out dimensions are bigger than input dimensions. Whereas in the identity block, output dimensions are same as that of input. In case of the both blocks, at the start and end, 1x1 convolution layers are present. This kind of approach is known as bottleneck design used for reducing number of parameters without performance degradation. In the empirical study some deep shortcut modules are removed and some classification layers are added.

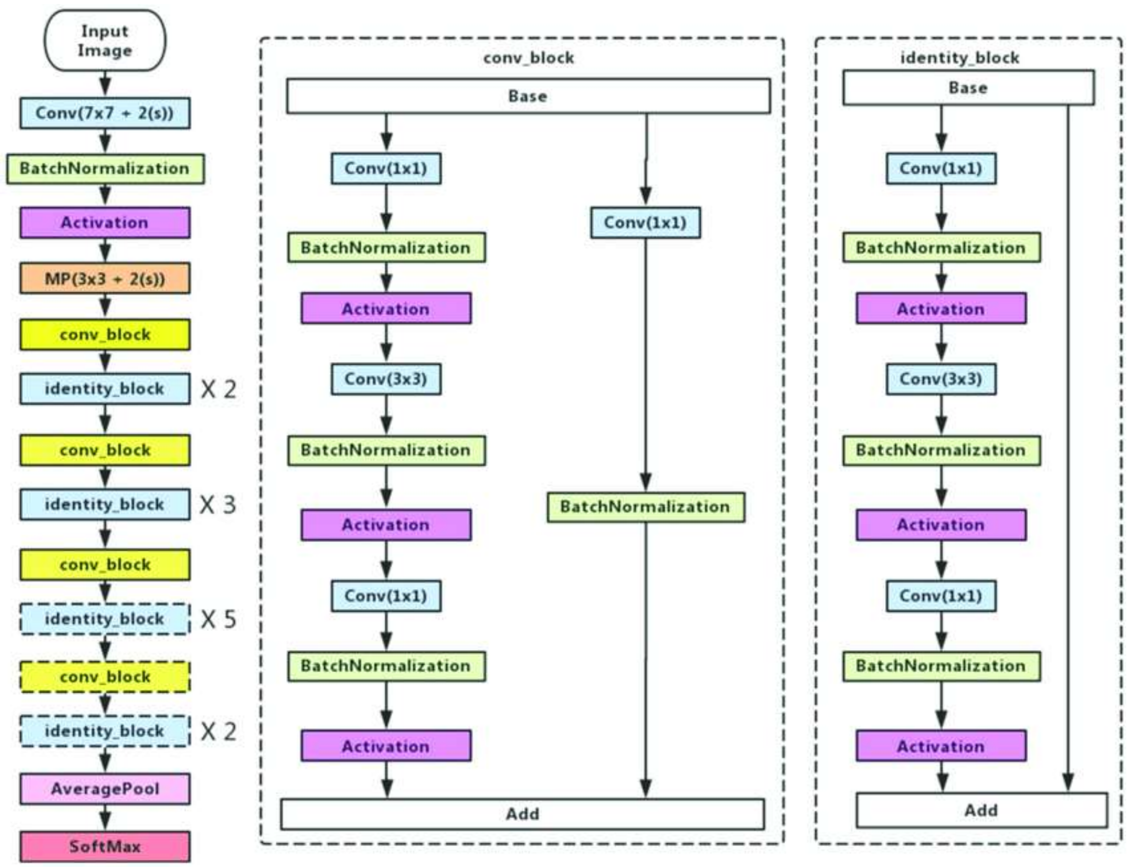

Figure 3: Resnet50 Architecture (Left), Convolution Block (Middle) And Identity Block (Right)

As presented in Figure 3, the modified ResNet architecture is shown while the middle and right diagrams show the convolution block and identity block respectively. The blocks in ResNet50 architecture with dotted line indicate the ones that are removed in our study based on requirement. The convolution block changes input dimensions while the identity block does not change dimensions of input. A building block in the residual learning process is expressed as in Eq. 1.

$$y= F(x, \{W_i\}) + x. \quad (1)$$

The input and output vectors are denoted by x and y while the process of residual mapping is denoted by F(x, $\{W_i\}$). Eq. 1 also expresses shortcut connection without introducing extra parameters and does not lead to computational complexity. In practice, it is the optimized approach that improves performance. If the dimensions of x and F are not same in the Eq. 1, then a linear projection is performed as expressed in Eq. 2 for achieving that.

$$y= F(x, \{W_i\}) + W_s x. \quad (2)$$

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where W_s refers to the linear projection and it is used appropriately only when there are matching input and output dimensions. The residual function is flexible and F(x, $\{W_i\}$) can denote multiple convolutional layers.

