EEG Classification For Stroke Detection Using Deep Learning Networks

Suranjan Kumar
Electrical Engineering
National Institute of Technology
Rourkela, India
suranjankumar94@gmail.com

Anwesha Sengupta
Electrical Engineering
National Institute of Technology
Rourkela, India
senguptaan@nitrkl.ac.in

2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET) | 978-1-6654-8875-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICEFEET51821.2022.9847883

***Abstract*—Stroke is currently a major public health concern. Hence more accurate and objective methods for diagnosis and prognosis are required to enable better clinical decision making. Electroencephalogram (EEG) is a non-invasive, low-cost method that can provide information regarding changes in the cerebral cortex throughout the recovery process following a stroke. EEG gives information on the progression of brain activity patterns. Many strategies have recently been developed to improve detection accuracy such as Support Vector Machine (SVM), Artificial Neural Network (RNN), Logistic Regression (LR), etc. VGG-16 and RESNET-50 are two non-invasive, low-cost transfer learning methods compared in this study. The results show that the proposed models can correctly classify EEG signals as stroke or not-stroke with 90% accuracy and 100% sensitivity for RESNET-50 while VGG-16 has a 90% accuracy, 100% specificity, and 100% precision. The work also compares other parameter i.e., F1-score between VGG-16 and RESNET-50 for this purpose. RESNET-50 is a major improvement over VGG-16 in terms of speed. Based on the results, this work appears to have been a success in terms of deep learning. Automation and great accuracy are achievable with this technique, which may be used in instances where Computed Tomography (CT) scans or Magnetic Resonance Imaging (MRI) examinations are not accessible.**

Keywords— ***Stroke, EEG, Discrete Wavelet Transform, Fast Fourier Transform, VGG-16, RESNET-50.***

I. INTRODUCTION

A stroke happens when a blood artery in the brain bursts and bleeds, or when the blood supply to the brain is blocked off. According to World Health Organization (WHO), stroke is the world's second leading cause of death and the third leading cause of disability [1]. The global incidence of stroke has more than doubled over the last few years [2].

Strokes can be detected by blood tests and brain imaging such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), X-ray, ECG, EEG. The two most common procedures for identifying stroke are CT and MRI, although they also include hazards, such as radiation exposure and possible allergic responses to the contrast chemicals employed. Because of their limited area, continual monitoring and separate medical fees for each test, these instruments may be cumbersome and difficult to use. New wearable electrodes have made it feasible to conduct portable EEG. The activity of brain nerve cells is measured using electrodes attached to the head in an environment that is more natural and unrestricted than the typical laboratory setting. It is also possible to conduct a pain-free and speedy examination of the brain during sleep. The patient's mobility and outside sounds might corrupt the EEG data. EEG data can be collected, tested at a decent price and with fewer negative side effects than the imaging methods listed above [3]. This makes 24-hour EEG readings an attractive, low-cost option for patients with recurrent strokes that need to be closely monitored regularly. The above problem is taken into account and is solved by the use of deep learning networks because in recent years it is more effective than others. Deep learning is use to solve an issue from end to end. For Machine learning approaches to work, the problem statements must be broken down into smaller portions that must be solved separately and then their results must be combined at the end. Increase in computing power, growth in amount of parameters available in the dataset, enhancement in deep learning models and their algorithms has been seen in recent years. In this paper, VGG-16 and RESNET-50 models have been used. The main objective is to extract more information from the signal as it passes through multiple convolution layers, hidden layers and filters in an efficient manner and when its training progress is seen, it is faster and cheaper among all deep learning networks.

AF Setiawan suggested that EEG band filtering in alpha, beta, delta, theta, and gamma and their frequency calculations should be done before monitoring parameters. Mean, Standard deviation and variance are examples of EEG Statistical metrics that can be used to monitor parameter during stroke rehabilitation [4]. Using Reccurent Neural Network (RNN) and genetic algorithms, Guntari classified EEG patterns after a stroke in a separate study [5]. A stroke detection study using EEG and electrooculography (EOG) recordings was carried out by Giri using 1D Convolutional Neural Network (CNN) with batch normalization [6]. This study's F-Score was 86.1 percent due to the feature extraction phases, which included calculating brain wave indices including entropy, kurtosis and variance as well as determining their relative values, correlation characteristics, and variance. S Poudel investigated the use of deep learning i.e., Resnet 50 for colorectal endoscopic image classification. He shows that the proposed strategy generates the F1-score of 0.93 for colorectal dataset. He also calculated the accuracy, recall and precision [7]. AS Ananda investigated EEG based post-stroke recognition using Principal Component Analysis (PCA) and Reccurent Neural Network (RNN). He used wavelet and FFT to preprocess and extract features [8]. S Guefrechi investigated the detection of Covid-19 from chest X-ray images using deep learning networks (RESNET-50, VGG-16, InceptionV3) [9]. This allows for the high accuracy detection of X-rays to be automated and it can also be employed in situation where the materials and RT-PCR

