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Enhanced Deep Learning Models for Efficient Stroke Detection Using MRI Brain Imagery

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Abstract: Deep learning models are widely used for solving problems in different applications. Especially Convolutional Neural Network (CNN) based models are found suitable for medical image analysis. As brain stroke is increasing in alarming rate, it is essential to have better approaches to detect it in time. Brain MRI is one of the medical imaging technologies widely used for brain imaging.we proposed certain advancements to well-known deep learning models like VGG16, ResNet50 and DenseNet121 for enhancing brain stroke detection performance. These models are optimized based on the brain stroke detection problem in hand as they are not specialized for a specific problem. We proposed an algorithm, named Deep Efficient Stroke Detection (ESD), that exploids enhanced deep learning models in pipeline. The experimental results revealed that there is performance improvement with optimized models. Highest accuracy is achieved by ResNet50 with 95.67%.

Keywords – Deep Learning, Brain Stroke Detection, DenseNet121, ResNet50, VGG16

I. INTRODUCTION

Problem solving became easier with the emergence of AI in different domain. Healthcare is no exception. With CNN based models and pre-trained variants, there are improved possibilities in improving quality in healthcare industry. Particularly, as per WHO guidelines, AI is being explored for disease diagnosis. CNN is found suitable for medical image analytics. In this paper, our research is centred on brain stroke detection with MRI scans. We preferred MRI scans to CT scans due to improved clarity and efficiency that can be achieved with MRI scans with deep learning. We investigated on different pre-trained models to deal with MRI imagery for stroke detection. We found that one size does not fit all. In other words, the models best used for one computer vision application renders quite mediocre performance with other application. This fact has enabled us to enhance models to be optimal for image analysis with brain stroke research.

There are many existing methods that are used for brain stroke detection using brain imagery. Some important deep learning models have provided useful insights. One important insight is that most of the models are based on CNN. Tanzila et al. [14] defined a model that exploits features learned using deep learning and hand crafted features to detect brain tumor. Andreas [18] investigated on focal brain pathology using deep learning techniques. Many deep learning approaches including pre-trained models are found in the literature. From the literature it is observed that CNN is the model highly suitable for image analysis. However, CNN and its variants or pre-trained models are found lacking in optimal performance if they are used directly. They needed certain enhancements based on the problem in hand. Towards this end, we proposed our methodology for efficient stroke detection. Our contributions in this paper are as follows.

1. We proposed certain advancements to well-known deep learning models like VGG16, ResNet50 and DenseNet121 for enhancing brain stroke detection performance.
2. We proposed an algorithm, named Deep Efficient Stroke Detection (ESD), with supervised learning approach to use all these advanced deep learning models in pipeline.
3. We built an application to evaluate performance of the enhanced models. Highest accuracy is achieved by ResNet50 with 95.67%.

   The remainder of the paper is structured as follows. Section 2 threw light on literature findings on existing methods. Section 3 provides details of our methodology

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with enhanced pre-trained models. Section 4 presents our experimental results. Section 5 concludes our work and gives scope for future work.

II. RELATED WORK

This section reviews existing methods found in the state of the art. Noah et al. [1] focused on the detection if ischemic stroke using tissue fate features by training deep learning models. Asit et la. [2] proposed a detection method for ischemic stroke using MRI. Their research has used Delaunay triangulation method in the training process. Ander et al. [3] focused on a controlled study to explore interface between human brain and machine with respect to the research linked to stroke rehabilitation. Similar kind of research in carried out in [4] as well. In [5] different ML approaches are explored to analyse human brain imagery. Lundervold et al. [6] investigated on different kinds of medical images and deep learning techniques suitable for analysis of MRI scans. Andra et al. [7] focused on understanding chronic stroke issues in humans and proposed an interface for brain-machine interaction with an optimized modelling. Sucheta et al. [8] investigated on the subtle differences between deep and shallow learning models in terms of cognitive abilities linked stroke patients. Zeynettin et al. [9] focused on segmentation of brain images using deep learning. Segmentation is found useful for understanding brain abnormalities. Myung et al. [10] proposed novel methods using deep learning to detect problems associated with cerebral microbleeds.