3.5VGG16

VGG16 is a variant of CNN with 16 layers. Its architecture was originally introduced by "Karen Simonyan and Andrew Zisserman from the University of Oxford, in the year 2014". It is widely used for large scale image analysis applications. It has the following 16 layers as illustrated in Figure 4.

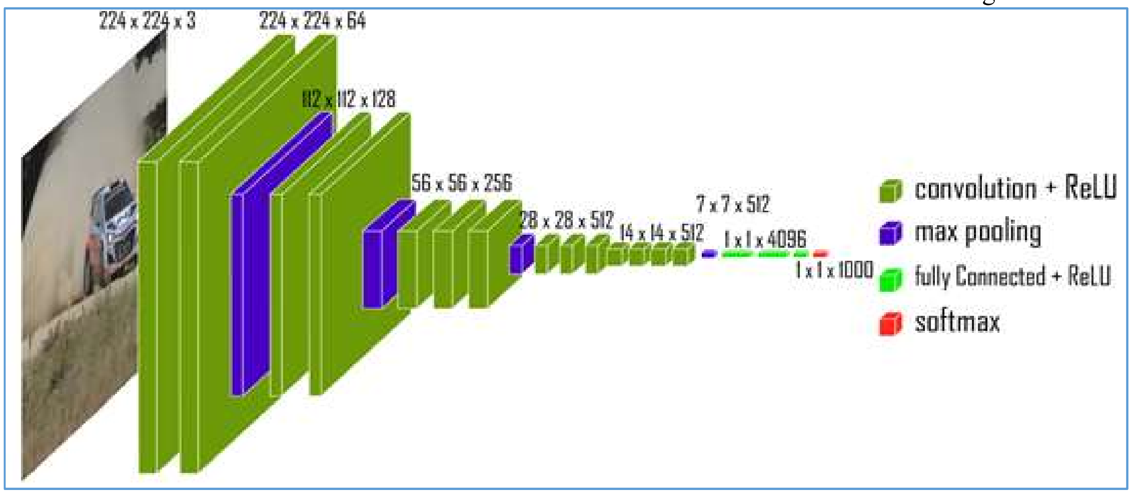

Figure 4: Architecture Of VGG16 Model

The VGG16 model widely used in computer vision applications. It is an innovative approach in which CNN is modified. Its layers include Convolution using 64 filters, Convolution using 64 filters + Max-pooling, Convolution using 128 filters, Convolution using 128 filters + Max-pooling, Convolution using 256 filters, Convolution using 256 filters, Convolution using 256 filters + Max-pooling, Convolution using 512 filters, Convolution using 512 filters, Convolution using 512 filters + Max-pooling, Convolution using 512 filters, Convolution using 512 filters, Convolution using 512 filters + Max-pooling, Fully connected with 4096 nodes, Fully connected with 4096 nodes and Output layer with Softmax activation with 1000 nodes.

