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BRAIN HEMORRHAGE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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Abstract : Brain hemorrhage is the severe disease occurs when the arteries in the brain burst due to high blood pressure or blood clots, which can lead to severe injury or death. In this type of medical emergency, a doctor must have years of experience in order to identify the site of internal bleeding quickly enough to begin treatment. In this study, deep learning models such as Convolutional Neural Network (CNN), hybrid model of U-Net autoencoder, Transfer learning VGG19 are proposed for the Brain Hemorrhage classification. The 368 head Magnetic resonance imaging (MRI) scan images dataset is used to boost the accuracy rate and computational power of the deep learning models. The primary goal of this work is comparative analyses of the proposed models that are used to evaluate the experimental results to a smaller set of images, as large datasets are frequently unavailable quickly. The outcome demonstrates the class of the hemorrhage and efficiency of the suggested model

***IndexTerms* - Brain Hemorrhage, Deep Learning, Convolution Neural Network, U-Net, MRI**

I. INTRODUCTION

Brain hemorrhage, is a kind of bleeding that happens when a blood vessel bursts inside the brain. This bleeding may result in death or major complications, including damage to brain tissue. This results from either internal bleeding in the brain's surrounding tissues caused by an artery rupture or an abrupt blood clot in the arteries supplying blood to the brain. Improving patient outcomes requires early diagnosis and treatment. The bleeding caused damage to brain cells, and the most common causes are bleeding disorders, brain hemorrhage, trauma, high blood pressure, aneurysms, and abnormalities in blood vessels. These are the main factors that lead to death and serious disability.

Radiologists require fast diagnoses and effective initial treatment in these cases to prevent disability and death. The Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) are used to visualize the internal structure of the brain. The MRI scan is mostly used to diagnose infection, tumor, traumatic injuries and hemorrhagic strokes inside the brain. The identification of the brain hemorrhage is a challenging phase because it is caused by internal bleeding in the head and the medical experts also need years of experience to identify the region of bleeding in the MRI scan.

The Brain Hemorrhage Classification Using Deep learning is proposed to distinguish the brain hemorrhage using MRI brain image based on Convolutional Neural Network (CNN). The image preprocessing methods such as resize the image, flipping of image and image augmentation is adopted to enhance the efficiency of training process to gain the highest accuracy rate and performance of the CNN. The experiments are carried out with various deep learning models such as CNN, U-Net, Auto-encoder, Transfer learning VGG19.

Brain Hemorrhage classes considered are Bleed, Calcified and Bleed/Clacified. Bleed is used to describe where blood escapes from the neural system and enters surrounding tissues. In the context of the brain, bleeding can lead to serious complications such as stroke, neurological damage, or even death and Calcified brain hemorrhage refers to a specific subtype of chronic subdural hematoma that occurs when a hematoma is caused by head trauma and calcifies over time.

II. LITERATURE SURVEY

[1] MUHAMMAD FAHEEM MUSHTAQ published a paper on Neural network-based identification of brain hemorrhage by studying several deep learning models such as CNN, hybrid CNN+LSTM and CNN+GRU. Dataset with CT scanned images are increased for training purpose by performing augmentation. CNN model had achieved 95% accuracy, but it concentrates more on false negative results which means it classifies the actual brain hemorrhage as non-brain hemorrhage. To overcome this issue hybrid CNN+LSTM and CNN+GRU models are proposed which achieve 100% accuracy 95.54% precision. The proposed model diagnoses the brain hemorrhage image with fast speed which helps doctors to know the condition of patients and for further treatment.