Karthik et al. [11] studied neuroimaging techniques and explored deep learning towards stroke diagnosis. In [12] an ensemble learning approach is preferred using deep learning models that are used as regression models to diagnose brain abnormalities. In [13] proposed a methodology for understanding existing techniques based on deep architectures for MRI image analysis. Tanzila et al. [14] defined a model that exploits features learned using deep learning and hand crafted features to detect brain tumor. Wood et al. [15] used MRI scans to perform labelling of them automatically using deep learning techniques. Saifeng et al. [16] used deep learning with different kind of imaging for cerebral microbleed detection process. Kai et al. [17] used deep learning in their stroke detection research based on the Penumbral tissue identification. Andreas [18] investigated on focal brain pathology using deep learning techniques.

Other important contributions include NLP and ML hybrid [19], ensemble learning [20], synergic deep learning [21], transfer learning [22] and ischemic stroke detection by exploiting higher order spectra [23]. From the literature it is observed that CNN is the model highly suitable for image analysis. However, CNN and its variants or pre-trained models are found lacking in optimal performance if they are used directly.

III. MATERIALS AND METHODS

We collected dataset from [24]. Our research in this paper focused on the utility of pre-trained models for brain stroke detection using MRI scans. Our preliminary study has revealed that one size done not fit all. It does mean that pre-trained models do not provide consistent performance across many computer vision applications. We realized that they are to be optimized in terms of configurations and hyper parameters. Figure 1 shows overview of the proposed methodology.

3.1 Our Framework

Our framework is based on supervised learning using enhanced deep learning models. Enhancement of deep learning models is discussed in Section 3.2. We analyse brain MRI dataset in order to discover any imbalances in dataset and overcome the issue with data augmentation strategies. Once data is augmented to get rid of overfitting problem, the data is split into training set and testing set. Instead of using pre-trained models like VGG16, ResNet50 and DenseNet121 directly we enhanced them for better performance.

The enhanced models are used in pipeline to train them with training samples. Once the training is done, the models are persisted in order to reuse them later. This can help in avoiding training the models every time. The result of the training is a knowledge model that is used to detect stroke in given test samples. Novelty in our approach is the enhancement of models and data augmentation that could improve training quality.

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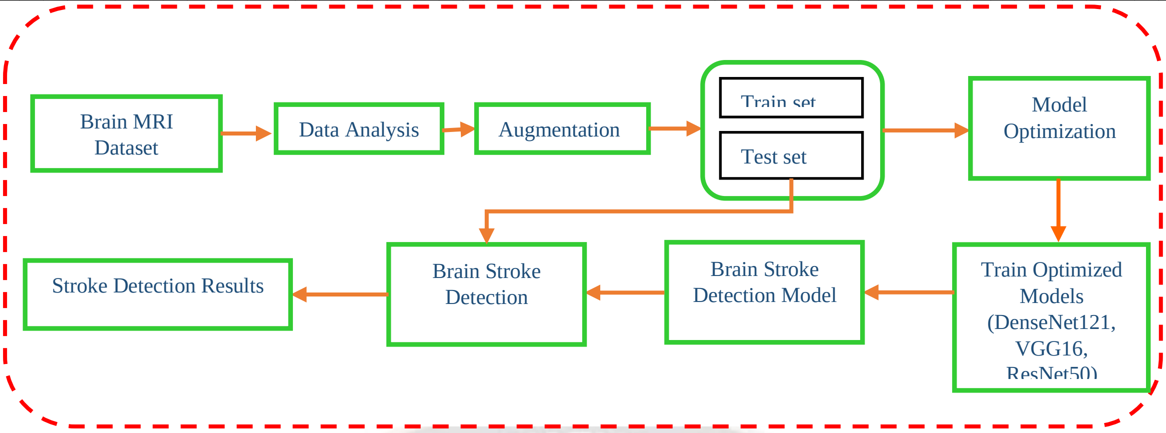

Figure 1: Our framework for enhancing brain stroke detection performance

3.2 Model Enhancement

ResNet50 is widely used model. However, we found that it needs enhancement for efficient stroke detection. The architecture of this model has identity blocks and convolutional blocks. The input and output dimensions of the two kinds of blocks are different. However, both do have 1x1 convolutions in the beginning and end. It is observed with empirical study that by modifying the layers in the ResNet50, it is possible to improve stroke detection performance.