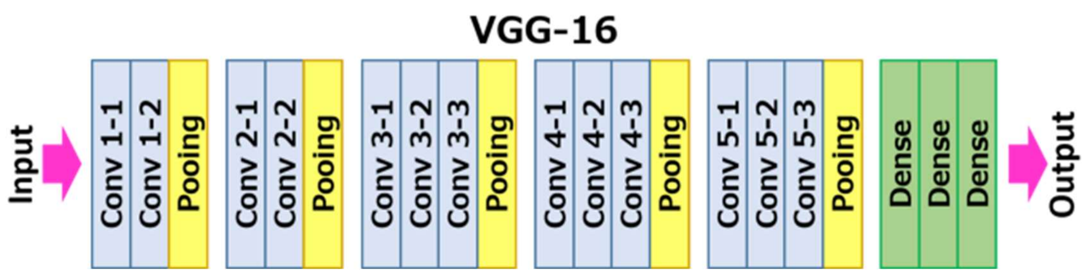

Figure 5: Architecture Of VGG-16 With Different Layers

As presented in Figure 5, it has different layers. The convolution layers are following by pooling layer. At the end, it has three dense layers prior to producing its outcomes. The given brain MRI scan image is processed by first 2 convolution layers of size 3x3 followed by activations (ReLU). Each convolution layer as 64 filters. They preserve spatial resolution and output is same as that of input in terms of dimensions. This way different stacks of convolution layers are executed with given number of filters and other configurations. Finally, after all stacks of convolution layers, there are three fully connected layers with flattening layer between them. There are 4096 neurons in first two while the last layer has 1000 neurons. The softmax activation layer finally provides classification results.

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Table 2: Hyper Parameters Used In The Deep Learning Models

Hyper Parameter	Value		
	VGG16	**ResNet50**	**DenseNet121**
Batch size	16	16	16
Loss function	Binary cross entropy	Binary cross entropy	Binary cross entropy
Optimizer	Adam	Adam	Adam
No. of Epochs	50	50	50
Learning rate	0.001	0.001	0.001
Activation function	Sigmoid	Sigmoid	Sigmoid

As presented in Table 2, different hyper parameters used in each deep learning model are provided with corresponding values.

3.5 Proposed Algorithm

An algorithm named Optimized Deep Learning for Brain Stroke Detection (ODL-BSD) is proposed and implemented.

Algorithm: Optimized Deep Learning for Brain Stroke Detection (ODL-BSD)

Inputs:
Brain MRI dataset *D*
Pipeline of deep learning techniques *T*
(pipeline includes VGG16, ResNet50 and DenseNet121)
Output:
Brain stroke prediction results *R*
Performance statistics *P*

1. Start
2. Initialize results map *M*
3. *findings*←EDA(*D*)
4. IF *findings*are true reflecting need for augmentation THEN
5. D'←DataAugmentation(*findings*, *D*)
6. End If
7. *D*←*D'*
8. (*T1*, *T2*)←PreProcess(*D*)
9. For each technique *t* in *T*
10. *F*←FeatureExtraction(*T1*)
11. Train the model *t* using *F*
12. Fit the model *t* for *T2*
13. Add results to *R*
14. Add performance statistics to *P*
15. Add *P* and *R* to *M*
16. End For
17. For each map entry m in *M*
18. Display *R*
19. Display *P*
20. End For
21. End

Algorithm 1: Optimized Deep Learning for Brain Stroke Detection (ODL-BSD) algorithm

Algorithm 1 takes brain MRI dataset D and pipeline of deep learning techniques *T* (pipeline includes VGG16, ResNet50 and DenseNet121) as input and returns outputs in the form of brain stroke prediction results *R* and performance statistics *P*. The algorithm has exploratory data analysis and it is followed by required data augmentation to improve quality of training data. The dataset is subjected to pre-processing where it is split into training and testing sets. The training set is used by the deep learning models in order to predict class label for the unlabelled data. Each model provides the results of classification and also performance metrics.

3.5 Brain MRI Dataset

The brain MRI dataset collected from Kaggle datasets [24]. It has 2251 brain MRI scans. Out of which 1801 samples are in training set and 450 samples are in test set.