978-1-6654-8875-4/22/$31.00 ©2022 IEEE

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.

testing are in short supply. KH Cheah examined the performance of Residual Networks and Vgg for classification of EEG Signals [10]. In comparison to the original Resnet 18 classifier, which had an accuracy of 87.06 %, he suggested Resnet 18 classifier, which had an accuracy of 93.42 %.

This paper is arranged in following manner. The suggested framework is described in detail in Section 2. Section 3 presents and discusses the results. Section 4 concludes the papers and discusses the future scope of the work.

II. METHODOLOGY

A. Datasets

EEG datasets for the study have been taken from PhysioNet. It is used for both training and testing. The dataset contains instances of both normal and abnormal EEG activity. It has 33 signals and each of those signals has duration of recording of 132sec. It has sampling frequency 500Hz. 70% of the data used during the training and 30% for testing.
Two well-known deep learning architectures i.e., VGG-16 and RESNET-50 are evaluated and tested in this work to categorize stroke and non-stroke. As seen in Figure 1, the suggested deep learning approach is outlined.

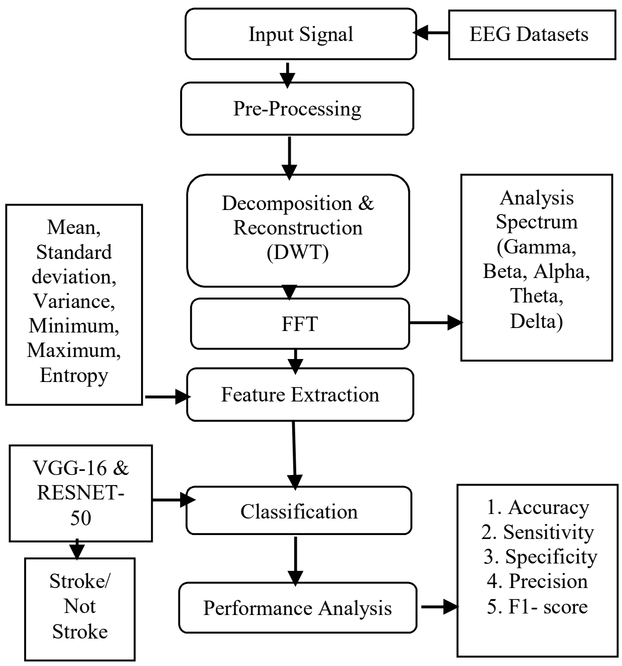

Fig. 1. Block Diagram

B. Data Pre-processing

Preprocessing is the term used to describe the process of reducing noise from data in order to come closer to the genuine neural signals. Firstly, the signal size in this work is restricted to 2000 number of samples so that the extracted feature analysis and EEG signal classification are done on the same number of samples because if number of samples are taken under 2000, then it shows a large variation in extracted featured values and curve of training progress of deep learning networks is not so much smooth but as number of samples are taken greater than 2000, then it shows very little variation in extracted featured values and plot of training progress is almost smooth. Hence for optimum consideration 2000 number of samples is good one.

It is necessary to clean up the obtained data as they include noise so discrete wavelet transformation is used. After noise is suppressed, the data is first decomposed into frequency bands and then reconstructed. Subsequently, the spectra are analyzed and the Gamma, Beta, Alpha, Theta, and Delta parameters are determined.

A strong filtering strategy for frequency or temporal signals can be built using wavelet decomposition. In this case, the Daubechies 8 (db8) wavelet is employed for noise reduction and compression since Daubechies wavelets employ overlapping windows.