As presented in Figure 2, the enhanced model is provided. In the architecture some blocks are provided using dotted line (left most). It indicates that changes are made at those layers in the architecture. The residual learning process in the model is as expressed in Eq. 1.

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

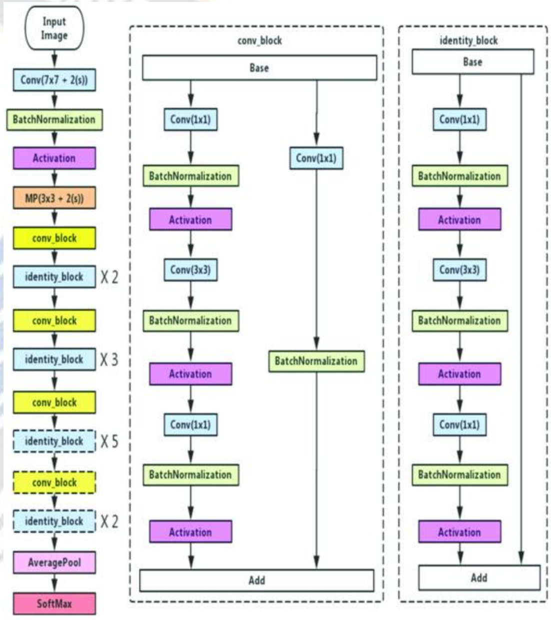

Figure 2: Enhanced architecture of ResNet50

$F(x, \{ W_i \})$ denote residual mapping, input vector is denoted by x and output vector is denoted by y. As expressed in Eq. 1, there is there is presence of shortcut connection. However, it does not introduce overhead. It is the enhanced phenomenon which leads to performance improvement. Eq. 2 expresses a mechanism that overcomes a situation where F and x are not identical.

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

Linear projection is denoted by W_s which is exploited in situation where dimensions of input and output match. It is designed in such a way that the residual function is very flexible and can use convolutional layers appropriately.

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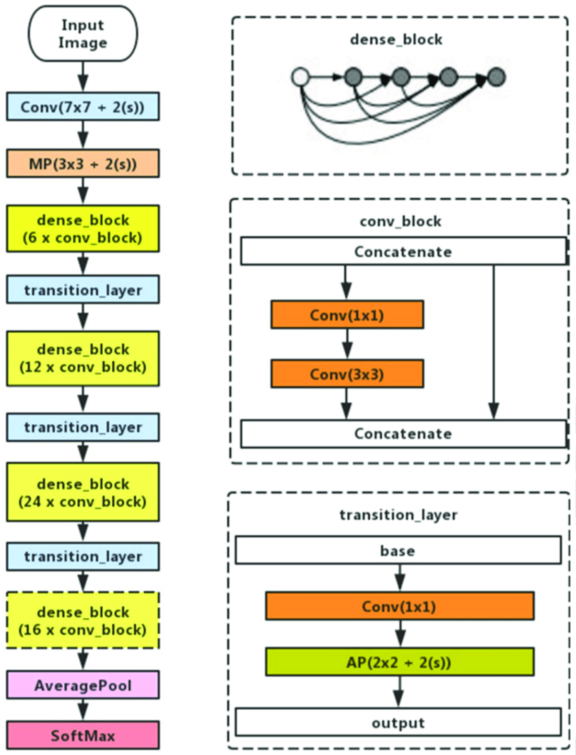

Figure 3: Architectural overview of enhanced DenseNet121

As presented in Figure 3, it has different types of blocks as provided (right side). However, convolutional block is the basic one in the architecture. Dense block is very important in the architecture of the model. Transition layer is used to connect two dense blocks. It plays vital role in optimizing feature maps. In the enhanced architecture (left most), the dotted lines indicate that those are the layers subjected to modifications.