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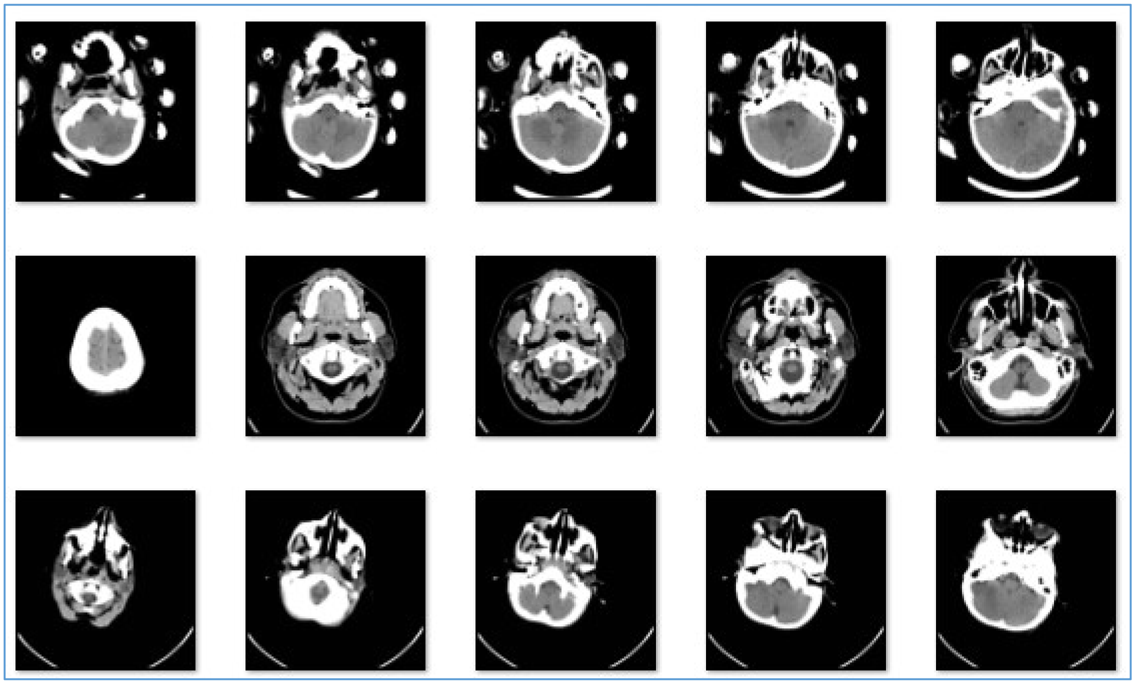

Figure 6: *Brain stroke MRI samples*

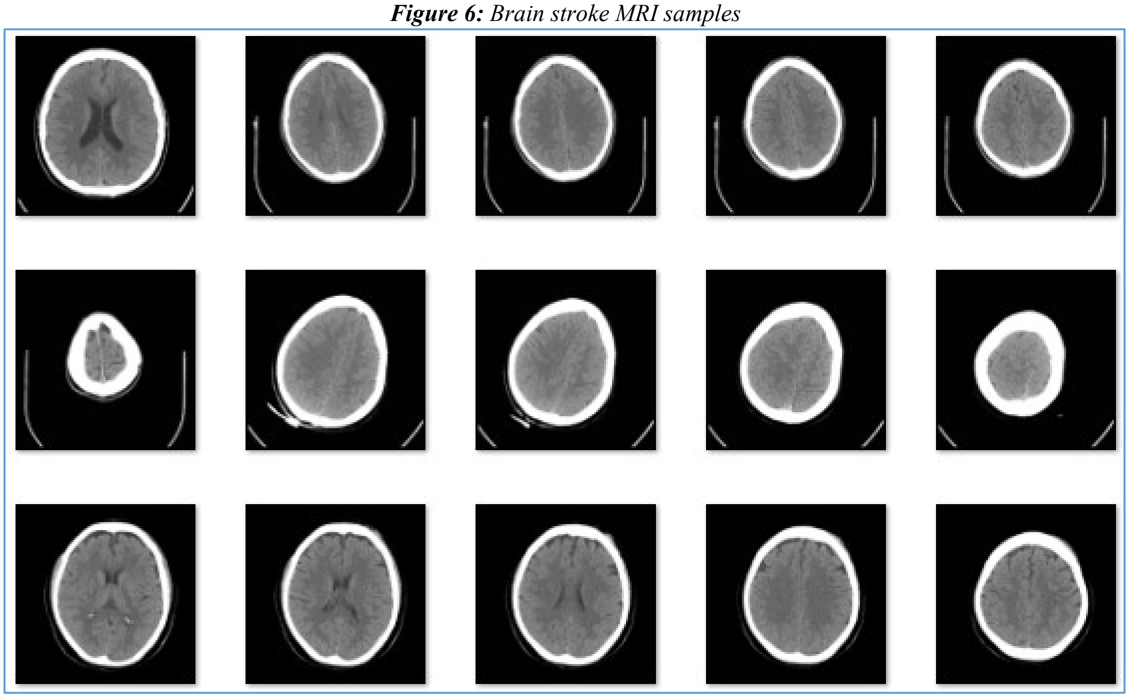

Figure 7: Normal Brain MRI Samples

As presented in Figure 6, the brain stroke MRI samples are provided while Figure 7 shows the normal brain MRI samples.

