

## BRAIN TUMOR DISEASE DETECTION USING MACHINE LEARNING TECHNIQUES

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**Abstract**—The purpose of this research is to discover the causes of brain tumors and improve the treatment of such conditions. Tumors are abnormal growths of brain cells, and malignant tumors are malignant tumors. ACT or MRI scans are usually used to identify cancerous areas in brain. In addition to positron emission tomography and cerebral angiography, spinal taps and molecular tests are used to detect brain tumors. Our study aims to identify abnormal images and segment the tumor area. Anomalies in MRI images can be detected using deep learning techniques. Multi-level thresholding methods is a method to divide the area surrounding the tumors. Deep learning techniques provide indications of the density of the affected areas based on the number of malicious pixels.

**Keywords:** Tumor; CNN; Classification; Segmentation.

## I. INTRODUCTION

Brain tumour early identification and treatment can aid in early detection and lower mortality. In recent years, image processing is currently more prevalent and has grown to be essential in the medical industry. Brain tumours are caused by aberrant brain cell growth. Intracranial tumours are another name for brain tumours. Tumors come in two varieties: malignant and benign. Based on visual quality and a study of the soft tissue contrast texture, It is widely used to discriminate between different types of brain cancers using normal MRI sequences. The World Healthcare Organization (WHO) has discovered more than 120 distinct types of brain tumours., and they can be categorised into 4 phases based on their malignancy [1]. Depending on the part of the brain that is affected, Any kind of brain tumour may cause issues. Common symptoms include headaches, convulsions, vision impairment, nausea while moving, mental disorders, and memory loss, and loss of balance [2]. Genetics, ionising radiation from cell cellular devices, extremely slim energy magnetic forces, chemicals, brain injuries, immune system components like bacteria, allergies, and infections, etc. are all variables that contribute to the occurrence of brain tumours. [3]. There are two forms of malignant tumors, commonly referred to as malignant malignancies: Tumors come in two varieties: primary tumours that secondary tumours that develop somewhere spread to brain tissue after initially starting in the skull. ionising radiation, brain damage, and vinyl chloride exposure radiation, and other conditions are risk factors for

brain tumours. A few examples of Imaging with magnetic resonance imaging and biopsy of tissue constitute two diagnostic methods., and computed tomography. There are currently improved therapies for brain tumours. During treatment, focal neurological abnormalities such aphasia, visual field defects, and mobility difficulties could develop. Measuring tumour growth and time-to-total- progression (TTP) can help prevent side effects [4]. Better measurements for therapy are made possible by estimating the density of the affected areas. Use the Morphological Open feature to divide the area into sections. The tumour area is located in the region with the biggest area when the contours of all the regions are shown. A Gaussian distribution can be used to estimate tumour area density.

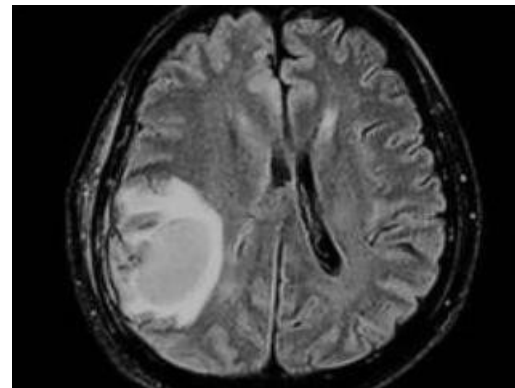
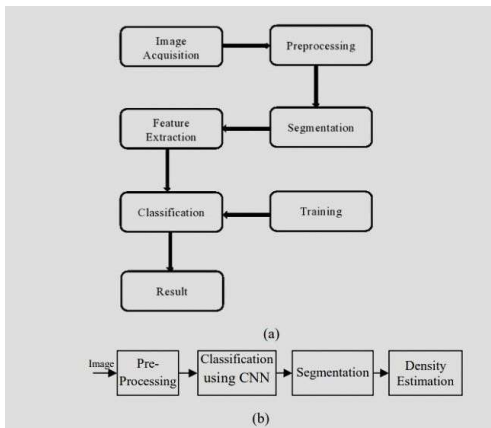


