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A Review on Comparative analysis and methods of Early detection of Brain tumor using Deep Learning CNN

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***Abstract*. According to the last Report of International Association of Cancer Registries which is a Global cancer observatory of World health organization has reported 28,000 cases in India each year and more than 24,000 people reportedly die due to brain tumor annually. Harmful Brain tumor have three types that is Glioma, Meningioma and Pituitary tumor. For image data of brain tumor, MRI and CT Scan are mostly used. But as per research study, MRI is used more compare to CT scan and others. Deep learning has a capability to work on very deep neural network process. Convolutional neural network works on more efficient way to improve object detection. The Aim of this paper is to compare different pretrained convolution neural network based developed methods and models to predict or detect tumour symptoms early through Image data using Deep Learning technique. The main focus of this paper about study and review of different CNN models, algorithms, datasets and compared their results for accuracy as well as pictorial view of the tumor shape.**

Keywords : Brain tumor, CNN architecture, MRI images, Deep neural network.

I. INTRODUCTION

A. *Brain Tumour*

Brain tumor is an expansion of tissues inside the brain. It is classified in two types where first is Benign and second is Malignant[1]. It is shown in figure 2 and figure 3.1, 3.2, 3.3. Benign is a primary stage tumor. In that It is a starting phase of tumor. It is not harmful and we can also say It has early prediction of tumour. Malignant is the second or third stage of tumor. It is harmful and can be life threatening. Benign tumor cannot expand to other body whereas Malignant can expand to other body part.

B. *MRI*

It is a non-harmful technique which shows a three-dimensional anatomical body structure for any part of body. RF pulses and a strong magnetic field is used to gain images. Water molecules of the human body is attracted toward the magnetic field After then RF energy is applied to the direction of magnetic field. After turn of the RF energy pulses water molecules comes in their initial position and this process is repeated. During this process water molecules emit RF energy and this is detected by the scanner which converts them in viewable images.

TE(Time to echo) and TR(Repetition time) is an important factor which controls mri images[3]. Emission of RF energy depends upon tissue structure. CRF (cerebrospinal Fluid) is a colourless liquid which protects brain and spinal cord from physical and chemical damage. Gray matter is place of neural cell bodies, axon terminals, dendrites and also all nerve synapses. It is shown in figure 1.This brain tissue is generous in the cerebellum, cerebrum, and brain stem. Central spinal cord is formed in butterfly shape. The backside of butterfly shape is called a posterior, or also called as dorsal Gray horn. It is used to passes information that it sense through upside sloping nerve signal to the brain. White matter is integration of bundles of axons. It is shown in figure 1. It is used to conduct, process, and send nerve signals upside and downside the spinal cord.

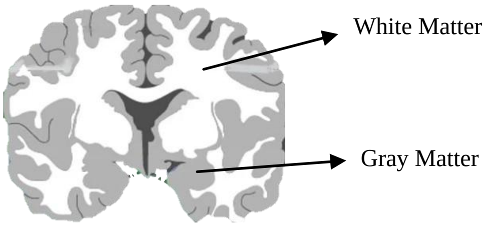

Fig. 1. Central nervous system of Brain cClassificatioMatter

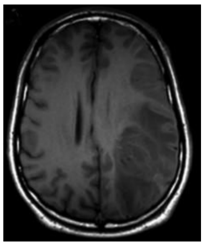

Fig. 2 **:** Benign type[1]

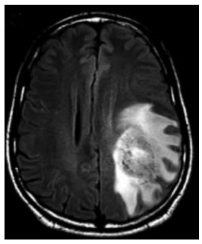

Fig. 3.1 **:** Malignant[1]

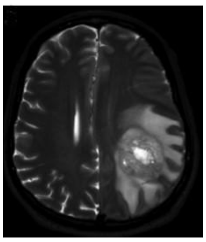

Fig.3.2 **:** Malignant[1]

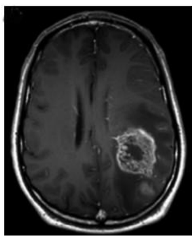

Fig. 3.3 **:** Malignant[1]

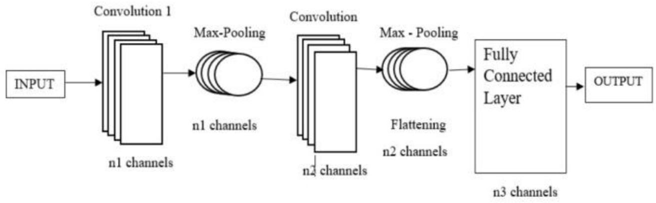

Fig. 4. General CNN architecture

II. LITERATURE REVIEW

M.o. khairandish and Sharma[1] has worked on Brain tumour detection with Hybrid model where they used convolutional neural network with support vector machine as a classifier. To obtain effective result they also explain a role of mathematical function so that It can try to detect the best features in brain tumor images. As per the Paper they got highest accuracy which is around 98 % by using hybrid model comparing with only convolutional neural network and only support vector machine.