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3.6 Evaluation Methodology

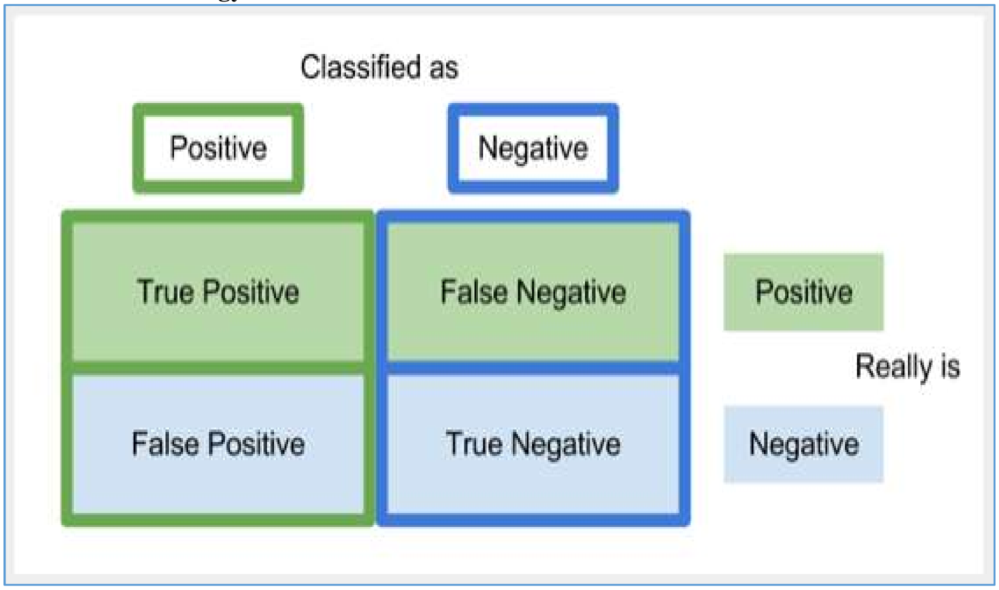

Figure 8:Confusion Matrix Block Diagram

The evaluation procedure for the proposed methods is based on confusion matrix presented in Figure 8.

Table 2: Hyper Parameters Used In The Deep Learning Models

Metric	**Formula**	**Value range**	**Best Value**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$ (3)	[0; 1]	1
Precision (P)	$\frac{TP}{TP+FP}$ (4)	[0; 1]	1
Recall (r)	$\frac{TP}{TP+FN}$ (5)	[0; 1]	1
F1-Score	$2*\frac{(p*r)}{(p+r)}$ (6)	[0; 1]	1
Area under the receiver operating characteristic curve (ROC AUC)	$\frac{1}{2}\left(\frac{TP}{TP+FN}+\frac{TN}{TN+FP}\right)$ (7)	[0.5; 1]	1

***Table 2:** Performance evaluation metrics*

Based on the confusion matrix, performance evaluation metrics are computed. They are provided in Table 2.

$$h_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i.\log(p(y_i)) + (1 - y_i).\log(1-p(y_i)) \quad (8)$$

In the deep learning models, binary cross entropy is used for computing loss function. It is expressed in Eq. 8.

4. EXPERIMENTAL RESULTS

Experiments are made with the optimized deep learning models and the performance of the models are observed in terms of precision, recall, accuracy, F1-score and AUC.

Table 3: Performance Of The Deep Learning Models

Deep Learning Model	**Precision**	**Recall**	**AUC**	**F1 Score**
DesnseNet121	**0.97457**	0.92	**0.969**	0.94685
ResNet50	0.95212	**0.952**	0.96819	**0.952**
VGG16	0.91129	0.90399	0.94268	0.90763

As presented in Table 3, the performance of the deep learning models in brain stroke detection using MRI scans is provided.

