# DETECTION OF INTRACRANIAL TUMOR USING CONVOLUTION NEURAL NETWORK

Dr. P. Visu[1], K Swetha[2], V Priya Darshini[2] and S Meena[2]

[1]Professor, Department of Computer Science Engineering, Velammal Engineering College, Ambattur Red Hills Road, Chennai, Tamil Nadu 600066.

[2]UG Scholars, Department of Computer Science Engineering, Velammal Engineering College, Ambattur Red Hills Road, Chennai, Tamil Nadu 600066.
visu.p@velammal.edu.in

**Abstract - Brain tumor image classification is a vital a part of medical image processing. It assists doctors to create accurate diagnosis and treatment plans. resonance (MR) imaging is one among the most imaging tools to review brain tissue. In our proposed system propose the neoplasm MR image classification method using transfer learning-based CNN-pretrained VGG-16. When these algorithms are applied on the MRI images the detection of neoplasm is completed in no time and the next accuracy helps in providing the treatment to the patients. This detection also helps the radiologist in making quick decisions. As an outcome, we will estimate that the pretrained model VGG-16 determines highly adequate results with a rise within the accuracy rate of coaching and validation.**

***Keywords - Brain Tumor, Detection, Classification, MRI images, CNN, VGG-16.***

## I. INTRODUCTION

In today's digital era, capturing, storing and analysis of medical image had been digitized. Even with state of the art techniques, detailed interpretation of medical image may be a challenge from the angle of your time and accuracy. The challenge stands tall especially in regions with abnormal color and shape which has to be identified by radiologists for future studies. The key task in designing such image processing and computer vision applications is that the accurate segmentation of medical images. Image segmentation is that the process of partitioning different regions of the image supported different criteria. Surgical planning, post-surgical assessment, abnormality detection, and far other medical application require medical image segmentation. In spite of wide number of automatic and semi – automatic image segmentation techniques, they fail in most cases largely thanks to unknown and irregular noise, in homogeneity, poor contrast and weak boundaries which are inherent to medical images.

MRI and other medical images contain complicated anatomical structures that need precise and most accurate segmentation for clinical diagnosis. Brain image segmentation from MRI images is complicated and challenging but its precise and exact segmentation is important for tumors detection and their classification, edema, hemorrhage detection and necrotic tissues. For early detection of abnormalities in brain parts, MRI imaging is that the best imaging technique. Unlike computerized axial tomography (CT), MRI image acquisition parameters will be adjusted for generating high contrast image with different gray level for various cases of neuropathology. Therefore, MRI image segmentation stands within the upcoming research limelight in medical imaging arena. within the field of neuroscience, mapping of functional activation onto brain anatomy, the study of brain development, and therefore the analysis of neuron anatomical variability in normal brains requires the identification of brain structures in MRI images. Other than this, segmentation of MRI images is important in clinical diagnosis of neurodegenerative and psychiatric disorders, treatment evaluation, and surgical planning. Brain cancer may be a very serious form of malignancy that happens when there's an uncontrolled growth of cancer cells within the brain.

Brain cancer is caused by a malignant neoplasm. Not all brain tumors are malignant (cancerous). Some kinds of brain tumors are benign (non-cancerous). Brain cancer is additionally called glioma and meningioma. Brain cancer is one in all the leading causes of death from cancer. There are two main sorts of brain cancer. They include primary brain cancer, within which the brain cancer originates within the brain itself. Primary brain cancer is that the rarest style of brain cancer. It can spread and invade healthy tissues on the brain and medulla spinalis but rarely spreads to other parts of the body. Secondary brain cancer is more common and is caused by a cancer that has begun in another a part of the body, like carcinoma or carcinoma that spreads to the brain. Secondary brain cancer is additionally called metastatic brain cancer. Brain cancer is most treatable and curable if caught within the earliest stages of the disease. Untreated and/or advanced brain cancer can only spread inward because the skull won't let the neoplasm expand outward. This puts excessive pressure on the brain (increased intracranial pressure) and might cause permanent brain damage and eventually death. This process ends up in symptoms, like headache, and other neurological problems. For more details on other key symptoms and complications, sit down with symptoms of brain cancer.