[2] Ebrahim Mohammed Senan, Taha H. Rassem proposed the Early detection of brain stroke and hemorrhage with deep and machine learning with two datasets. The first dataset is a medical record of medical examination and physiological changes. KNNInputer method is used for filling the missing pixels and outliers are removed. High dimensional data was represented in a low dimensional space by t-SNE algorithm. The extracted features are fed to SVM, KNN, Decision tree, Random Forest and MLP machine learning algorithms. Random forest achieved the best results by achieving 99% accuracy. Other datasets had MRI images that had undergone an optimization process to remove noise. Overfitting is overcome by data augmentation. Deep layers were extracted by deep learning (AlexNet) model which are classified by using machine learning algorithm (SVM). AlexNet+SVM achieves accuracy, sensitivity, specificity, and AUC of 99.9%, 100%, 99.80% and 99.86%, respectively. This research works only for particularly collected dataset.

[3] In research conducted by Anjali Gautam and Balasubramanian Raman, new classification method using image fusion and deep learning method. Quadtree image fusion technique is used to preprocess the input data and to improve the contrast of stroke region. CNN model is proposed to classify the input CT images into three categories (hemorrhagic, ischemic and normal). 80% of data is used for training purposes and the rest for testing. The method used to classify and train the image dataset performed better than AlextNet and ResNet50 of CNN architecture, helping the physicians for medical practice.

III. METHODOLOGY

The MRI brain hemorrhage images need to be preprocessed first before applying deep learning processing. Further, the images are resize into a fixed size because images collected have different size, as real time images are collected. So suitable size 256 x 256 selected. After applying the Pre-Processing, split the dataset as train-test split, Image augmentation is applied to increase the number of training images and to boost the performance.

1. **Dataset Description**: Dataset is collected from the Medical Institute that consists of MRI images of the different types of cases such as Gender, Age, Hypertension. There is total 397 MRI images in which 90% of the dataset is used for training and 10% is used for testing.

2. **Pre-processing**: Before training Data pre-processing is required to resize and remove unwanted noise from the images. Techniques used in the pre-processing:
   i. Resizing the images: Images with different dimensions are resized to 256 × 256 fixed size.
   ii. Noise removing: Median filter is nonlinear filtering technique used to remove noise from images.
   iii. Augmentation: Image augmentation is used to artificially increase the training and validation dataset by flipping horizontally or vertically, rescaling, shearing, by increasing or decreasing the zoom range, by rotating image at different angles, by increasing or decreasing the width or height ranges.

3. **Implementation**:
   By training this dataset to the model, we are going to predict that the person having a Brain Hemorrhage or not. If the patient is detected with Hemorrhage, then model able to identify the class of that Hemorrhage that belongs. By doing this we can assist the doctors to identify the class of the brain hemorrhage in a short period of time, so that they can start treatment in the early stage. Below Figure 1 shows some of the brain hemorrhage MRI images that belongs to different classes.

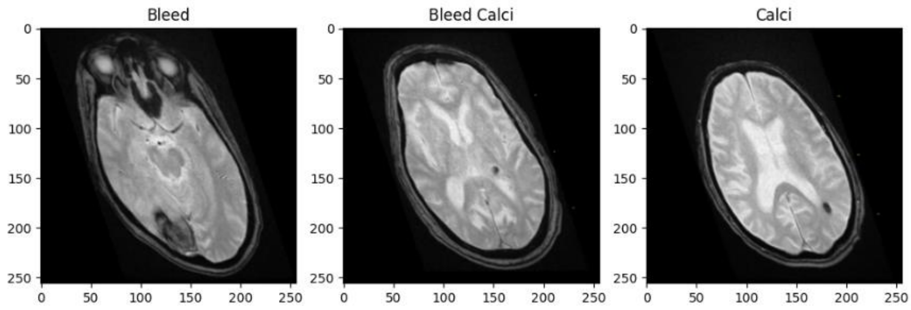

FIGURE 1. Dataset of Brain hemorrhage MRI images

4. **Detailed Design:**

   Figure 2 shows the detailed design of the proposed model. After pre-processing dataset is split into 90% of the images for training purpose and 10% for the testing purpose. At first images are input to the segmentation algorithm. U-Net is a convolutional neural network architecture for biomedical image segmentation and also suitable for the small set of datasets. After this used a Autoencoder model. Autoencoder is a type of artificial neural network that learns to compress and encode data, and then recreate the data from the encoded representation. At last input to the CNN model. Changed the parameters like activation functions, added additional layers to increase the accuracy of the model and analyzed the precision matrix.