Firstly, wavelet decomposition of 1-D signal at level 8 using wavelet 'db8' is determined. Then extraction of detail coefficients at level 8 from wavelet decomposition structure is done. After that reconstruction of coefficients is determined.

We don't go directly to feature extraction before that we use FFT transformation method which is used to estimate the EEG signals frequency level. The frequencies of Gamma, Beta, Alpha, Theta, and Delta are derived from the Fourier spectrum.

TABLE I. FREQUENCY SPECTRUM ANALYSIS

Serial Number	***Spectrum***	***Freq (Hz)***
1	Gamma	34
2	Beta	25
3	Alpha	15
4	Theta	5
5	Delta	3

The spectral parameter frequencies were entered into a table.

C. Feature Extraction

The process of selecting a subset from the original pool of features is called feature selection and the extraction of useful features from this subset of original pool of features is called feature extraction. After obtaining the spectral parameters, the features are retrieved from the spectrum. Statistical metrics in the temporal domain are used to extract the pure EEG signals. In this paper 6 parameters i.e., Mean, Standard Deviation, Variance, Minimum, Maximum, Entropy are calculated.
Extracted features are designed to prevent crucial information from being lost in the signal. Following feature extraction, the feature values are passed to both VGG-16 and RESNET-50 networks. Both networks use the SoftMax classifier for classification.

From the Table II, it is observed that Theta and alpha has high mean, standard deviation, variance than others. Delta has lowest min and max values while Beta has highest min and max values. Gamma has highest entropy.

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.

TABLE II. EXTRACTED FEATURE VALUES

Features	***Delta***	***Theta***	***Alpha***	***Beta***	***Gamma***
Mean	$-7.8e^{-15}$	7.3	5.4	1.6	-4.0
Standard Deviation	4.2	68.7	69.7	54.0	51.5
Variance	18.4	$4.7e^{+03}$	$4.8e^{+03}$	$2.9e^{+03}$	$2.6e^{+03}$
Minimum Value	-137.7	-137.7	-129.4	-92.4	-94.3
Maximum Value	4.0	158	139.4	159.4	113.4
Entropy	333.0	154.9	216.8	300.0	532.8

D. Deep Learning Networks

EEG signals including a stroke are analyzed using the two transfer learning networks VGG-16 and RESNET-50. There are 39 layers used in the VGG-16 which is a sequential network. Using the shot connection, the RESNET-50 has 177 layers which solves the issue of disappearing gradients. Model accuracy may be improved by using deep residual nets, which incorporate residual blocks. This kind of neural network's strength comes from the concept of "skipping connections," which is at the heart of the leftover blocks. This is shown in Figure 4.

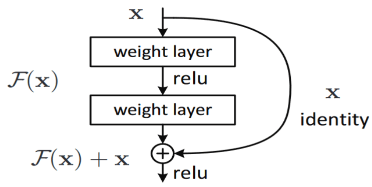

Fig. 4. Skip connection of RESNET-50

These connections may be made in two ways. To begin, they provide an alternative route for the gradient to follow, thereby resolving the issue of disappearing gradients. Using these, the model may pick up on an identity function. As a result, the model's higher and bottom layers function equally well. Residual blocks, in a nutshell, make it considerably simpler for the layers to learn identity functions. Reducing the error rate while increasing the performance of deep neural networks is the outcome of using RESNET. By combining the outputs of previous layers with the outputs of stacked layers, skip connections enable far deeper network training than was previously possible [11].

The size of the input to VGG-16 is (75,1,1). The first 2 convolutional layers each have 64 channels with filter size 1*1 and same padding with max pool layer of stride of (2,2). Then two layers are utilized, each with a convolutional layer of 128 filter and a filter size of (1,1) and a max pooling layer of stride (2,2). Then there are 3 convolution layers of filter size (1,1) and each with 256 filter and 2 convolution layers with 512 filter with same padding and a max pool layer. There are 3 Fully-Connected (FC) layers: the first two each have 4096/4 channels, while the third performs two Classification. The last and most important layer is soft-max which is employed in classification algorithms that require the output to be probability.