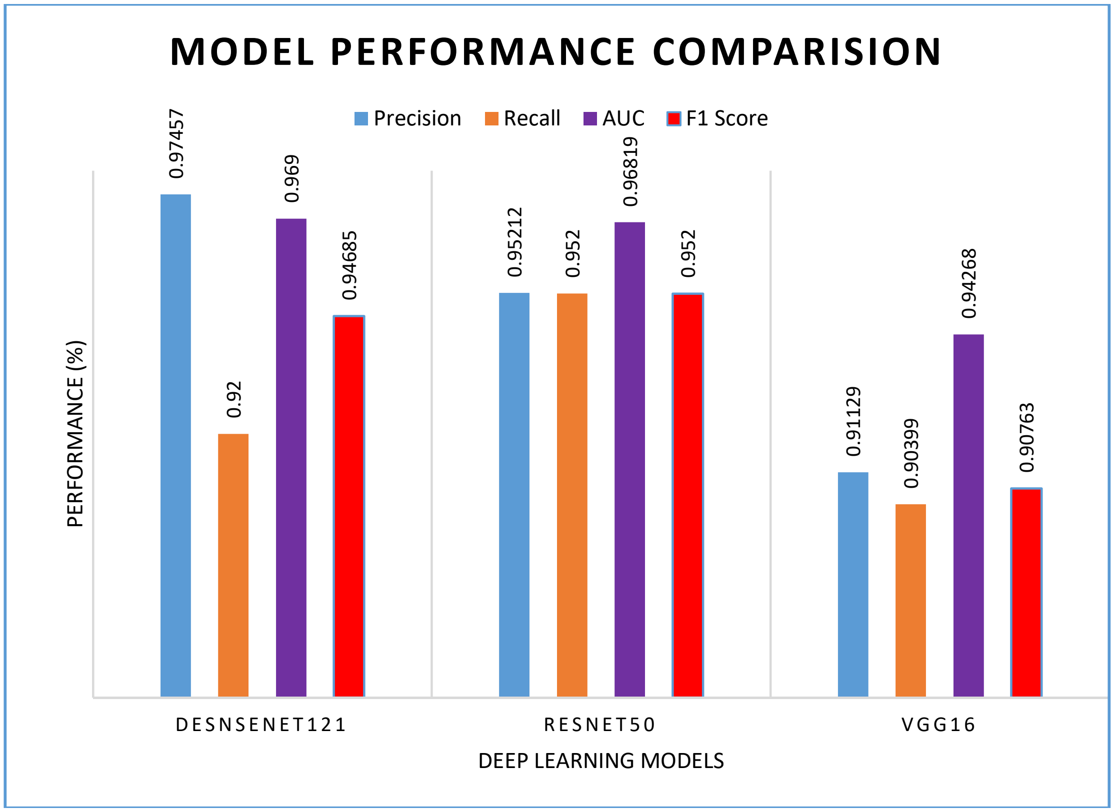

Figure 9: *Performance in brain stroke detection by optimized deep learning models*

As presented in Figure 9, the performance of the deep learning models in detection of brain stroke using MRI imagery is provided. The deep learning models that are optimized for this purpose are shown in horizontal axis and the performance is provided in vertical axis. The results revealed that each model has its own performance based on its configurations and layers. The precision of DenseNet121 is 97.45%, ResNet50 is 95.21% and VGG16 is 91.12%. The recall of DenseNet121 is 92%, ResNet50 is 95.20% and VGG16 is 90.39%. The AUC of DenseNet121 is 96.90%, ResNet50 is 96.81% and VGG16 is 94.26%. The F1-score of DenseNet121 is 94.68%, ResNet50 is 95.20% and VGG16 is 90.76%. Highest precision is exhibited by DenseNet121. Highest recall is achieved by ResNet50. Highest AUC is shown by DenseNet121 while highest F1-score is exhibited by ResNet50.

Table 4: Performance Of The Deep Learning Models In Terms Of Accuracy

Deep Learning Model	**Accuracy**
DesnseNet121	0.948
ResNet50	**0.952**
VGG16	0.908

As presented in Table 4, the performance of the deep learning models in brain stroke detection using MRI scans is provided in terms of accuracy.