People in danger for developing brain cancer include people with a case history of brain cancer and folks who have had actinotherapy of the pinnacle. Diagnosing brain cancer begins with taking a radical personal and family case history, including symptoms and risk factors for brain cancer. The diagnostic process also includes completing an intensive physical and neurological exam. A neurological helps to gauge the brain and systema nervosum and such functions as reflexes, sensation, movement, balance, alertness, coordination, vision, and hearing. A diagnosis of brain cancer is mostly made by a specialist called a neurologist. Imaging tests that will be performed include MRI and/or CT scan which use technology to create detailed pictures of the brain. A procedure called a brain angiogram may be done to illuminate blood vessels within the brain that feed blood to a brain tumor. Diagnostic testing also includes a biopsy. during a biopsy a sample of cells or tissues are taken from the brain during surgery performed on a tumor.

MACHINE LEARNING:

Machine learning (ML) could be a field of inquiry dedicated to understanding and building methods that 'learn', that is, methods that leverage data to boost performance on some set of tasks. it's seen as part of computer science Machine learning algorithms build a model supported sample data, called training data, so as to create predictions or decisions without being explicitly programmed to try to to so. Machine learning algorithms are employed in a good type of applications, like in medicine, email filtering, speech recognition, and computer vision, where it's difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

A subset of machine learning is closely associated with computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the sector of machine learning. data processing could be a related field of study, that specialize in exploratory data analysis through unsupervised learning. Some implementations of machine learning use data and neural networks in an exceedingly way that mimics the working of a biological brain.

The use of machine learning allows businesses to accelerate repetitive tasks and shift human resources to higher value activities. as an example, machine learning technology can perform exhaustive document searches during a fraction of the time it takes people to perform scanning and cross-referencing tasks. These capabilities allow companies to scale back costs for information retrieval activities associated with regulatory compliance and legal research, while also freeing employees to focus their efforts elsewhere. The recommendations provided by popular streaming platforms like Spotify and Netflix are supported machine learning algorithms. By analyzing the songs you've listened to or the shows you've watched – together with masses of knowledge about other songs, shows and consumer habits – these algorithms identify and suggest additional content you'll enjoy.

CONVOLUTION NEURAL NETWORK:

A convolutional neural network may be a feed forward neural network that's generally accustomed analyze visual images by processing data with grid-like topology. It's also referred to as a ConvNet. A convolutional neural network is employed to detect and classify objects in a picture.

A convolution neural network has multiple hidden layers that help in extracting information from a picture. The five important layers in CNN are:

- Convolution layer
- ReLU layer
- Pooling layer
- Flattening layer
- Fully connected layer

DEEP LEARNING:

Deep learning is computer software that mimics the network of neurons during a brain. it's a subset of machine learning and is termed deep learning because it makes use of deep neural networks.

Deep learning algorithms are constructed with connected layers.

- The first layer is called the Input Layer
- The last layer is called the Output Layer
- All layers in between are called Hidden Layers.

Each Hidden layer consists of neurons. The neurons are connected. The neuron will process then propagate the sign it receives within the layer above it. The strength of the signal given to the neuron within the next layer depends on the load, bias and activation function. The network consumes large amounts of computer file and operates them through multiple layers; the network can learn increasingly complex features of the info at each layer.

Deep learning could be a powerful tool to create predictions and actionable results. Deep learning excels in pattern discovery (unsupervised learning) and knowledge-based prediction. Big data is that the fuel for deep learning. When both are combined, a company can reap unprecedented leads to terms of productivity, sales, management, and innovation. Deep learning can outperform the standard method. for example, deep learning algorithms are 41% more accurate than machine learning algorithms in image classification, 27 yet one more accurate in identity verification, and 25% in voice recognition.