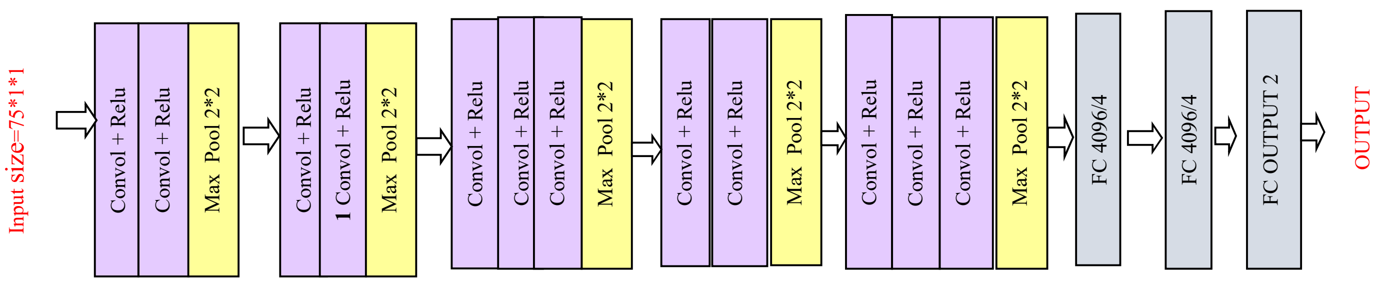

Fig. 2. VGG-16 Block

RESNET-50	Input Size=75*1	7*7, 64, stride 2 Output size=38*1	3*3 max pool, stride 2	1*1, 64 3*3, 64 1*1, 256 Multiply this block 3 times Output size=19*1	1*1, 128 3*3, 128 1*1, 512 Multiply this block 4 times Output size=10*1	1*1, 256 3*3, 256 1*1, 1024 Multiply this block 6 times Output size=5*1	1*1, 512 3*3, 512 1*1, 2048 Multiply this block 3 times Output size=3*1	Average pool, Fc=2, Soft-max Output size=1*1
		Conv-1	Conv-2		Conv-3	Conv-4	Conv-5	

Fig. 3. RESNET-50 Architecture

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.