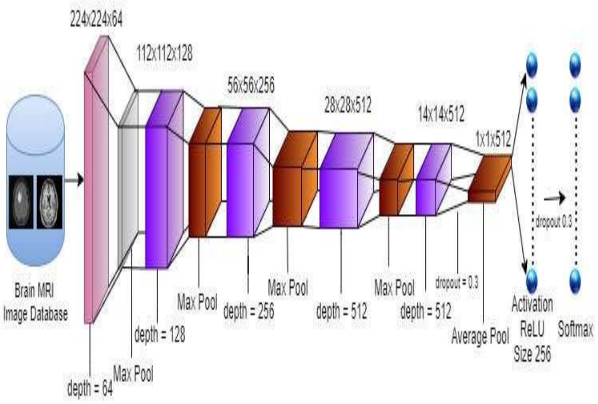

Figure 4: Architectural overview of VGG-16 model

As presented in Figure 4, the VGG16 model has number of layers. It is particularly tuned in our work for optimal performance. Since it is widely used pre-trained mode, we made empirical study on it and found that it needs to be enhanced for stroke detection using MRI imagery. Small changes are made in convolutional and pooling layers in order to see that it bestows considerable performance improvement.

3.3 Our Algorithm

We proposed an algorithm known as Deep Efficient Stroke Detection (ESD) which is designed in such a way that it could effectively realize the proposed methodology. It exploits enhanced pre-trained models.

Algorithm: Deep Efficient Stroke Detection (ESD)
Inputs:
Dataset D (brain MRI)
Enhanced models pipeline T
Output:
Detection results R

1. Begin
2. D'←Augmentation(D)
3. (*T1*, *T2*)←SplitData(*D'*)
4. For each model m in pipeline T
5.   Train m using T1
6.   Save m
7. End For
8. For each saved model m in T
9.   Use m to detect brain stroke in T2
10.   Assign results to R
11.   Output R
12. End For
13. End

Algorithm 1: Deep Efficient Stroke Detection (ESD)

As presented in Algorithm 1, it takes Dataset D (brain MRI) and Enhanced models pipeline T as input and produces detection results R. In the process, the algorithm performs data augmentation in order to leverage training quality. It exploits enhanced pre-trained models, as discussed in Section 3.2, for training and also performing efficient detection of brain stroke.

3.4 Performance Evaluation

Our enhanced models are evaluated to know their efficiency using confusion matrix that reflects the difference between ground truth and predicted values. Eq. 3 to Eq. 7 are different metrics used for evaluation.

$$\text{Precision (p)} = \frac{TP}{TP+FP} \qquad (3)$$

$$\text{Recall (r)} = \frac{TP}{TP+FN} \qquad (4)$$

$$\text{F1-score} = 2 * \frac{(p * r)}{(p+r)} \qquad (5)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (6)$$

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$$\text{AUC} = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \quad (7)$$

These measures result in a range between 0 and 1 reflecting least and highest performance ranges.

IV. RESULTS AND DISCUSSION

This section presents results of experiments made with an application implemented based on the proposed framework. Different hyper parameters are set prior to training the improved models. For all models batch size is set to 16, number of epochs is set to 50, learning rate 0.001, activation function sigmoid, optimizer Adam and loss function is set to binary cross entropy. Dataset used for our experiments is collected from [24].

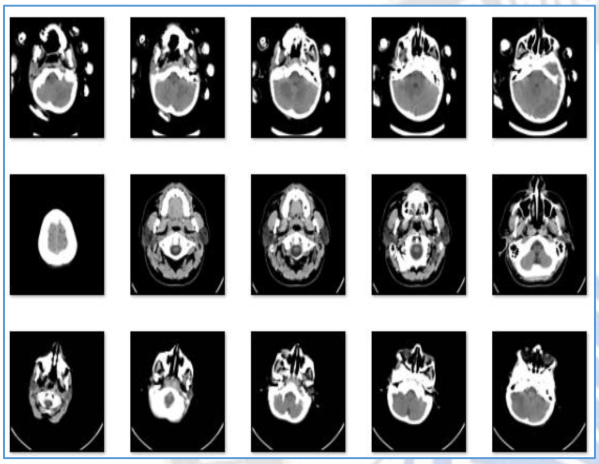

Figure 5: An excerpt from MRI brain stroke dataset reflecting stroke images

As presented in Figure 5, an excerpt taken from brain MRI imagery used for experiments consisting of stroke samples is provided.