.

## II. RELATED WORKS

### A. *Brain Tumor Classification Using Convolutional Neural Network" World Congress on Medical Physics and Biomedical Engineering 2018*

Nyoman Abiwinanda et.al implemented the best possible architecture of CNN; i.e. one each of convolution, max-pooling, and flattening layers, followed by a full connection from one hidden layer. The CNN was trained on a brain tumour dataset consisting of 3064 T-1 weighted CE-MRI images publicly available via figshare Cheng (Brain Tumor Dataset. Using our simple architecture and with none prior region-based segmentation, we could achieve a training accuracy of 98.51% and validation accuracy of 84.19% at the best. Misdiagnosis of brain tumour types will prevent effective response to medical intervention and reduce the possibility of survival among patients. One conventional method to differentiate brain tumors is by inspecting the MRI images of the patient's brain. for big amount of information and different specific sorts of brain tumors, this method is time consuming and susceptible to human errors. during this study, we attempted to coach a Convolutional Neural Network (CNN) to acknowledge the three commonest forms of brain tumors, i.e. the Gli.

### B. *"Brain Tumor Classification Using Convolutional Neural Networks" Biomedical & Pharmacology Journal, September 2018.*

In this work, automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification. The deeper architecture design is performed by using small kernels. The weight of the neuron is given as small. Experimental results show that the CNN archives rate of 97.5% accuracy with low complexity and compared with the all other state of arts methods. The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI)and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate…etc. Especially, in this work MRI images are used to diagnose tumor in the brain. However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time The automatic brain tumor classification is very challenging task in large spatial and structural variability of surrounding region of brain tumor.

### C. *" Multi-classification of Brain Tumor Images using Deep Neural Network" IEEE Access 2019*

In this paper, a DL model supported a convolutional neural network is proposed to classify different tumour types using two publicly available datasets. the previous one classifies tumors into (meningioma, glioma, and pituitary tumor). the opposite one differentiates between three glioma grades (Grade II, Grade III, and Grade IV). Datasets include 233 and 73 patients with a complete of 3064 and 516 images on T1-weighted contrast-enhanced images for the primary and second datasets respectively. The proposed network structure achieves a major performance with a best overall accuracy of 96.13% and 98.7% respectively for the 2 studies. Results indicate the power of the model for neoplasm multi-classification purposes. Brain tumor classification may be a crucial task to judge the tumors and make a treatment decision in step with their classes. There are many imaging techniques wont to detect brain tumors. However, MRI is often used thanks to its superior image quality and therefore the fact of looking forward to no radiation. Deep learning (DL) could be a subfield of machine learning and recently showed an interesting performance especially in classification and segmentation problems.

### D. *"Brain Tumor Detection Using Convolutional Neural Network" 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT 2019)*

In this paper, they proposed a technique to extract neoplasm from 2D resonance brain Images (MRI) by Fuzzy C-Means clustering algorithm which was followed by traditional classifiers and convolutional neural network. The experimental study was carried on a real-time dataset with diverse tumor sizes, locations, shapes, and different image intensities. In traditional classifier part, we applied six traditional classifiers namely Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest which was implemented in scikit-learn. Afterward, we moved on to Convolutional Neural Network (CNN) which is implemented using Keras and Tensorflow because it yields to a much better performance than the normal ones. In our work, CNN gained an accuracy of 97.87%, which is incredibly compelling. the most aim of this paper is to differentiate between normal and abnormal pixels, supported texture based and statistical based features.