   Compared this proposed model with the transfer learning model VGG19, CNN model. In which our proposed model U-net Autoencoder model is able to perform more accurately.

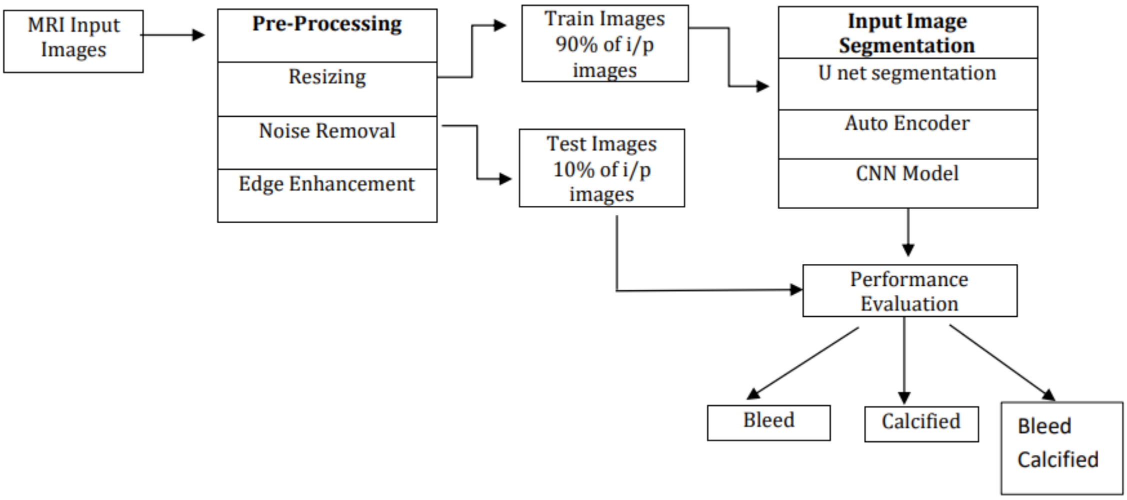

FIGURE 2. Proposed methodology of the Deep learning model.

4.1 U-Net Autoencoder model:

The main purpose of effective deep learning architecture U-Net is to solve the problem of the medical field's insufficient annotated data. This network was made to perform efficiently with little data while being accurate and quick. TensorFlow and Python env (3.10.11) will be used to implement the U-Net architecture. There are three elements in the implementation. We will begin by defining the encoder block that is utilized in the contraction path. This block is made up of two 3x3 convolution layers, a 2x2 max pooling layer, and a ReLU activation layer. The second component is the decoder block which executes two 3x3 convolution layers and ReLU activation after extracting the feature map from the below layer and upconverting, cropping, and concatenating it with the encoder input of the same level. Using these blocks, the U-Net model is defined in the third section.

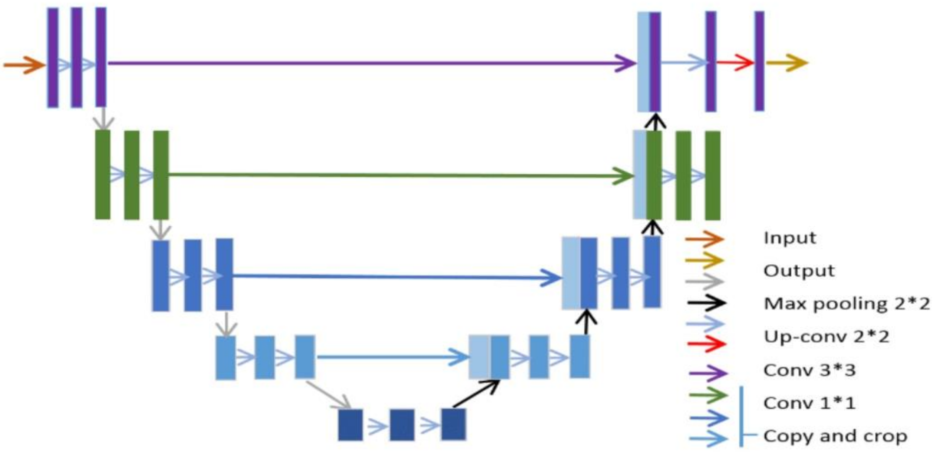

FIGURE 3. U-Net model Architecture.

