Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7764663

TUMOR DETECTION USING DEEP LEARNING FROM MEDICAL IMAGE

Daakshayani Allu
PG Research Scholar, Department of Computer Science Engineering, Raghu Engineering College, Dakamarri, Visakhapatnam – 531162, Andhra Pradesh, India.
daaksha9999@gmail.com

S.Srinadh Raju
Associate Professor, Department of Computer Science Engineering, Raghu Engineering College, Dakamarri, Visakhapatnam – 531162, Andhra Pradesh, India.
ssraju@raghuenggcollege.in

ABSTRACT:
Brain tumor (BT) are collections of abnormal brain cells, and they have the potential to cause death. A total of 4.4 per 100,000 men and women died from BT each year. From 2017 to 2019, around 0.6 percent of the population was detected with BT. Thus, identifying BT is crucial for providing effective care to patients. Nowadays, MRI scans are frequently used to diagnose BT. The manual examination may introduce inaccuracy due to the BTs' complexities and peculiarities. The practice of BT identification involves the expertise and experience of doctors; yet not everybody has immediate access to such professionals, therefore automating the practice would be useful. Deep learning (DL) has achieved great levels of effectiveness in identifying tumours from MRI to automate the process. Gray Level Co-occurrence Matrix (GLCM) and Convolution Neural Networks (CNN) are used to identify BT in the proposed work. Features are extracted using GLCM, while classification is performed using CNN. Data from Kaggle is used for both the model's training and its subsequent testing. The proposed approach is compared against a conventional CNN model to determine its effectiveness. The experimental findings indicate that GLCM-CNN is superior to CNN in terms of accuracy.
KEYWORDS: Brain, Tumor, Image processing, Resize, Filter, Deep Learning, Accuracy, Epochs, Feature Extraction

INTRODUCTION:

The brain is the most important physical part since it regulates every other system and plays a role in making decisions. The human body's primary control station, the central nervous system, is responsible for both the deliberate and involuntary actions that occur every day [1]. The tumor is a fibrous web of abnormal brain tissue that has grown unrestrained and invaded healthy brain tissue. Approximately 85–90% of initial CNS tumor are BTs. Primary brain or spinal cord tumor are anticipated to affect 308,102 people worldwide in 2020 [2]. A thorough understanding of BTs and their progression is essential for prevention and the execution of the phases in treatment. MRI scans are commonly used by radiologists to analyse BTs.
Usually, research has employed CNN approaches to identify the tumor. The image is resized and undergoes many processing techniques before getting into the CNN. In CNN, the image

size is reduced without sacrificing the data required for training at each layer of CNN. The model is created using a variety of processing techniques, including convolve, max pooling, dropout, flattening, and dense [3]. It has numerous layers of neurons that are interconnected. The data set applied during the training phase can be used by the neural network to acquire expertise [4]. Throughout the training process, each layer's neurons are assigned weight and bias based on the data from the previous layer and the data from the current layer. When a model is trained, an activation function is applied to the model's input features and hidden layers, resulting in additional learning to achieve the desired outcomes. To improve the attained accuracy by the conventional CNN method, we suggest GLCM-CNN-based model.

LITERATURE REVIEW:

Many works carried out on BT detection and some of the recent work with good accuracy rate is detailed. In the paper [5], a CNN was trained on a Brain Tumor Segmentation (BraTS) image data set and then applied to MR images for semantic segmentation-based pixel classification. To categorize pixels, two unique groups, "background" and "tumor," were designated. The semantic segmentation procedure was evaluated using metrics such as mean IoU and mean Fscore. In contrast, they utilized a dice score to assess how well the network's final layer predicted labels matched the actual picture data's ground truth labels. Finally, ground truth and expected labels were applied to 3D brain and tumor images. Finally, by applying semantic segmentation to a test image, a highly accurate tumor prediction was obtained.

The goal of this study [6] is to create a hybrid classifier that uses DL and ML algorithms to identify BT MRI scans as meningioma, glioma, or pituitary. A ten-layer DL model based on a simple CNN is constructed to extract significant features from tumor. Following that, a variety of Machine Learning (ML) algorithms are used to improve the accuracy rate beyond that of the traditional SoftMax classifier. They may evaluate the performance of the simulated hybrid classifiers using these four statistical metrics of verification. The testing results show that the CNN-KNN classifier outperforms the other seven hybrid classifiers when it comes to categorizing BT photographs. When compared to the other six classifiers, the CNN-KNN classifier had the highest classification accuracy (1.45%).