### E. *"Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm" 9th International Conference on Computer and Knowledge Engineering (ICCKE 2019)*

In this paper, a Convolutional Neural Network (CNN) has been accustomed detect a tumor through brain resonance Imaging (MRI) images. Images were first applied to the CNN. The accuracy of Softmax Fully Connected layer accustomed classify images obtained 98.67%. Also, the accuracy of the CNN is obtained with the Radial Basis Function (RBF) classifier 97.34% and therefore the Decision Tree (DT) classifier, is 94.24%. additionally to the accuracy criterion, we use the benchmarks of Sensitivity, Specificity and Precision evaluate network performance. in line with the results obtained from the categorizers, the Softmax classifier has the most effective accuracy within the CNN in line with the results obtained from network accuracy on the image testing. this can be a replacement method supported the mixture of feature extraction techniques with the CNN for tumor detection from brain images. the tactic proposed accuracy 99.12% on the test data. because of the importance of the diagnosis given by the physician, the accuracy of the doctors help in diagnosing the tumor and treating the patient increased.

*F. "Brain Tumor Detection Using Color-Based K-Means Clustering Segmentation" Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP 2007)*

In this paper, they propose a color-based segmentation method that uses the K-means clustering technique to trace tumor objects in resonance (MR) brain images. The key concept during this color-based segmentation algorithm with K-means is to convert a given gray-level MR image into a color space image and so separate the position of tumor objects from other items of an MR image by using Kmeans clustering and histogram-clustering.

*G. "Brain Tumor Detection Using Neural Network" International Journal of Science and Modern Engineering (IJISME) ,August 2013*

In this paper, a modified Probabilistic Neural Network (PNN) model that's supported learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to hold out an automatic tumor classification using MRI-scans. The assessment of the modified PNN classifier performance is measured in terms of the training performance, classification accuracies and computational time. The simulation results showed that the modified PNN gives rapid and accurate classification compared with the image processing and published conventional PNN techniques. Simulation results also showed that the proposed system out performs the corresponding PNN system presented and successfully handle the method of neoplasm classification in MRI image with 100% accuracy.

## III. PROPOSED MODEL

In our proposed system propose the deep transfer learning approach with CNN pretrained models such as VGG-16 to perform brain tumor disease detection. Based on training time and epoch number, this work presents the overall classification accuracy rate of three pretrained architectures. At first perform the data collection process and preprocessing. Second we split our dataset into three segments required for training, testing, and validation. Third perform CNN pretrained models VGG-16 based training model for training image. Finally predict the tumor type for given testing image.

### *A. DATASET COLLECTION*

The dataset acquired in this study is a collection of images of brain MRI scans. There exist around 256 raw MRI images of different dimensions (width height), usually measured in terms of pixel values. The sample MRI brain images are gathered from the Kaggle dataset. The collected images are in Joint Photographic Experts Group (JPEG) format . The image database is categorized into four segments, meningioma, glioma, pituitary tumor, Normal based on the existence of the tumor in an MRI brain image. Generally, in our work, we split our dataset into three segments required for training, testing, and validation.

### *B. PREPROCESSING*

Due to MRI machinery limitations, anomalies could be found in MRI brain images. The abnormalities such as poor quality image resolution, distortion, inhomogeneity, misinterpretation, and motion heterogeneity are produced by limitations in MRI image processing. These inaccurate analyses of scanned images could result in false positives while investigating the brain MRI image. This poor diagnosis further affects patient treatment options. The CNN-pretrained models require the brain MRI to be resized with a $224 \times 224 \times 3$ dimension , so the dataset MRI images are reformatted to a specific dimension.

### *C. TRANSFER LEARNING WITH VGG-NET*

In this proposed model, a pretrained CNN architecture is employed for the classification that uses many labeled images for training the model obtained from large-scale datasets like the ImageNet. VGG-16-pretrained CNN model. Because of the small image dataset and to avoid overfitting problems, our model is fine-tuned by freezing some of the convolution (Conv) layers. VGG-16 is a CNN model with sixteen convolution layers developed in 2014 by researchers. The model accepts brain MRI images as an input with a dimension of $224 \times 224 \times 3$. It incorporates Conv layers with kernels (filters) of fixed $3 \times 3$ filter size and 5 max-pooling layers of dimension $2 \times 2$ in size within the network. It also includes extensively ReLU activation functions and 4 fully connected layers with a softmax output layer. After training this weight of the model is stored.