4.2 VGG 19 Model:

VGG Net, also known as the visual geometry group network, is a multilayered deep neural network. Utilizing the ImageNet dataset, the VGG Net is based on the CNN model. The simplicity of VGG-19, which has 3 × 3 convolutional layers positioned on top to rise with depth level, makes it helpful. Max pooling layers were used as a controller in VGG-19 to reduce the volume size.

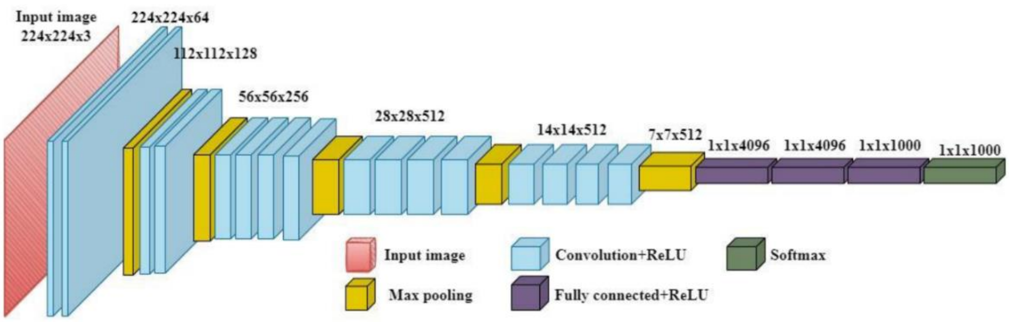

FIGURE 4. VGG19 architecture model.

4.3 CNN Model:

The primary function of a convolutional neural network is to extract features from grid-like matrix datasets. For instance, visual datasets with a lot of data patterns, like pictures. The input layer, pooling layer, convolutional layer, and fully connected layers are some of the layers that make up a convolutional neural network. The input image is processed by the Convolutional layer to extract features, the Pooling layer reduces computation by downsampling the image, and the fully connected layer generates the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

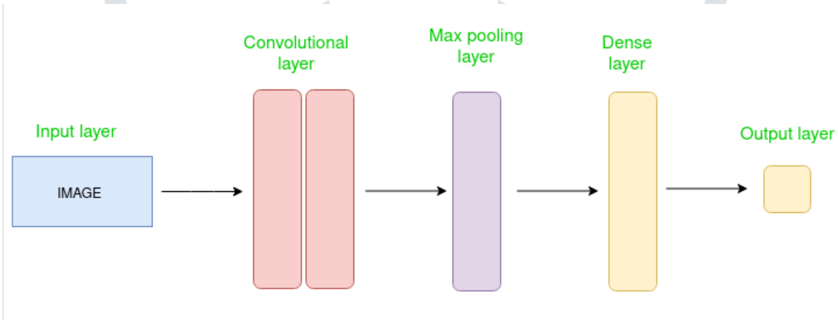

FIGURE 5. CNN architecture model.

IV. RESULTS

U-Net: Experimental analysis showed in Figure 6. The 85% accuracy is achieved using U-Net Autoencoder model.