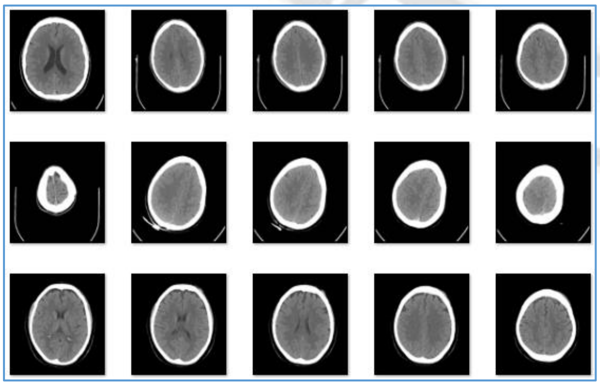

Figure 6: An excerpt from MRI brain stroke dataset reflecting normal samples

As presented in Figure 6, an excerpt taken from brain MRI imagery used for experiments consisting of normal samples is provided.

Stroke Detection Model	Performance (%)				
	Precision	Recall	AUC	F1 Score	Accuracy
VGG16	0.915846	0.90851	0.947393	0.912168	0.91254
DesnseNet121	0.979443	0.9246	0.973845	0.951584	0.95274
Resnet50	0.956881	0.95676	0.973031	0.95676	0.95676

Table 1: Performance comparison of optimized models

As presented in Table 1, it is observed that performance of optimized models used for brain stroke detection is provided.

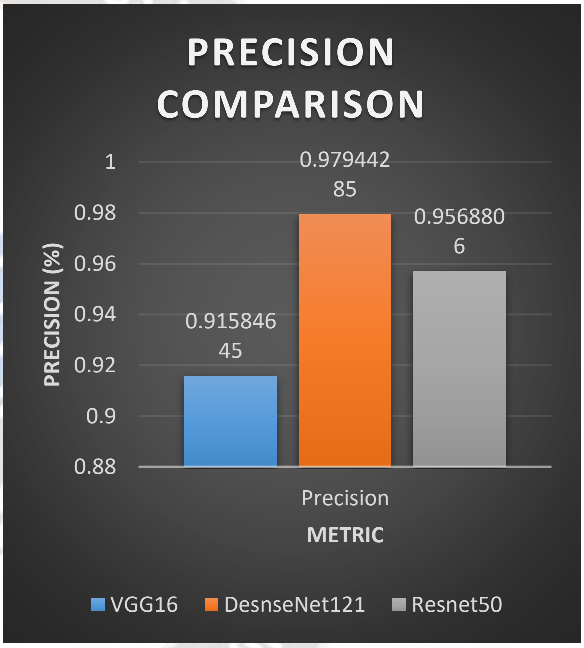

Figure 7: Precision of optimized models

As presented in Figure 7, the optimized models are evaluated in terms of precision. It is known from the observation of results that each model has different level of precision. The rationale for this is attributed to their architecture and internal functioning. Least precision is achieved by VGG-16 with 91.58%. ResNet50 model showed 95.68% while DenseNet121 exhibited highest precision 97.94%.

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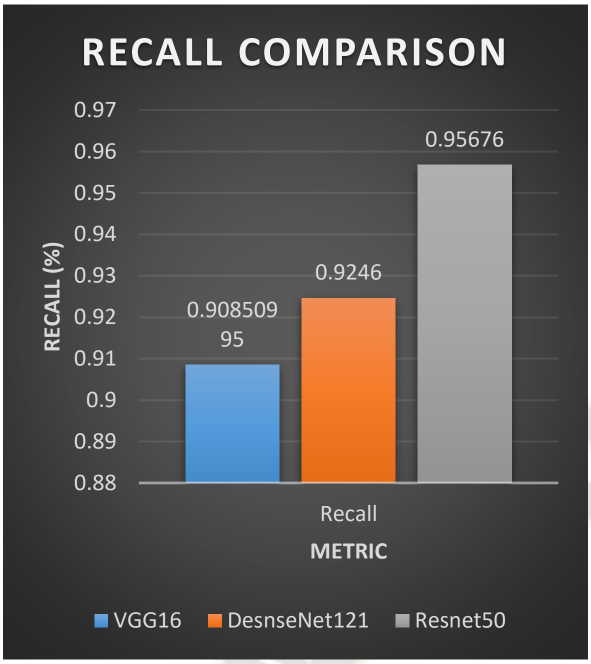

Figure 8: Recall of optimized models

As presented in Figure 8, the optimized models are evaluated in terms of recall. It is known from the observation of results that each model has different level of recall. The rationale for this is attributed to their architecture and internal functioning. Least recall is achieved by VGG-16 with 90.85%. DenseNet121 model showed 92.46% while ResNet50 exhibited highest recall 95.67%.