TABLE I. MODEL CLASSIFICATION ACCURACY[1]

Stage of brain tumour	CNN	SVM	Hybrid
Benign	97.7%	61.7%	98.58%
Malignant	97.4%	67.99%	98.67%

Iftekharuddin[11] use fractal Wavelet features as input to a self-organizing map classifier and achieved an average precision of 90%. T.kalaiselvi, padmapriya[6] used 6 different model of CNN. In that they used different number of layers with dropout and batch normalization. In those layers they used different number of datasets and also obtain a bit or more different accuracy in that. The highest accuracy that they obtained is 96%. Kurup et al [7] use data pre-processing to improve efficiency by using CNN. In this pre-processing their main focus is on augmenting data where the process name is rotation and patch extraction. Patch extraction means extracting group of pixels. Capsulnet model is used here for image classification. In Capsule Net We can add more layers inside the single layer which is also called as nestation. It has relu as an activation function and Caps layer for filtering.

Togacar et al[3] has used machine learning techniques in that their idea is that first they enhance features using hyper column technique. Alexnet and VGG16 is used for feature extraction. At a pixel, Hyper column as shown in figure 5 is the vector of activations of all convolutional neural network units. It can keep the local discriminative features, which are extracted from the layers located at the different levels of the deep architectures.

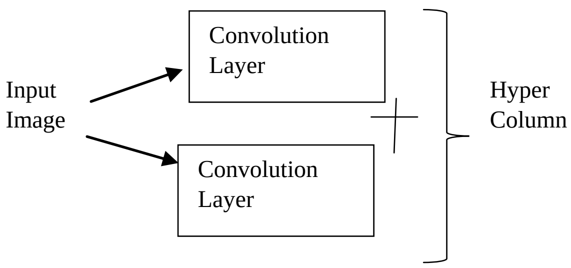

Fig. 5. Hyper column Process[3]

For feature selection algorithm they use recursive feature elimination which select feature from training dataset which is more relevant. For classification is done by support vector machine which gives accuracy about 96%.

Raja and Viswasa[4] uses deep learning and statistical model to discriminate between tumour and non-tumour images. For pre-processing they use median filtering after then for segmentation they use Bayesian Fuzzy C-means algorithm. Utilization of feature extraction, Information theoretic measures, wavelet packet Thalis entropy and scattering transform are done. For classification It was done using Deep autoencoder based jaya optimization algorithm and softmax regression. SoftMax is an activation function.

$$SF(x_j) = \frac{e^{x_j}}{\sum_{k=1}^{z} e^{x_z}}$$

Amin [5] discuss about the data pre-processing and segmentation before giving it as an input to a deep learning algorithm. Author's idea is to make better MRI images then apply median filtering which is used for noise smoothing. At a later with the use of stacked sparse autoencoder model, Tumour area is segmented. For training and testing brats dataset is used. With the help of a proposed technique, accuracy and sensitivity are improved. Poonguzhali [6] use faster recurrent neural network algorithm for efficient detection and classification of brain tumour mri images. The images are given as input to a general convolutional neural network through which a feature map for convolution is obtained and later feature map is converted to a feature vector by using region of interest pooling layer. Here region of interest is used as input to faster recurrent neural network for classification on support vector machine. Accuracy that is obtained is around 95%. Maharjan[7] used modified form of proposed solution by Ari and Hanboy[8]. In that they modify pre-processing and classification stage. They used modified softmax function and loss function in convolution layer which can be used as an alternative of sigmoid function. Watershed algorithm is used for segmentation using morphological operations. Accuracy is around 97% and also required less processing time. Cinar and Yildirim[9] used modified version of RESnet50 for classification of brain tumor and non-tumor. In those 8 additional layers have been used with the general Resnet50 architecture. Result of this is also compared with other advance convolutional neural network architectures like Googlenet, Alexnet, Densenet etc. Accuracy that obtained from the proposed system is better compare to other deep learning architectures. Ghassemi[12] used a generative adversarial networks architecture. Their thought is to use convolutional neural network as generative adversarial networks discriminator and pre-train it using datasets. For more realistic images they used data augmentation. In the last layer they used softmax activation function in place of convolutional neural network discriminator layer of generative adversarial networks. They used figshare dataset and accuracy is 88%.