Fig. 1. MRI Picture

## II. RELATED WORKS

One of the main functions of machine learning is image segmentation and classification, which is frequently used in clinical diagnostics as well. A approach using By Tim Lascu, Mihaela Lasccu, Mircea Gurbina, and others, Support Vec- tor Machine, Discrete Wavelet Transform, and Continuous Wavelet Transform were proposed [6]. (SVM). It employs several wavelet levels, and with practice, Tumors can be differentiated into cancerous and non-cancerous ones. The proposed method requires more computing time. According to Somasundaram S. and Gopinath R. et al [7], deep learning models are utilised to describe the current status of tumour segmentation and identification. SVM, ANN, and 3D-based CNN are utilised for segmentation that is more detailed. The extraction of pertinent Damodaran S., Raghavan D., et al. [8] address the features arising from every segmented



tissue and sorting of the cancer photos using a neural network. by dividing fluid, common tissues (white matter (WM) & colored matter (GM)), & diseased tissues (tumor) (cerebrospinal fluid, or CSF).

Fig. 2. Technique for detecting brain tumours architecture (a) utilising conventional techniques (b) via robust learning.

According to G. Hemanth, M. Janardhan, L. Sujihelen, and other authors [9], a early tumour identification is made achiev- able with the proper application of data mining categorization technique. It employs a CNN-based automatic segmentation technique. Dr. Babu Anton P., Reema on Mathew A., and other researchers assert [10], The segmentation allows for the identification of tumour regions of MRI images. The size and location of the tumour can be determined with the aid of radiological analyses. Here, segmentation is manually per- formed, which takes time. Anisotropic diffusion filters are used throughout the preprocessing procedure. Using support vector machines, the segmentation and classification are carried out. Using the characteristics of isolated local squares, Di Huang, Xu Qipao, Boqiang Lu, Xinyang Qi, and Rui Yang, and Xiaoya Wang et al. [11] present a novel technique. This approach for segmenting brain tumours uses segmentation of superpixels, feature extraction, and creation of segmentation models.

### III. PROPOSED METHOD

The first picture shows the suggested system's architecture. Segmentation, feature extraction, classification, feature extrac- tion, and image collection are the components.

#### PICTURE CAPTURE

Many bio medical imaging There are recordings available for the investigation tumors in brain tissue identification. Common imaging methods include computed This includes magnetic resonance imaging (MRI) and tomography. Brain tumour detection methods include Lumbar Puncture, Cerebral Arteriogram, Positron Emission Tomography Molecular, and evaluation.

Nonetheless, they appear pricey. The basis of MRI is The notion of that by detecting that there is the liquid molecules, A picture of the human body's inside may be obtained using both radio waves and the magnetic field. MRI devices that are portable and compact are now being developed to stay away from the intricacy of conventional scanning methods. MRI provides richer information and better resolution. Here, Navoneel Chakrabarty's Kaggle-uploaded MRI dataset has been employed [12]. It has 155 aberrant pictures and 98 photos of the normal brain. In this dataset, "yes" denotes photos of tumours and "no" denotes images of healthy tissue. Here, the procedure of augmentation is also used to enhance the sample size. The Augmentation step has a 10 degree rotation range, 0.1 degree width shift, 0.1 degree height shift, 0.3 degree brightness range, and 1.0 degree horizontal and vertical flip. 2530 photos in total were chosen from the enriched data. The final collection consists of 980 regular photos and 1550 abnormal images.