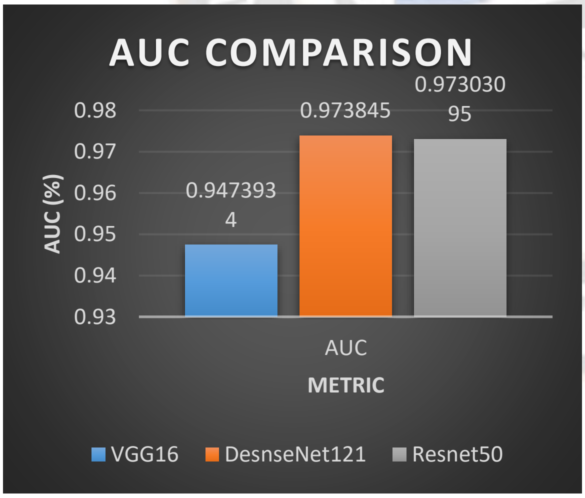

Figure 9: AUC of optimized models

As presented in Figure 9, the optimized models are evaluated in terms of AUC. It is known from the observation of results that each model has different level of AUC. The rationale for this is attributed to their architecture and internal functioning. Higher in AUC indicates better performance. Least AUC is achieved by VGG-16 with 94.73%. ResNet50 model showed 97.30% while DenseNet121 exhibited highest AUC 97.38%.

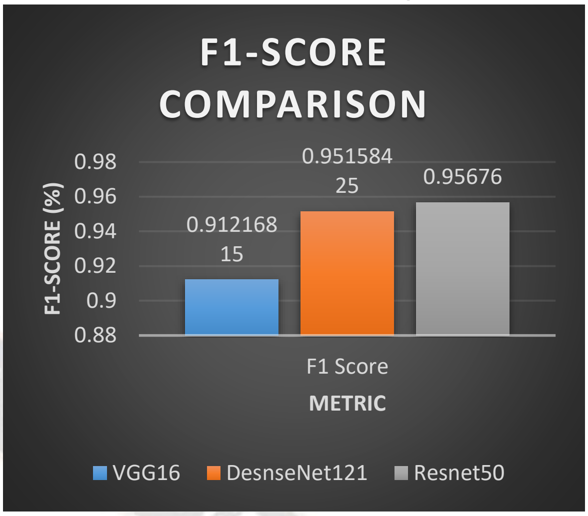

Figure 10: F1-score of optimized models

As presented in Figure 10, the optimized models are evaluated in terms of F1-score. It is known from the observation of results that each model has different level of F1-score. The rationale for this is attributed to their architecture and internal functioning. Higher in F1-score indicates better performance. Least F1-score is achieved by VGG-16 with 91.21%. DenseNet121 model showed 95.15% while ResNet50 exhibited highest F1-score 95.67%.

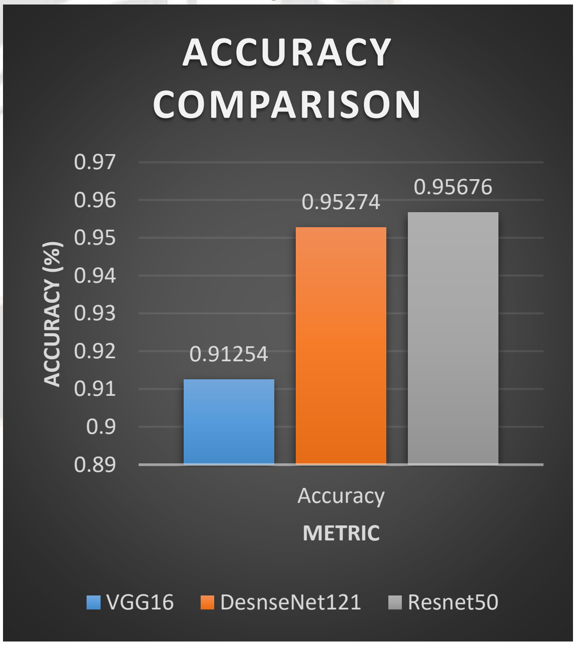

Figure 11: Accuracy of optimized models

As presented in Figure 11, the optimized models are evaluated in terms of accuracy. It is known from the observation of results that each model has different level of accuracy. The rationale for this is attributed to their architecture and internal functioning. Higher in accuracy indicates better performance. Least accuracy is achieved by VGG-16 with 91.25%. DenseNet121 model showed 95.27% while ResNet50 exhibited highest accuracy 95.67%.