The novel CNN-KNN architecture created in this study [7] can detect and categorize diverse tumor kinds automatically. Grayscale transformation is done before using a dataset to convert RGB pictures to grayscale. During the feature extraction procedure, CNN recovers various intensity-based characteristics. They use two ML classifiers—SoftMax and KNN—in the final classifier stage to automatically recognise and classify the various BTs. CNN-KNN, the suggested technique, detects and classifies many forms of cancer.

The authors of this paper [8] present a complete literature review of the strategies used to identify BTs using various scanning techniques to assist researchers. The structure and function of the brain, as well as publicly available datasets, modalities, and DL-based algorithms, are all discussed in this study. This paper shows how to apply a variety of DL approaches to the challenges of brain segmentation and classification. This poll also goes into detail about detecting BTs. Furthermore, their advantages and disadvantages are discussed. Finally, they examine advancements and emerging trends in the research to guide future research.

The authors of the study [9] propose a framework based on a segmentation model to locate the specific location and shape of BTs. To classify BTs in an MRI data set, the technique additionally employs a multi-level ensemble learning model. To evaluate a tumor geometric qualities, a statistical assessment technique based on area attributes is used. The model is built on three individual learners, two primary ensembles, and a final ensemble model rounding out the categorization framework. The knowledge for each of the three basic learners was transferred from a previously trained version of VGG16, Inception-V3, or ResNet50. Unlike many other models, this one trains on data from a normal brain as well as the three main types of MRI BTs. Re-tuning the least accurate base model in a multi-level ensemble is an approach that helps to improve the overall precision of the ensemble model. This study also demonstrates how a DL network may be used to disprove incorrect tumor segmentation in a normal MRI brain image.

The study [10] compares many different CNN-based transfer learning approaches for classifying BT MRI images and provides an experimental evaluation of generated attributes from MRI images. The findings highlight the utility of DL algorithms for detecting BT in MRI imaging. Training and test accuracy are used to assess performance. In this case, they use a binary classification to differentiate between the "no tumor" and "with tumor" categories. The research intends to improve the identification and classification of BT by combining image processing, pattern analysis, and computer vision.

The study [11] proposes an MRI-US multi-modality network (MUM-Net) to classify breast tumor into categories depending on 3D MR and 2D US data. MUM-Net's novelty is that it actively distils modality-independent knowledge for tumor classification. Create a module first, and then divide features into modality agnostic and specific elements using min-max training techniques. The study develops a feature fusion mechanism that integrates an affinity matrix and nearest neighbour search to reduce those modality-independent data. They constructed a paired MRI-US breast tumor and three clinical datasets to evaluate the accuracy of the proposed technique.

In the publication [12], the researcher adds the proposed layers to the deep CNN EfficientNet-B0 as a basic model to increase its ability to recognize and categorize BT images. Numerous filters are used in image enhancement procedures to increase the quality of an image. They employ data augmentation techniques to expand the size of the training data to enhance the model effectiveness. In terms of identification and prediction, the suggested fine-tuned EfficientNet-B0 beats earlier CNN models. They also use various DL approaches for evaluation.

According to the paper [13], the model for detecting BTs is an incremental learning approach. By using the proposed technique, they effectively extract MRI images, identify BTs, incorporate new data, and prevent failures. The technique doesn't need to access the old data to process the new data, yet the old data is not discarded either. The model's accuracy and precision were compared to those of Learn++, a CNN, and a Decision Tree technique, all applied to a dataset of MRI BT images. The former was ranked using the error rate, while the latter two were ranked using precision, accuracy, and processing time.

METHODOLOGY:

Kaggle BT data is used for analysis. There are a total of 4600 images (2513 tumor images and 2087 healthy images) used, 3200 taken for training, and 800 for testing. An easy-to-use, human-interface system for accurate tumor diagnosis was built using DL techniques, and the acquired image served as its backbone. Pre-processing techniques, including resizing, and eliminating noise, are used to increase the quality of the acquired BT image. After an image has been pre-processed, the DL model is trained and tested to detect the BT. The suggested DL system is composed of GLCM for feature extraction and CNN for classification. To identify the effectiveness of the suggested model the conventional CNN is taken and compared. The overall flow of the research is given in figure 1.