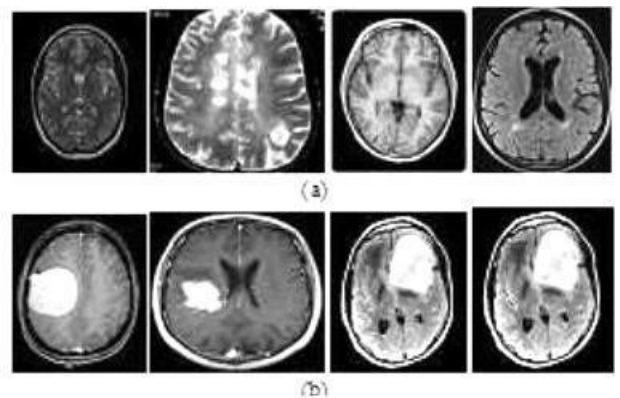


Fig. 3. Collection of MRI (a) Normal (b) Tumor

#### PRE-PROCESSING

The Augmentation step has a 10 degree rotation range, 0.1 degree width shift, 0.1 degree height shift, 0.3 degree brightness range, and 1.0 degree horizontal and vertical flip. 2530 photos in total were chosen from the enriched data. The total collection consists of 1650 weird pictures and 972 standard ones. The dataset includes pictures at various resolutions. Each image undergoes rotation and scaling to a common format as part of the augmentation process. Image quality can be improved via histogram equalisation. The photos are improved using a method of flexible graph fairness with intensity constraints.

#### MAGE SEGMENTS

In this procedure, an electronic picture is separated into various pieces. The background of the photograph is split from a certain area. It's important to extract features in this step. The basic steps to segment disease are thresholding and morphological operations (erosion,

dilation, opening). However, the Segments method to this point in time won't reveal the specifics of the tumour locations in photos of brain tumours. The intensity of the healthy photos is equivalent to the intensity of the tumour location. Hence, the division of the brain's skull can be accomplished through segment. This the size of Interest, also called ROI contains the tumour. A skull mask with segments is produced by an OTSU based approach for threshold [14]. The boundary of the confined unit is drawn by Active Contour. to get ready the tumour mask location, the ROI can also be subjected to the second stage of segmentation. This approach might not produce ideal representations of health. In order to estimate density, the features of the tumour region can be studied using this segmented image.

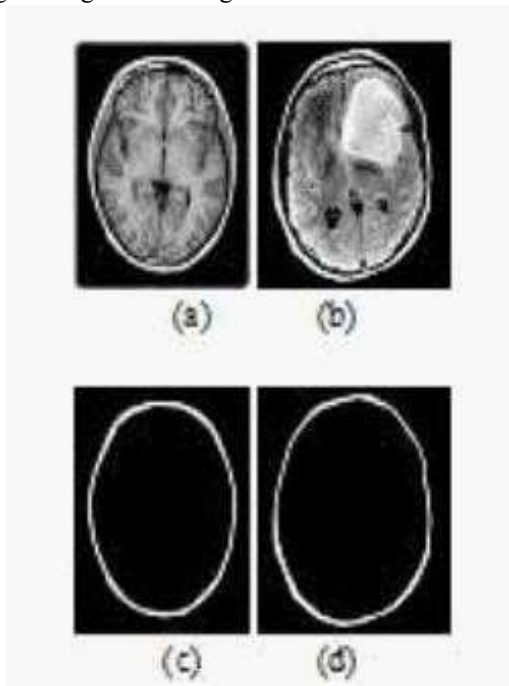


Fig No 4: Segmenting the skull (a) using standard input image (b) Using a strange input image (c) using strange segmentation (d) using strange segmentation.

FEATURE EXTRACTION

The behaviour or symptom of the disease can be illustrated by computing the real features. The choice of features has the biggest impact on classification. Asymmetry, diameter, and border irregularity are frequent characteristics [15].