### *D. VGG 16*

The "VGG-16 Neural Network" is defined as that type of neural network that is specifically trained for a more than million types of images concerning the database of the "ImageNet" and or the "ImageNet" database respectively, where the network consists of various types of the layers, and to be specific, there are 16 layers of additional data of media content available on the mesh of the "Neural Network" respectively. VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper

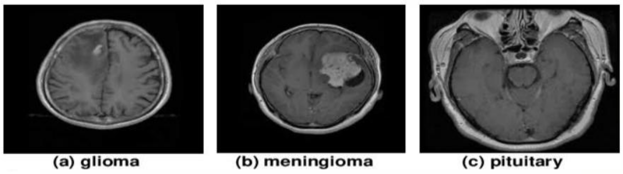
"Very Deep Convolutional Networks for Large-Scale Image Recognition". The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over Alex Net by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's. It is an easy and broadly used Convolutional Neural Network (CNN) Architecture used for ImageNet which is a huge visible database mission utilized in visual object recognition software research.

*E. TRANSFER LEARNING*

It is a technique in deep learning that focuses on taking a pre-trained neural network and storing knowledge gained while solving one problem and applying it to new different datasets. In this article, knowledge gained while learning to recognize 1000 different classes in ImageNet could apply when trying to recognize the disease.

*F. CLASSIFICATION*

In this module give input image to the Training model. This training model can predict the type of tumor such as meningioma or glioma, or pituitary tumor or Normal.




*G. METRICS CALCULATIONS*

For comparing stego image with cover image results requires a measure of image quality, commonly used,

- Loss
- Accuracy

*1. Loss*

Neural networks or neurons work with corresponding weight, bias and their respective activation functions. The weights get multiplied with the inputs and then activation function is applied to the element before going to the next layer. Finally, it will predict the value through the output layer. But prediction is always closer to the actual (y), which term as errors. So, it will define the loss/cost functions to capture the errors and try to optimize it though backpropagation. There are different types of loss functions based on the problem statement. Loss functions measure how far an estimated value is from its true value. A loss function maps decisions to their associated costs. Loss functions are not fixed, they change depending on the task in hand and the goal to be met.

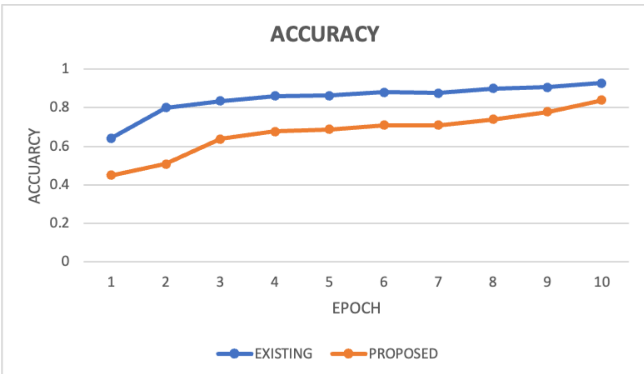
*2. Accuracy*

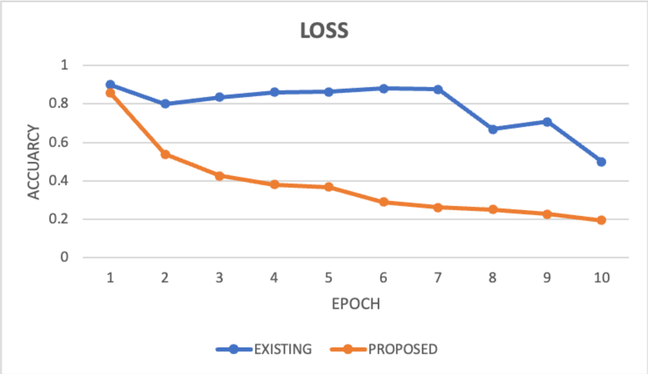
Accuracy is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions. Deep learning model accuracy is the measurement used to determine which model is best at identifying relationships and patterns between variables in a dataset based on the input, or training, data. The better a model can generalize to 'unseen' data, the better predictions and insights it can produce, which in turn deliver more business value. The cost of errors can be huge, but optimizing model accuracy mitigates that cost. There is, of course, a point of diminishing returns when the value of developing a more accurate model won't result in a corresponding profit increase, but often it is beneficial across the board. A false positive cancer diagnosis, for example, costs both the hospital and the patient. The benefits of improving model accuracy help avoid considerable time, money, and undue stress.