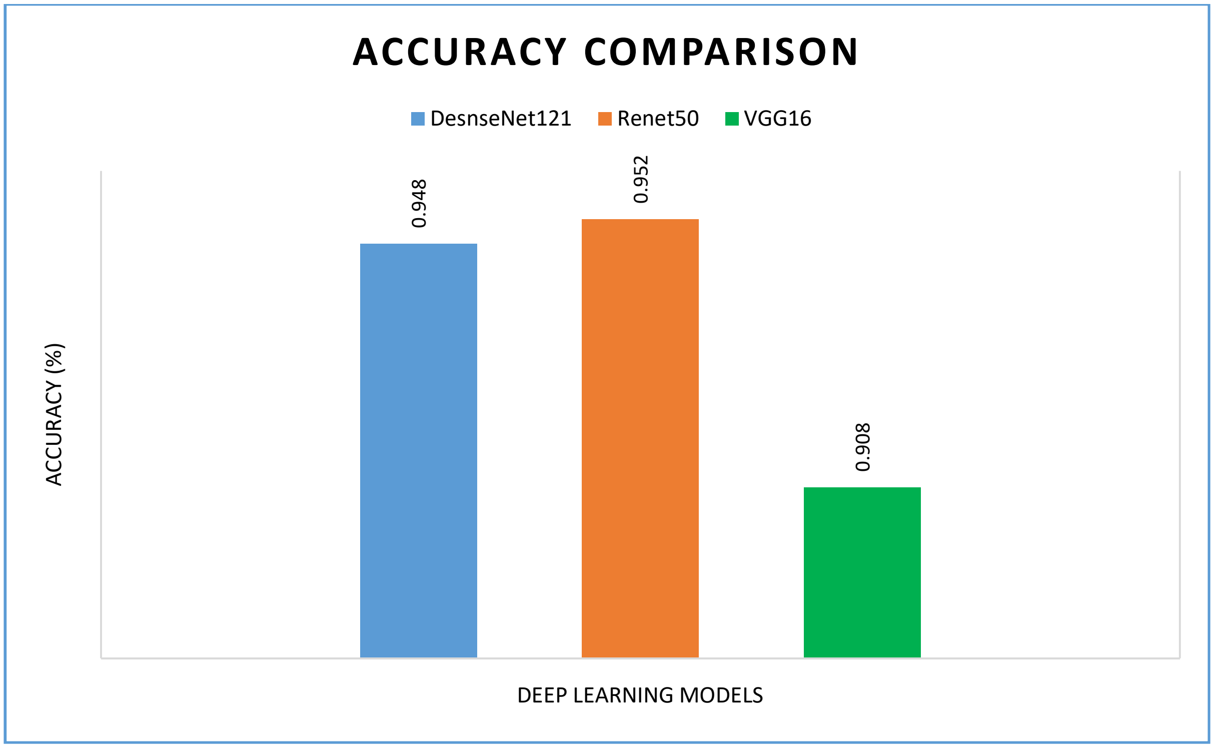

Figure 10:Accuracycomparison Of Optimized Deep Learning Models

As presented in Figure 9, the performance of the deep learning models in detection of brain stroke using MRI imagery in terms of accuracy is provided. The deep learning models that are optimized for this purpose are shown in horizontal axis and the accuracy is provided in vertical axis. The results revealed that each model has its own performance based on its configurations and layers. The accuracy of DenseNet121 is 94.80%, ResNet50 is 95.20% and VGG16 is 90.80%. The highest performance in terms of accuracy is shown by ResNet50 with 95.20%.

5. CONCLUSION AND FUTURE WORK

We proposed a framework and underlying mechanisms to optimize and exploit the deep CNN models such as VGG16, ResNet50 and DenseNet121 for efficient brain stroke detection. Each deep CNN model is optimized in terms of its configurations to meet the requirements of brain stroke prediction problem. Each model has its own architecture and underlying mechanisms for learning from given imagery data, extract features and make classification decisions. These are supervised learning models for which training MRI brain samples are provided. Each deep learning model is optimized to have better performance. Apart from the improving the models, an algorithm named Optimized Deep Learning for Brain Stroke Detection (ODL-BSD) is proposed. The novelty of this work lies in the modifications made to pre-trained deep CNN models. MRI scans are used to evaluate the proposed framework. The empirical results revealed that the proposed methodology has caused improvement in the performance of the deep CNN models significantly. This research likely has its impact on clinical decisions when AI based approach is used in healthcare units. The results also suggest that there is room for future scope of the research. In other words, model scaling is an open issue that enables deep learning models to perform even better when addressed properly. Therefore, an important direction for future work is that the deep learning models can be enhanced further with model scaling that has impact on the prediction performance of the models.

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