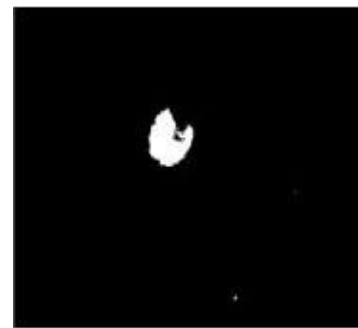


Fig No 4: Tumour region was divided using several thresholding

CLASSIFICATION

In order to identify diseases from brain pictures, numerous machine-learning techniques are being used. If the features are recovered in the correct order, The use of synthetic neural networks utilised to classify[16]. An ANN One feature is assumed to be free from all others by the classifier.

Here, segment free tumour picture classification using deep learning algorithms will be successful. Neural networks with deep structure can be constructed using convolutional neural network methods. [17]. In Figure 6 depicts the general architecture of convolutional Brain mechanisms. The function is continuous. extracted by deep learning from the entire image. The convolutional geometry of CNN performs this process.. With an increase in A few additional mappings of features in the CONV phase. The length needs to be decreased to start teaching. The feature dimension is sampled at the pooling layer below. Layers that are fully connected can change each label's score. Softmax layers use feature and class scores to prepare the model [18][19][20].

For the purpose of using the images of brain tumours as training, the CNN architecture's dimension is somewhat altered. In table 1, the changed model architecture is listed [21][22].

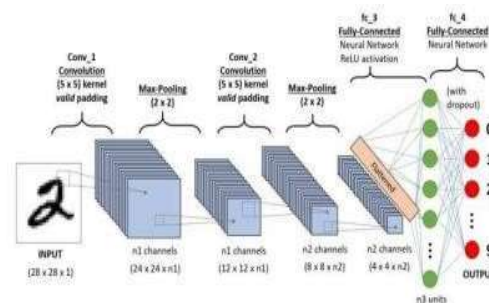


Fig No 6: CNN's overall architecture

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Model: "BrainTumorDetectionModel"
Layer (type) Output Shape Param #
-----
input_1 (InputLayer) [(None, 240, 240, 3)] 0
zero_padding2d (ZeroPadding2D) (None, 244, 244, 3) 0
conv0 (Conv2D) (None, 238, 238, 32) 4736
bn0 (BatchNormalization) (None, 238, 238, 32) 128
relu0 (Activation) (None, 238, 238, 32) 0
max_pool0 (MaxPooling2D) (None, 59, 59, 32) 0
max_pool1 (MaxPooling2D) (None, 14, 14, 32) 0
flatten (Flatten) (None, 6272) 0
fc (Dense) (None, 1) 6273
-----
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
    