Ozyurt[13] proposed a hybrid approach with fuzzy c-means with super resolution and convolution neural network. With super resolution and convolutional neural network, low resolution images can be converted into high resolution. Fuzzy c means used for image segmentation. Squeeze-net architecture is used for extracting features. Accuracy gets around 98%. Bhanothu[14] uses faster recurrent neural network approach with vgg-16 architecture for classification and detection. For accurate detection of tumour size, Region proposal network is used. Anil kumar and Rajesh Kumar[15] proposed algorithm using vggnet. Here vggnet is a pretrained architecture. They used two different datasets which is brats and ce-mri. Accuracy that they got is around 97.28% and 98% respectively. Megha [16] uses convolutional neural network architecture and also use graphical user interface for effective intersection with the algorithm. The designed algorithm shows 90-99% accuracy on the kaggle dataset. Adu[17] proposed capsnet model. They proposed dilated capsule network which is an extension of convolutional neural network. Convolutional neural network have many disadvantages. The most important and critical one is that it does not take into consideration the spatial relationship between the object and its circle range. Accuracy gets around 95 %. Siar and Teshnehlab[18] use convolutional neural network with different classifiers namely Radial Basis function and decision trees and for feature extraction they use centre clustering algorithm. Accuracy is around 96 %. Zhou[19] use three dimensional images with two dimensional slices and use it as an input. Three model densenet-RNN, densenet-LSTM and densenet-densenet are compared. Accuracy got respectively 87%, 91%, 92%. Muthu krishnammal and selvakumar raja[20] use a proposed alexnet architecture. Curvelet transform and grey level co-occurrence matrix is used for feature extraction. Accuracy gets around 96 %. Sivadas, Deepak and Ameer[21] uses Google net for automatic system with three classifications of tumour i.e., glioma, meningioma, pituitary tumour. To work on small dataset, they propose transfer learning approach. The transfer learned and fine-tuned model is then used for classification of tumour type[3]. Result shows accuracy around 98 %. Sultan[22] used CNN. First they pre-process and then perform augmentation and also used two dropout layers in a model of 16 layers to reduce overfitting[3]. In first dataset Accuracy gets around 96 %. and In second dataset Accuracy gets around 98 %. Ezhilarasi and varalakshmi[23] uses faster recurrent neural network. They uses pretrained Alexnet along with region proposal network. Afterwards convolution feature map from Alexnet is used as the input to region proposal network for calculating region of interest. This region of interest is used to train faster recurrent neural network. The authors have used both ends to end 4 stage training for proposed architecture[3]. Accuracy got around 99 %. Seetha and Raja[24] uses two different with CNN architecture which is brats 2015 and radiopedia dataset. The authors compared accuracy with support vector machine and deep neural network. Accuracy gets around 97 %. Vipin Makde[25] uses modified architecture of Alexnet and Zfnet for detection and classification[3]. Accuracy is around 97 %. Mohsen[26] uses Deep Neural Network classification[3] .Three types of brain tumour glioblastoma, Sarcoma, Metastatic bronchogenic carcinoma is considered here. Segmentation using fuzzy c-means clustering and then feature extraction with discrete wavelet transform. Principal component analysis is used to reduce features. Ye, Fangyan[27] uses deep convolutional neural network model with gated multimodal units Which is used to embed multimodal information from all three modalities for brain tumour classification[3]. First, convolutional neural network model is used to extract from all three image modalities i.e., T1,T2, Flair of brats 2015 dataset. Antony[28] works with convolutional neural network and Segmentation of tumour is done in three part which is necrosis, enhancing, non- enhancing tumour. NI4TK software is used for pre-processing. Tumours are classified in four parts. Banerjee[29]uses three convolutional neural network which is Patchnet, slicenet and volumenet. Patches, slices and three dimensional volumetric is used as input to make three different models. They also talk about vggnet and resnet for training and testing process. Accuracy gets around 97%.