V. CONCLUSION AND FUTURE WORK

In this paper we proposed certain advancements to well-known deep learning models like VGG16, ResNet50 and DenseNet121 for enhancing brain stroke detection performance. These models are optimized based on the brain stroke detection problem in hand as they are not specialized for a specific problem. Our methodology includes data analysis and also augmentation for improving balance in dataset for learning process. It is observed with empirical study that pre-trained models do not provide same performance in different computer vision applications. Therefore, we determined to optimize them to be more accurate for brain stroke detection using MRI scans. We proposed an algorithm, named Efficient Stroke Detection (ESD), with supervised learning approach to use all these advanced deep learning models in pipeline. The experimental results revealed that there is performance improvement with optimized models when compared with the baseline models. Highest accuracy is achieved by ResNet50 with 95.67%. Our study revealed that pre-trained models need optimization to perform well in any specific problem solving framework. Our research provides useful knowledge about the three models and their optimizations. In future, we intend to explore our optimized models in Generative Adversarial Network (GAN) setting for leveraging prediction performance further.

References

[1] Stier, Noah; Vincent, Nicholas; Liebeskind, David and Scalzo, Fabien (2015). IEEE International Conference on Bioinformatics and Biomedicine (BIBM) - Deep learning of tissue fate features in acute ischemic stroke. , p1316–1321.

[2] Subudhi, Asit; Acharya, U. Rajendra; Dash, Manasa; Jena, Subhransu and Sabut, Sukanta (2018). Automated approach for detection of ischemic stroke using Delaunay Triangulation in brain MRI images. Computers in Biology and Medicine, p1-35.

[3] Ramos-Murguialday, Ander; Broetz, Doris; Rea, Massimiliano; Läer, Leonhard; Yilmaz, Özge; Brasil, Fabricio L.; Liberati, Giulia; Curado, Marco R.; Garcia-Cossio, Eliana; Vyziotis, Alexandros; Cho, Woosang; Agostini, Manuel; Soares, Ernesto; Soekadar, Surjo; Caria, Andrea; Cohen, Leonardo G. And Birbaumer, Niels (2013). Brain-machine interface in chronic stroke rehabilitation: A controlled study. Annals of Neurology, 74(1), p100–108.

[4] Soekadar, Surjo R.; Birbaumer, Niels; Slutzky, Marc W. and Cohen, Leonardo G. (2014). Brain–machine interfaces in neurorehabilitation of stroke. Neurobiology of Disease, p1-8.

[5] C, B. (2021). Machine Learning for Interpretation of Brain Images: A Detailed Analysis through survey. 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS). P1-6.

[6] Selvikvåg Lundervold, Alexander and Lundervold, Arvid (2018). An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik, p1-26.

[7] Caria, Andrea; da Rocha, Josué Luiz Dalboni; Gallitto, Giuseppe; Birbaumer, Niels; Sitaram, Ranganatha and Murguialday, Ander Ramos (2019). Brain–Machine Interface Induced Morpho-Functional Remodeling of the Neural Motor System in Severe Chronic Stroke. Neurotherapeutics, p1-16.

[8] Chauhan, Sucheta; Vig, Lovekesh; De Filippo De Grazia, Michele; Corbetta, Maurizio; Ahmad, Shandar and Zorzi, Marco (2019). A Comparison of Shallow and Deep Learning Methods for Predicting Cognitive Performance of Stroke Patients From MRI Lesion Images. Frontiers in Neuroinformatics, 13, p1-12.

[9] Akkus, Zeynettin; Galimzianova, Alfiia; Hoogi, Assaf; Rubin, Daniel L. and Erickson, Bradley J. (2017). Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions. Journal of Digital Imaging, p1-11.