**ADVANTANGES IN PROPOSED SYSTEM:**

- It is effective for brain tumor MR image classification, and it could outperform other comparisons.
- Improve the classification accuracy.
- Reduce the prediction time.
-

**ANALYSIS:**






## IV.CONCLUSION

The main goal of this can be to style efficient automatic brain tumor classification with high accuracy, performance and low complexity. within the conventional brain tumor classification is performed by using VGG-16 based classification are applied. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to boost the accuracy and to cut back the computation time, a convolution neural network based classification is introduced within the proposed scheme. Also the classification results are given as tumor or normal brain images. VGG-16 is one among the deep learning methods, which contains sequence of feed forward layers. Also python language is employed for implementation. Image net database is employed for classification. it's one in all the pre-trained models. therefore the training is performed for less than final layer.

## IV. FUTURE WORKS

Since performance and complexity of ConvNets depend on the input data representation we can try to predict the location as well as stage of the tumor from Volume based 3D images. By creating three dimensional (3D) anatomical models from individual patients, training, planning and computer guidance during surgery is improved. For more complex datasets, we can use U-Net architecture rather than CNN where the max pooling layers are just replaced by upsampling ones. Unsupervised transfer learning may attract more and more attention in the future.

## VI. REFERENCE

[1] G. Litjens et al., "A survey on deep learning in medical image analysis," Medical image analysis, vol. 42, pp. 60-88, 2017

[2] K. Machhale, H. B. Nandpuru, V. Kapur, and L. Kosta, "MRI brain cancer classification using hybrid classifier (SVM-KNN)," in Industrial Instrumentation and Control (ICIC), 2015 International Conference on, 2015, pp. 60-65: IEEE.

[3] M. Shasidhar, V. S. Raja, and B. V. Kumar, "MRI brain image segmentation using modified fuzzy c-means clustering algorithm," in Communication Systems and Network Technologies (CSNT), 2011 International Conference on, 2011, pp. 473-478: IEEE.

[4] J. Cheng et al., "Enhanced performance of tumor classification via tumor region augmentation and partition," PloS one, vol. 10, no. 10, p. e0140381, 2015.

[5] J. S. Paul, A. J. Plassard, B. A. Landman, and D. Fabbri, "Deep learning for tumor classification," in Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging, 2017, vol. 10137, p. 1013710: International Society for Optics and Photonics.

[6] P. Afshar, K. N. Plataniotis, and A. Mohammadi, "Capsule Networks for neoplasm Classification supported MRI Images and Course Tumor Boundaries," arXiv preprint arXiv:1811.00597, 2018.

[7] A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based neoplasm grades classification and grading via convolutional neural networks and genetic algorithms," Biocybernetics and Biomedical Engineering, vol. 39, no. 1, pp. 63-74, 2019.

[8] R. Karuppathal and V. Palanisamy, "Fuzzy based automatic detection and classification approach for MRI-brain tumor", ARPN Journal of Engineering and Applied Sciences, 9(12): (2014).

[9] V. J. Nagalkar and S. S. Asole, "Brain tumor detection using digital image processing supported soft computing," Journal of Signal and Image Processing , Vol. 3,No. 3, pp.-102-105, 2012

[10] Jiachi Zhang et al, "Brain Tumor Segmentation supported Refined Fully Convolutional Neural Networks with A Hierarchical Dice Loss", Cornell University library, computer vision and pattern recognition, (2018).