Accuracy: 0.85
Classification report -

	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.75	1.00	0.86	15
1	1.00	0.67	0.80	18
2	0.88	1.00	0.93	7
ACCURACY			0.85	40
MACRO AVG	0.88	0.89	0.86	40
WEIGHTED AVG	0.88	0.85	0.84	40

Table 1. Experimental analysis for U-Net autoencoder model

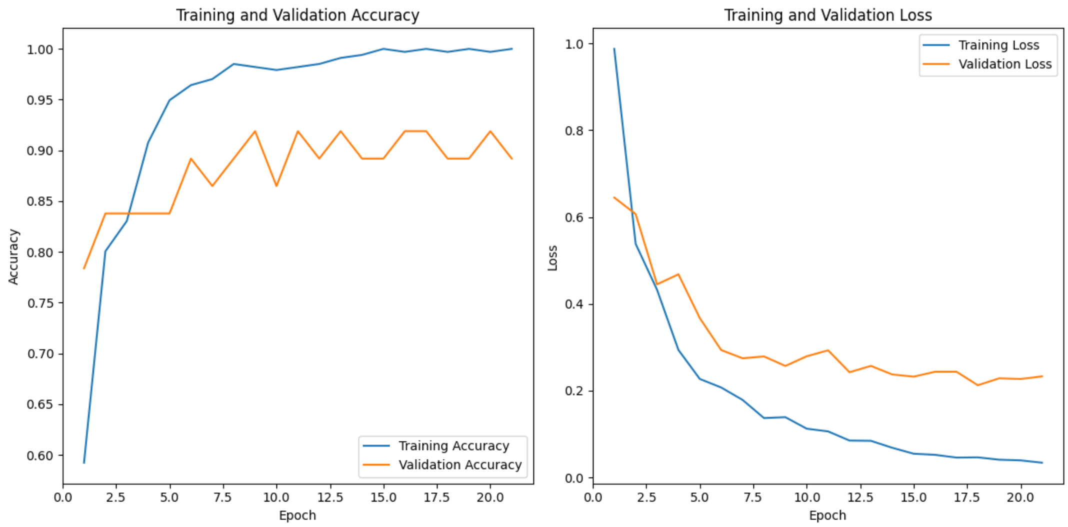

FIGURE 6. Experimental analysis for U-Net autoencoder model

VGG-19: Experimental analysis showed in Figure 7. The 80% is accuracy achieved using transfer learning VGG19 pretrained model.

Accuracy :0.8
Classification Report -

	Precision	Recall	F1-score	Support
0	0.68	1.00	0.81	15
1	1.00	0.56	0.71	187
2	0.88	1.00	0.93	7
ACCURACY			0.80	40
MACRO AVG	0.85	0.85	0.82	40
WEIGHTED AVG	0.86	0.80	0.79	40

Table 2. Experimental analysis for Transfer learning VGG19 model.

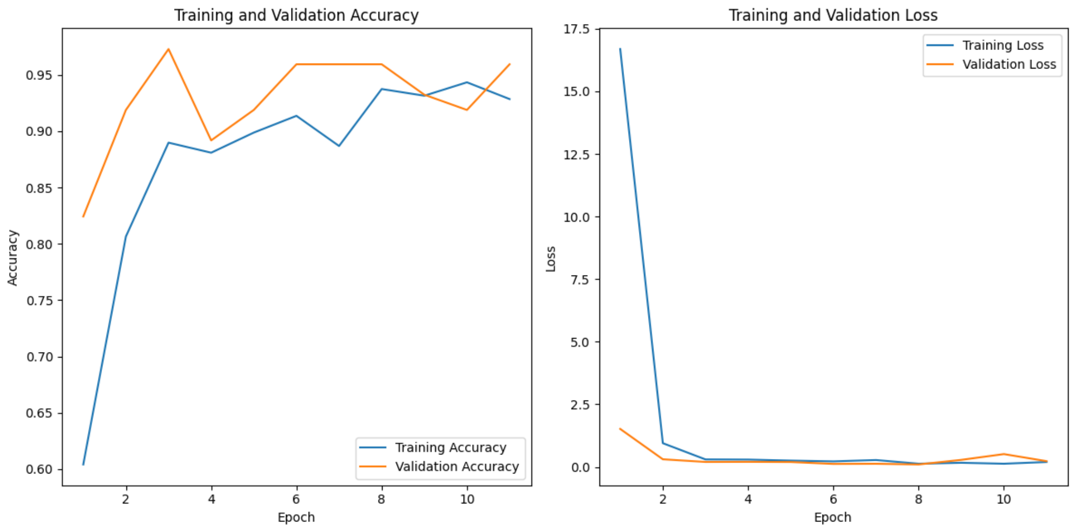

FIGURE 7. Experimental analysis for Transfer learning VGG19 model.