[10] Myung, M. J., Lee, K. M., Kim, H.-G., Oh, J., Lee, J. Y., Shin, I. And Lee, J. S. (2021). Novel Approaches to Detection of Cerebral Microbleeds: Single Deep Learning Model to Achieve a Balanced Performance. Journal of Stroke and Cerebrovascular Diseases, 30(9), 105886. P1-19.

[11] Karthik, R.; Menaka, R.; Johnson, Annie and Anand, Sundar (2020). Neuroimaging and deep learning for brain stroke detection - A review of recent advancements and future prospects. Computer Methods and Programs in Biomedicine, 197,p1-17.

[12] Suk, Heung-Il; Lee, Seong-Whan and Shen, Dinggang (2017). Deep ensemble learning of sparse regression models for brain disease diagnosis. Medical Image Analysis, 37, p101–113.

[13] Sabaa Ahmed Yahya Al-Galal, Imad Fakhri Taha Alshaikhli and M. M. Abdulrazzaq (2021). MRI brain tumor medical images analysis using deep learning techniques: a systematic review. Springer, p1-16.

[14] Saba, Tanzila; Sameh Mohamed, Ahmed; El-Affendi, Mohammad; Amin, Javeria and Sharif, Muhammad (2020). Brain tumor detection using fusion of hand crafted and deep learning features. Cognitive Systems Research, 59, p221–230.

[15] Wood, D. A., Kafiabadi, S., Al Busaidi, A., Guilhem, E. L., Lynch, J., Townend, M. K. and Booth, T. C. (2021). Deep learning to automate the labelling of head

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MRI datasets for computer vision applications. European Radiology. P1-12.
[16] Liu, Saifeng; Utriainen, David; Chai, Chao; Chen, Yongsheng; Wang, Lin; Sethi, Sean K.; Xia, Shuang and Haacke, E. Mark (2019). Cerebral microbleed detection using Susceptibility Weighted Imaging and deep learning. NeuroImage, 198, p271–282.
[17] Wang, Kai; Shou, Qinyang; Ma, Samantha J.; Liebeskind, David; Qiao, Xin J.; Saver, Jeffrey; Salamon, Noriko; Kim, Hosung; Yu, Yannan; Xie, Yuan; Zaharchuk, Greg; Scalzo, Fabien and Wang, Danny J.J. (2019). Deep Learning Detection of Penumbral Tissue on Arterial Spin Labeling in Stroke. Stroke, p1-9.
[18] Holzinger, Andreas (2016). Machine Learning for Health Informatics Volume 9605 || Deep Learning Trends for Focal Brain Pathology Segmentation in MRI. , 10.1007/978-3-319-50478-0(Chapter 6), p125–148.
[19] Kim, Chulho; Zhu, Vivienne; Obeid, Jihad; Lenert, Leslie; Shawe-Taylor, John (2019). Natural language processing and machine learning algorithm to identify brain MRI reports with acute ischemic stroke. PLOS ONE, 14(2), p1-13.
[20] Ashwini Kadam1. (2020). Detection and Classification of Brain Hemorrhage Using Ensemble Learning. International Journal of Research and Analytical Reviews (IJRAR). 7 (1), p520-521.
[21] Anupama, C. S. S.; Sivaram, M.; Lydia, E. Laxmi; Gupta, Deepak and Shankar, K. (2020). Synergic deep learning modelâ€ "based automated detection and classification of brain intracranial hemorrhage images in wearable networks. Personal and Ubiquitous Computing, p1-10.
[22] Talo, Muhammed; Baran Baloglu, Ulas; Yıldırım, Özal and Rajendra Acharya, U (2018). Application Of Deep Transfer Learning For Automated Brain Abnormality Classification Using Mr Images. Cognitive Systems Research, p1-27.
[23] Rajendra Acharya, U.; Meiburger, Kristen M.; Faust, Oliver; En Wei Koh, Joel; Lih Oh, Shu; Ciaccio, Edward J.; Subudhi, Asit; Jahmunah, V. and Sabut, Sukanta (2019). Automatic detection of ischemic stroke using higher order spectra features in brain MRI images. Cognitive Systems Research,p1-19.
[24] Kaggle Datasets. Retrieved from https://www.kaggle.com/datasets

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