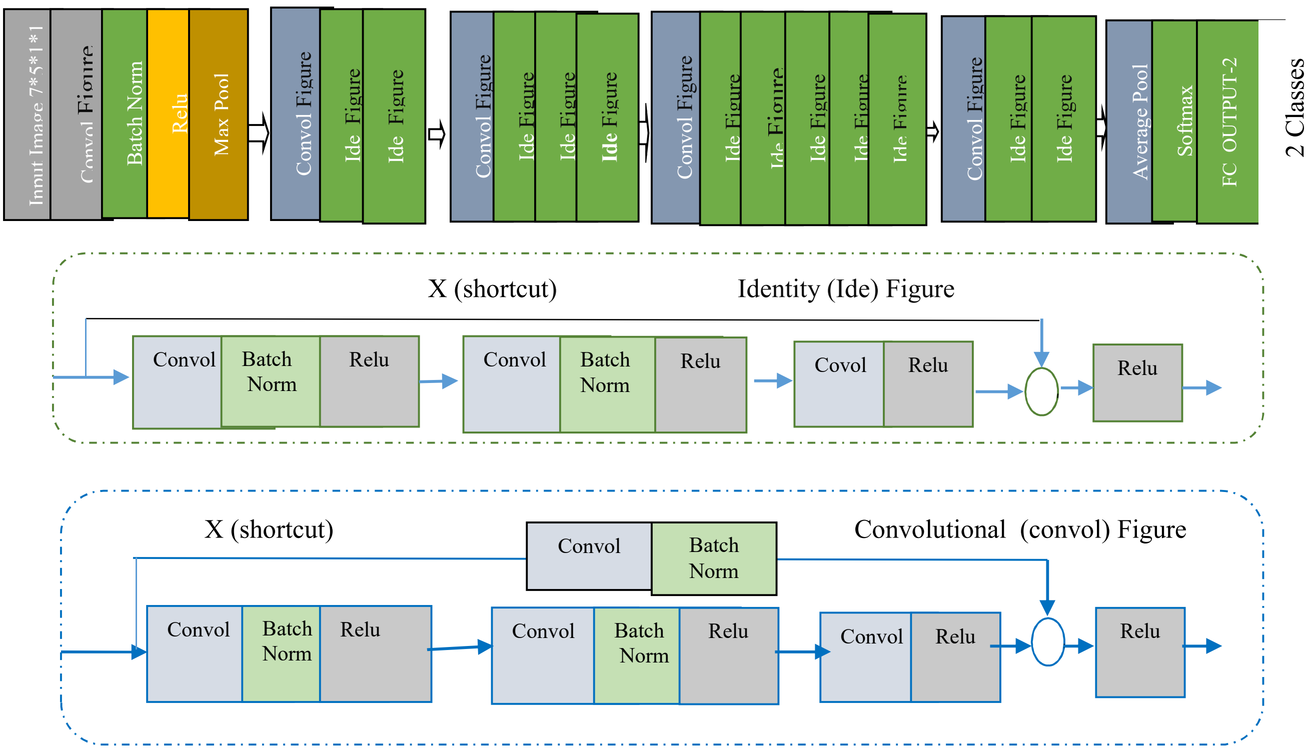

Fig. 5. RESNET-50 Block

III. RESULTS AND DISCUSSION

Normal: Not Stroke sample
Abnormal: Stroke sample

TABLE III. PERFORMANCE CALCULATION OF CONFUSION MATRIX

		Target Class	
		Stroke	Not Stroke
Output Class	Stroke	True positive (Tp)	False positive (Fp)
	Not Stroke	False negative (Fn)	True negative (Tn)

Accuracy-The accuracy is used to determine the percentage of values that are correctly categorized. It indicates how frequently our classifier is correct.

Accuracy= $(Tp + Tn)/(Tp + Tn + Fp + Fn)$ (1)

Sensitivity- It is used to figure out how well the model can predict positive values and how frequently the model can correctly forecast positive values.

Sensitivity = $Tp/(Tp + Fn)$ (2)

Specificity- It is used to figure out how well the model can predict negative values.

Specificity= $Tn/(Tn + Fp)$ (3)

Precision- It is used to determine the model ability to correctly categorize positive values. It answers the question of how often the model is correct when it predicts a positive number.

Precision= $Tp/(Tp + Fp)$ (4)

F1 score- It is the sensitivity and precision's harmonic mean. It is useful when we need to find the right balance between precision and sensitivity.

F1 score= $(2 * Tp)/(2 * Tp + Fp + Fn)$ (5)

Fig. 6. Training progress plot for VGG-16

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.

The training progress is shown in Figure 6, together with the accuracy in relation to the loss function and the algorithm curve, which indicates how it varies with iteration.

TABLE IV. TRAINING OPTION OF VGG-16

Training option	*Max Epoch*	*IntitalLearn Rate*	*MiniBatch Size*	*SquaredGradient DecayFactor*
Adam optimizer	150	$3e^{-4}$	10	0.99

If in the diagnostic, if someone wants high precision or high accuracy or high sensitivity or high specificity, depending on the requirement, the settings of the training option should be altered and then the best performance measures can be acquired.

TABLE V. ACCURACY VS LOSS OF VGG-16

Iteration	*Time Elapsed (hh: mm: ss)*	*Accuracy (%)*	*Loss*
1	00:00:05	70	3.5259
50	00:01:27	80	0.3709
100	00:02:46	90	0.1440
150	00:04:09	90	0.1389

It has been observed that when accuracy improves loss reduces. Model accuracy is linked to loss functions. Loss function is a way to see how effectively our algorithm models our dataset. It will produce a large number if our predictions are completely off. It will generate a lower number if accuracy reaches 90 to 100%.

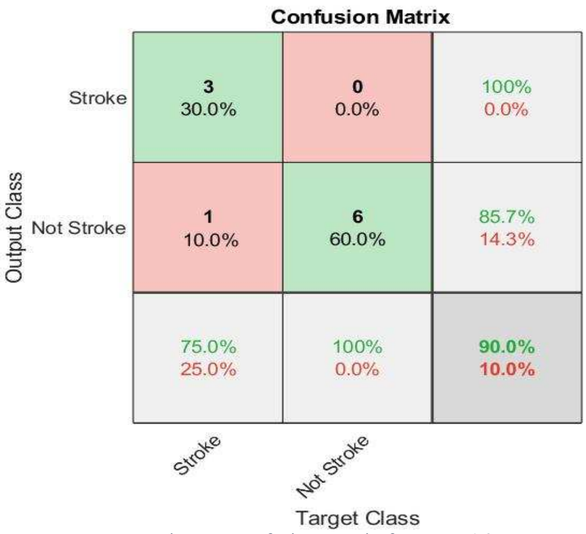

Fig. 7. Confusion Matrix for VGG-16

The matrix utilised for two prediction classes of classifiers is 2*2, with 90% of true predictions and 10% of wrong predictions.