```

Table 1: Modified Model architecture

A binary crossentropy loss and the "Adam" optimizer were used to construct the model in Keras. The default learning rate is set at 0.001. The simulation is prepared over 24 epochs having a 32-batch size. The team of model that is trained achieves a match rate of 95.7 percent for the test photographs.. The tumour location is identified for those photos that has migrated to the brain and were initially diagnosed utilising a mix of multilayer thresholding, morphological processes, and contour extraction.

$$g(x, y) = \begin{cases} 1, & f(x, y) > T \\ 0, & f(x, y) \leq T \end{cases} \dots (1)$$

Where T are the picture's the standard intensities from maximum to minimum. To divide the regions into subregions, utilise the access morpho structure. Plotting all of the regions' contours reveals that the tumour region is located in the region with the largest area.

The Gaussian kernel distribution can be used to estimate the tumour area's density;

$$f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^n e^{-\frac{1}{2}\left(\frac{x_i-x}{\sigma}\right)^2} \dots (2)$$

IV. RESULTS AND DISCUSSIONS

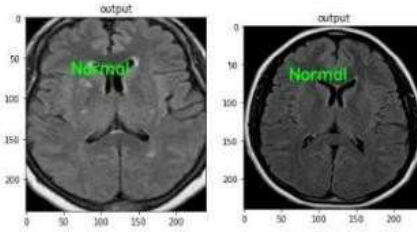


Fig No 7: Standard Picture Results

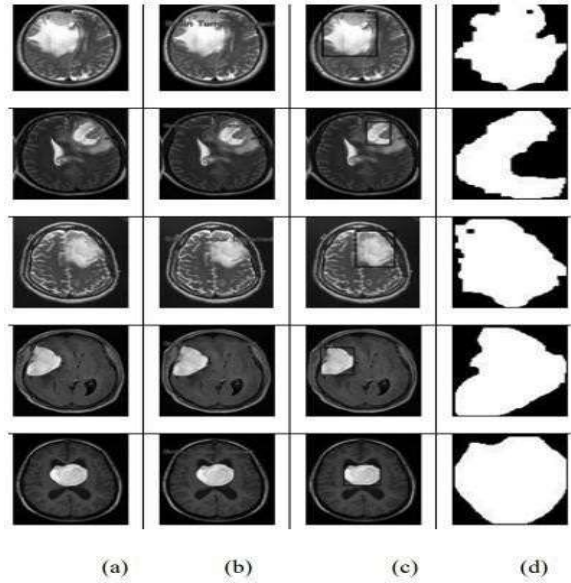


Fig No 8: Tumor detection outcomes include: (a) the sample picture (b) Detection of anomalies (c) the identification of tumour areas (d) A tumour mask for estimating density.

The proposed method aims to classify malignant brain tumours from MRI data. The Kaggle dataset had 243 an MRI.. In order to simulate an intricate brain structure, the number of data points is insufficient. As a result, the enhancement process has produced 2530 photos. Following cropping, the retrieved photos are scaled to (240, 240) resolution. The model is developed using the Keras framework (with a Tensor flow backend). To assess For system revenue, multiple segments are applied at various places. Both before and after classification, segmentation was performed. According to the performance analysis, segmentation comes first, followed by classification, for the best outcome. When used with typical MRI pictures, this technique runs more quickly. If aberrant photos are found, segmentation is the next process that is taken. The link between sensitivity and specificity is depicted by the ROC curve.

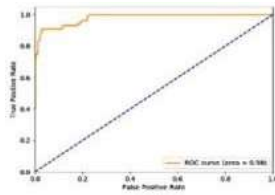


Fig 9: Plot of ROC for Normal instances

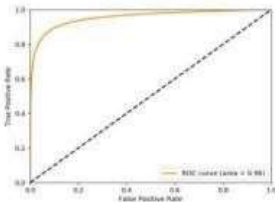


Fig 10: Abnormal instances' ROC plot

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} = 0.98$$

$$Sensitivity = \frac{TP}{TP+FN} = 0.97$$

$$Specificity = \frac{TN}{TN+FP} = 0.99$$

Table 2: Performance Analysis

Algorithm	Over all Accuracy
Nandpuru[18]	96.77%
El-Dahshan[19]	97%
Ibrahim[20]	96.33%
Rajini[21]	90%
Proposed Method	98%

## V. CONCLUSION AND FUTURE SCOPE

This study presents a novel robust learning approach to the purpose of stroke being detected early. Early cancer detection is important. important for prompt and efficient treatment. For research purposes, the Kaggle dataset includes high-quality MRI pictures. various segmentation algorithms were tested. Hence, the optimal approaches for the dataset are multilevel thresholding and OTSU thresholding. A Convolutional Neural Network with a modified methodology enabled the achievement of a 98% accurate outcome. Furthermore offered is the density estimation approach

utilising the Gaussian kernel distribution.

To enable a web interface, this system can be upgraded. The MRI scans can also be used to diagnose other disorders. Several characteristics besides density can also be assessed for therapeutic purposes.

## REFERENCES

- [1] David N. Louis, Aria Perry, et al., “The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary”, *Acta Neuropathol*, Springer May 2016.
- [2] Par Salander, A Tommy Bergenheim, Katarina Hamberg, Roger Henriksson, Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumor patients, *Family Practice*, Volume 16, Issue 2, April 1999, Pages 143–148.