CNN: Experimental analysis showed in Figure 8. The 60% accuracy is achieved using simple CNN model.

Accuracy: 0.6
Classification report –

	Precision	Recall	F1-score	Support

0	0.52	0.80	0.63	15
1	1.00	0.50	0.67	18
2	0.38	0.43	0.40	7
ACCURACY			0.60	40
MACRO AVG	0.63	0.58	0.57	40
WEIGHTED AVG	0.71	0.60	0.61	40

Table 3. Experimental analysis for Convolution neural network model.

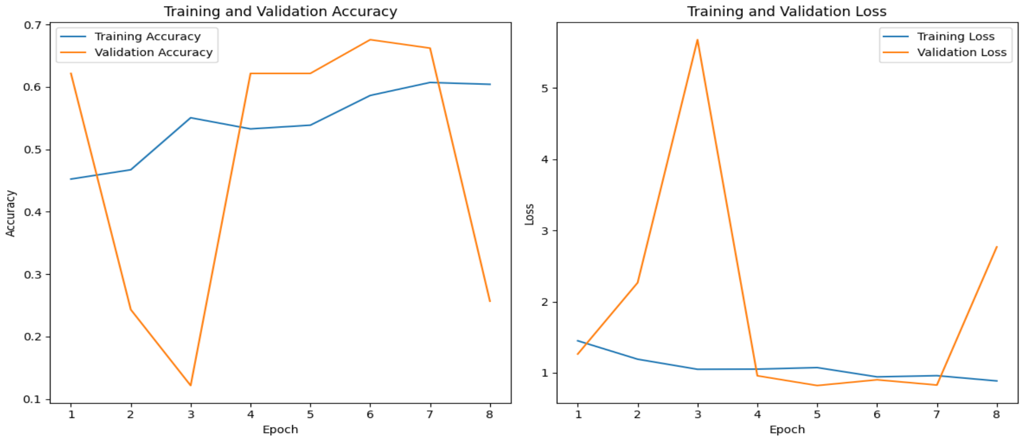

FIGURE 8. Experimental analysis for Convolution neural network model.

Figure 9 shows the comparative test results of the test images with the original label and predicted class of the images.

	Image File	Original Label	Predicted Class	Confidence (%)
0	1.png	Bleed	bleed	57.379705
1	12.png	Bleed	bleed	54.682273
2	13.png	Bleed	bleed	56.357539
3	14.png	Bleed	bleed	57.455552
4	15.png	Bleed	bleed	57.241178
5	16.png	Bleed	bleed	54.479408
6	17.png	Bleed	bleed	57.097232
7	18.png	Bleed	bleed	57.520688
8	2.png	Bleed	bleed	57.209104
9	3.png	Bleed	bleed	57.583106
10	4.png	Bleed	bleed	57.544386
11	5.png	Bleed	bleed	57.469994
12	6.png	Bleed	bleed	57.460463
13	7.png	Bleed	bleed	57.458508
14	8.png	Bleed	bleed	57.344371
15	21.png	Bleed-calified	bleed_calci	54.026639
16	c1.jpg	Bleed-calified	bleed_calci	56.889975
17	c10.jpg	Bleed-calified	bleed	50.032669
18	c11.jpg	Bleed-calified	bleed	38.801190
19	c12.jpg	Bleed-calified	bleed	38.801190
20	c13.jpg	Bleed-calified	calci	50.412536
21	c14.jpg	Bleed-calified	bleed_calci	57.370251
22	c15.jpg	Bleed-calified	bleed_calci	56.372505
23	c16.jpg	Bleed-calified	bleed	43.715358
24	c17.jpg	Bleed-calified	bleed_calci	34.415787
25	c2.jpg	Bleed-calified	bleed_calci	56.512779

FIGURE 9. Comparative results of different classes image using proposed models.