TABLE VI. THE PERFORMANCE OF VGG-16

	Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*	*Precision (%)*	*F1Score (%)*
VGG-16	90	75	100	100	85.7

When compared to earlier work, the suggested technique performs well in terms of accuracy, f1-score, precision, sensitivity, and specificity as performance metrics.

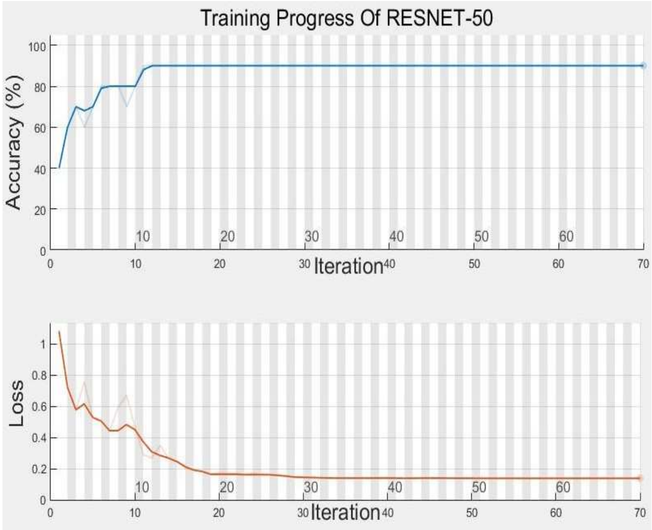

Fig. 8. Training progress plot for RESNET-50

The training progress is shown in Figure 8, together with the accuracy in relation to the loss function and the algorithm curve, which indicates how it varies with iteration.

TABLE VII. TRAINING OPTION OF RESNET-50

Trai-ning option	*Max Epoch*	*Intital LearnRate*	*MiniBatch Size*	*Shuffle*	*Verbose*
Sgdm optimizer	150	$3e^{-4}$	30	Every epoch	True

TABLE VIII. ACCURACY VS LOSS OF RESNET-50

Iteration	*Time Elapsed (hh: mm: ss)*	*Accuracy (%)*	*Loss*
1	00:00:06	40	1.0834
50	00:02:18	90	0.1392
70	00:03:09	90	0.1388

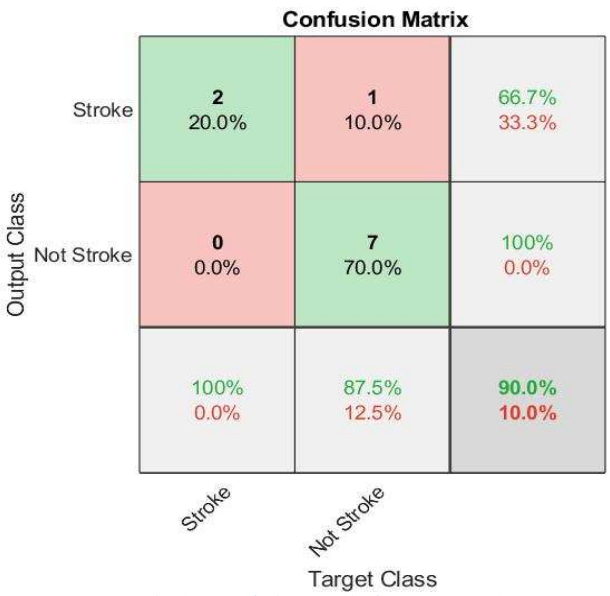

Fig. 9. Confusion Matrix for RESNET 50

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.

The matrix utilised for two prediction classes of classifiers is 2*2, with 90% of true predictions and 10% of wrong predictions.

TABLE IX. THE PERFORMANCE OF RESNET-50

	Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*	*Precision (%)*	*F1Score (%)*
RESNET- 50	90	100	87.5	66.66	80

When compared to earlier work, the suggested technique performs well in terms of accuracy and sensitivity as performance metrics.