- [3] McKinney PA,” Brain tumors: incidence, survival, and etiology”, *Journal of Neurology, Neurosurgery & Psychiatry* 2004;75:ii12-ii17.
- [4] Heimans, J., Taphoorn, M. Impact of brain tumor treatment on quality of life. *J Neurol* 249, 955–960 (2002).
- [5] Malavika Suresh, et al. “Real-Time Hand Gesture Recognition Using Deep Learning”, *International Journal of Innovations and Implementations in Engineering*(ISSN 2454- 3489), 2019.
- [6] M. Gurbină, M. Lascu, and D. Lascu, “Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines”, 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 2019.
- [7] Somasundaram S and Gobinath R, “Early Brain Tumour Prediction using an Enhancement Feature Extraction Technique and Deep Neural Networks”, *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*,

- [8] Damodharan S and Raghavan D, "Combining Tissue Segmentation and Neural Network for Brain Tumor Detection", *The International Arab Journal of Information Technology*, Vol. 12, No.1, January 2015.
- [9] G. Hemanth, M. Janardhan and L. Sujihelen, "Design and Implementing Brain Tumor Detection Using Machine Learning Approach", *3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, Tirunelveli, India, 2019.
- [10] A. R. Mathew and P. B. Anto, "Tumor detection and classification of MRI brain image using wavelet transform and SVM", *International Conference on Signal Processing and Communication (ICSPC)*, Coimbatore, 2017.
- [11] W. Chen, X. Qiao, B. Liu, X. Qi, R. Wang and X. Wang, "Automatic brain tumor segmentation based on features of separated local square", *Chinese Automation Congress (CAC)*, Jinan, 2017.
- [12] Navone Chakrabarty, "Brain MRI Images for Brain Tumor Detection Dataset", *Kaggle*, April 2019.
- [13] S. Poornachandra and C. Naveena, "Preprocessing of MR Images for Efficient Quantitative Image Analysis Using Deep Learning Techniques," *2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT)*, Bangalore, 2017, pp. 191-195, DOI: 10.1109/ICRAECT.2017.43.
- [14] Mohammed Thanveersha N., et al. "Automatic Brain Hemorrhage Detection Using Artificial Neural Network", *International Journal of Innovations and Implementations in Engineering*(ISSN 2454- 3489), 2019, vol 1.
- [15] Soumya R S, et al. "Advanced Earlier Melanoma Detection Algorithm Using Colour Correlogram", *2016 International Conference on Communication Systems and Networks (ComNet)* | 21-23 July 2016 | Trivandrum.
- [16] J. A. Akhila, C, Markose, et al. "Feature extraction and classification of Dementia with neural network," *2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT)*, Kerala, India, 2017, pp. 1446-1450.
- Avigyan Sinha, Aneesh R. P., "Real Time Facial Emotion Recognition using Deep Learning", *International Journal of Innovations and Implementations in Engineering*(ISSN 2454- 3489), 2019, vol 1.
- H. B. Nandpuru, S. S. Shankar, and V. R. Bora, "MRI brain cancer classification using support vector machine," in *Proc. IEEE Students' Conf. Electr., Electron. Comput. Sci.*, Mar. 2014, pp. 1–6.
- [19] kumar Mall, Pawan, et al. "Self-Attentive CNN+BERT: An Approach for Analysis of Sentiment on Movie Reviews Using Word Embedding." *International Journal of Intelligent Systems and Applications in Engineering* 12.12s (2024): 612-623.
- [20] Narayan, Vipul, et al. "7 Extracting business methodology: using artificial intelligence-based method." *Semantic Intelligent Computing and Applications* 16 (2023): 123.
- [21] Saxena, Aditya, et al. "Comparative Analysis Of AI Regression And Classification Models For Predicting House Damages In Nepal: Proposed Architectures And Techniques." *Journal of Pharmaceutical Negative Results* (2022): 6203-6215.
- [22] Narayan, Vipul, et al. "A Comprehensive Review of Various Approach for Medical Image Segmentation and Disease Prediction." *Wireless Personal Communications* 132.3 (2023): 1819-1848.