TABLE II. COMPARISON OF DIFFERENT CNN ARCHITECTURE WITH DIFFERENT DATASETS

Model	Description	Dataset	Accuracy
Alexnet CNN architecture	It is one of the most used CNN architectures. It is 5 convolution layer, 3 max-pooling, 2 Normalization layer and 1 SoftMax layer. It has 60 million parameters which is a huge channel to handle it. It has a complex architecture.	Chakraborty 2019 from Kaggle	96.77%
		Brain tumour detection from Kaggle	97%
		Miccai BRATS(2013-2017) ISLES strokes	97 %
		(Alexnet + Googlenet) Private Dataset contains 153 patients and 1892 images	99 %
		BRATS 2015 (Alexnet with VGG16)	98%
		Figshare dataset (Alexnet +Googlenet + VGG16)	98.5%
		Rembrandt and APIE-AAPM-CT Challenge	97 %
ResNet	It has a unique feature which is a skipping connection without compromising quality while building deep neural network. The skipping actually enabled skipping one or more layers. It can use upto 152 layers , Resnet is one of the first to use batch normalization. Vanishing gradient problem is also avoided.	Brain Tumour dataset from Kaggle	97%
		FigShare	96%
		BRATS 2016	91%
		BRATS 2017 AND TCIA	97%
GoogleNet	It has 4 million parameters. It gives same quality compare with AlexNet. It has multiple small convolution which is used to bringdown the number of parameters. It has 22 layers.	Figure Dataset T1-CE (3064 Images)	92%
ZFnet	It is a modified version of Alexnet. Major Difference in the architecture is that ZFnet has 7*7 filters whereas Alexnet has 11*11 filters. It was gained lot of attention during ILSVRC 2013 Contest and It is a winner of that contest too.	Rembrandt and SPIE-AAPM-CT challenge	97%

III. Methodology

Among this all-CNN architecture, Alexnet is one of the best. It has lot of similarity with Lenet. Remember, there were many convolution layers in the Lenet architecture. This is called deep neural network and 60 million parameters are there which makes it very difficult. One major difference with lenet with alexnet is about depth . It has good amount of deepness with having more filters per layer. Also, It has a greater number of convolution layer so that it can also called as Deep Neural Network. Here It uses dropout feature which is used to avoid overfitting. Data augmentation is also done which is used to make mirror image and also for improvement in training volume. With more reliability of GPUs and storage, alexnet can be one of the proper architectures as shown in figure 6. But alexnet is very complex architecture because of their huge number of parameters. So, to reduce this complexity we can work with googlenet or zfet. As an optimizer stochastic gradient decent is used.

$$Loss = \sum_{i=1}^{n} (y - \hat{y})^2$$

$$W_{\eta e\omega} = w_0 - nx \frac{\partial L}{\partial \omega_0}$$

Where,n = Learning Rate, $W\eta e\omega$ = Updated weight, w_0 = present weight, L = Loss

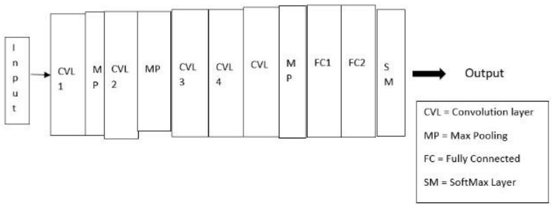

Fig. 6. Alex Net architecture

After Evolution of VGG16, It has number of other models were being coming out and a good number of innovations happened. Googlenet was founded by google team which attracted everyone and gained lots of attention. It is shown in figure 7. It is also known as Inception. This model was also emerged as the winner of the popular and challenging ImageNet contest which is also known as Inception model. Image distortion, batch normalization and rmsprop was used by Inception modules, which is an optimization of gradient based technique. Batch normalization is an important technique which is used in Googlenet for improving the speed, performance, and stability as we used in other ANN applications.

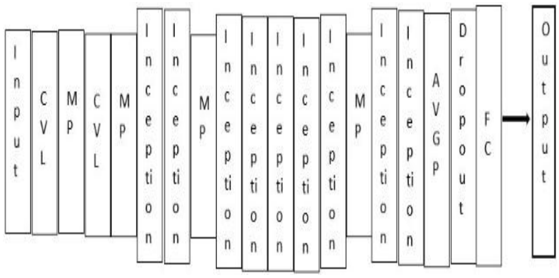

Fig. 7. GoogleNet architecture

IV. Conclusion

This Paper presents a review of research work for brain tumour detection and classification with MRI images by using Deep Learning and some part of machine learning. In that we compare a different dataset result with different convolutional neural network approach like Alexnet, vgg16, Googlenet, Zfnet, Capsulenet. We divide tumour in two classification which benign and malignant . Here we clearly seen that all convolutional neural network architecture have different number of layer and hybridization of this architecture gives a significant result compare to use single one. In future, We will try to optimize more so that accuracy and other useful parameters will increase in their efficiency. As per the study of Hybrid model, CNN with SVM got around 98 % accuracy. But time required is large so Now we can try to propose a model which has same amount of accuracy with less time and we will also try to extract size of the tumour and location of tumour. For that Faster CNN with SVM can be used.

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