TABLE X. COMPARISON BETWEEN THE PERFORMANCE OF RESNET-50 AND VGG-16

	Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*	*Precision (%)*	*F1Score (%)*
RESNET- 50	90	100	87.5	66.66	80
VGG-16	90	75	100	100	85.7

Both algorithms are used after features extraction from Discrete wavelet Transform for classification of EEG signals on 33 EEG public datasets.

IV. CONCLUSION AND FUTURE SCOPE

We examined the benefits of employing deep learning networks for stroke detection in this research. Deep learning models could be successful in predicting the spread of stroke victims. In contrast to Figure 6 and 8, RESNET-50 is more efficient than VGG-16 and also has a smoother curve than VGG-16. Figure 8 also shows that the training progress curve never decreases with iteration, this is a positive indicator for the RESNET-50 model. There was a gradual decrease in the amount of losses as well. In this way, when the characteristics are learned progressively, the detection accuracy will increase. RESNET-50 has more sensitivity than VGG-16.On the other hand VGG-16 has more specificity, precision, F1 score than Resnet50.

When iteration is reduced, training time increases. When the maximum epoch is increased, accuracy improves. If the size of the minibatch is increased, training can be completed more quickly. When the learning rate is decreased, accuracy improves. Shuffle is used to eliminate overfitting and variation in order to improve training.
Observational evidence suggests that transfer learning is effective, as shown by a wide range of effects that are straightforward to track. This makes it possible to automate the procedure. For determining whether or not a patient has a stroke, the two transfer via testing that the RESNET-50 is more sensitive than the VGG-16. The VGG-16 has a greater computational complexity than the RESNET-50. As a result, hospitals and health care facilities may employ this technology to treat stroke victims.
In the future work, we will employ our deep learning models so that accuracy increases as in this paper specificity and precision of VGG-16 is 100% and Sensitivity of RESNET-50 is 100%. We also plan to extract more features from DWT so that when it goes to input to our deep learning network it can extract more information of patient having stroke and it will be helpful for doctor to do diagnosis.

REFERENCES

[1] Kalkonde, "Stroke Is the Leading Cause of Death in Rural Gadchiroli, India: a prospective community-based study," *Stroke,* vol. 46, no. 7, pp. 1764-1768, 2015.

[2] Whisnant, "Stroke incidence, prevalence, and survival: secular trends in Rochester, Minnesota, through 1989," *Stroke,* vol. 27, pp. 373-380, 1996.

[3] Kranczioch, "Real-time EEG feedback during simultaneous EEG–fMRI identifies the cortical signature of motor imagery," *Neuroimage,* vol. 114, pp. pp.438-447., 2015.

[4] Setiawan, "Identifying EEG Parameters to Monitor Stroke Rehabilitation using Individual Analysis," *In 2019 International Seminar on Intelligent Technology and Its Applications (ISITIA),* pp. 337-342, 2019.

[5] Guntari, "Classification of post-stroke eeg signal using genetic algorithm and recurrent neural networks," *In 2020 7th International Conference on Electrical Engineering, Computer Sciences and Informatics (EECSI),* pp. 156-161, 2020.

[6] P. Giri, "Ischemic Stroke Identification Based on EEG and EOG using 1D Convolutional Neural Network and Batch Normalization," *arXiv e-prints,* pp. 484-491, 2016.

[7] P. S, "Colorectal disease classification using efficiently scaled dilation in convolutional neural network," *IEEE Access,* vol. 8, pp. 99227-38., 2020 .

[8] Ananda, "Post-Stroke Recognition Based on EEG Using PCA and Recurrent Neural Networks," *In 2020 3rd International Conference on Computer and Informatics Engineering (IC2IE),* pp. 112-117, 2020.

[9] Guefrechi, "Deep learning based detection of COVID-19 from chest X-ray images," *Multimedia Tools and Applications,* vol. 80, no. 21, pp. 31803-31820., 2021.

[10] Cheah, "Optimizing residual networks and vgg for classification of eeg signals: Identifying ideal channels for emotion recognition," *Journal of Healthcare Engineering,* 2021.

[11] B. Li, "An improved ResNet based on the adjustable shortcut connections," *IEEE Access,* vol. 6, pp. 18967-18974., 2018.

Authorized licensed use limited to: NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA. Downloaded on September 08,2022 at 11:30:58 UTC from IEEE Xplore. Restrictions apply.