Below table 1 shows the comparative analysis of results of the proposed models. From this we can say that our proposed model that is U-Net model is working more accurately with the 85% of accuracy compare to other pre trained models.

Deep Learning Models	Accuracy	Precision	F1-Score	Support	Recall
Proposed U-net model	0.85	1.00	0.93	18	1.00
VGG-19	0.80	1.00	0.93	18	1.00
CNN model	0.60	1.00	0.67	18	0.80

TABLE 4. Comparative representation of results of Proposed models.

V. CONCLUSION

In this work, we have compared various deep learning models such as U-Net Autoencoder, VGG19 and CNN models on the basis of classification accuracy of images and confusion matrix. The proposed system helps to identify the Brain hemorrhage and class of the Brain hemorrhage such as Bleed and Calcified, in an efficient way with a help of deep learning and Machine learning models.

VI. FUTURE SCOPE

In future work, we aim to collect a greater number of the MRI images to create a huge dataset so that model can work with the more accurately. Our aim is to develop a system to identify class of the brain Hemorrhage with fast and reliable method.

VII. REFRENCES

1. Mobeen Shahroz, Ali M Aseere, Habib Shah – Department of computer science and engineering, BHCNet : Neural Network based Brain Hemorrhage Classification using head CT Scan, received-July 10 2021, accepted-August 1 2021.
2. Ebrahim Senan, Nasrin Makbol, Faud Ghaled – College of computer engineering, Deep learning and Machine learning for early detection of stroke and Haemorrhage.
3. Anjali Gautam, Balasubramanian Raman – Towards effective classification of brain hemorrhagic and ischemic stroke using CNN.
4. K. K. Ang, C. Guan, K. S. G. Chua, B. T. Ang, C. W. K. Kuah et al., "A large clinical study on the ability of stroke patients to use an EEG-based motor imagery brain-computer interface," Clinical EEG and Neuroscience, vol. 42, no. 4, pp. 253–258, 2011.
5. M. Naghavi, A. A. Abajobir, C. Abbafati, K. M. Abbas, F. Abd-Allah et al., "Global, regional, and national age-sex specific mortality for 264 causes of death, 1980–2016: A systematic analysis for the global burden of disease study 2016," The Lancet, vol. 390, no. 10100, pp. 1151–1210, 2017.
6. S. Al-Shoukry, T. H. Rassem and N. M. Makbol, "Alzheimer's diseases detection by using deep learning algorithms: A mini-review," IEEE Access, vol. 8, pp. 77131–77141, 2020.
7. A. Barman, V. Lopez-Rivera, S. Lee, F. S. Vahidy, J. Z. Fan, S. I. Savitz, S. A. Sheth, and L. Giancardo, ''Combining symmetric and standard deep convolutional representations for detecting brain hemorrhage,'' Proc. SPIE, vol. 11314, Mar. 2020, Art. no. 113140D.
8. M. Otterskog, N. Petrovic, and P. O. Risman, ''A multi-layered head phantom for microwave investigations of brain hemorrhages,'' in Proc. IEEE Conf. Antenna Meas. Appl. (CAMA), Oct. 2016, pp. 1–3.
9. F. Ahmadabadi, M. Mirzarahimi, A. Ahadi, and Z. Alizadeh, ''Frequency, causes, and findings of brain CT scans of neonatal seizure at Ardabil city hospital, Ardabil, Iran,'' Int. Surg. J., vol. 7, no. 8, pp. 2485–2489, 2020.
10. J. R. Little, B. Dial, G. Bélanger, and S. Carpenter, ''Brain hemorrhage from intracranial tumor,'' Stroke, vol. 10, no. 3, pp. 283–288, May 1979.

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