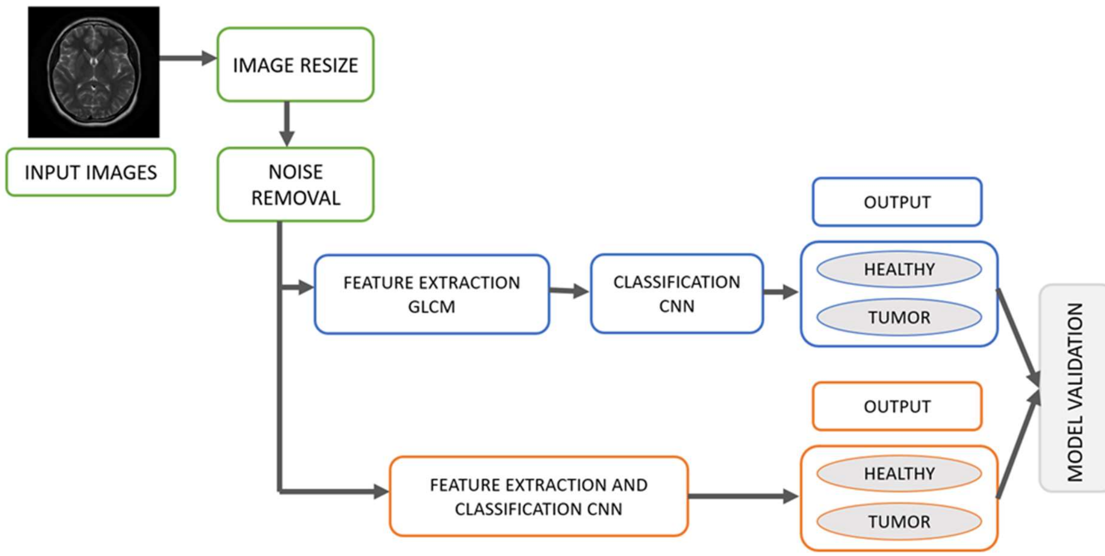
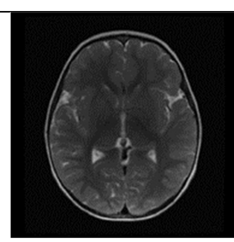
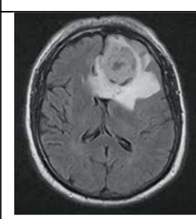
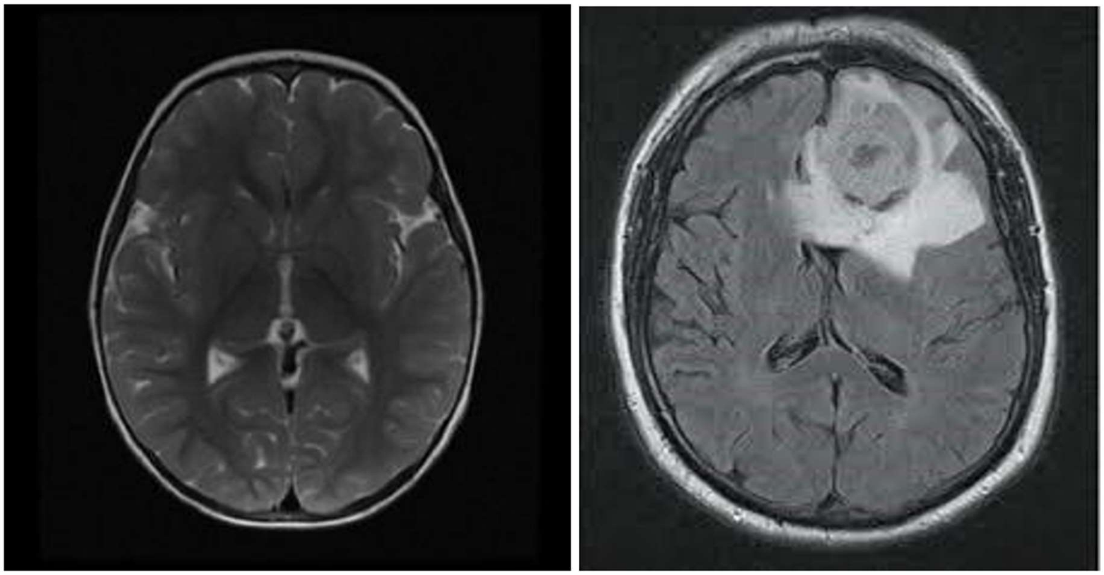


Fig 1. Flowchart of detecting BT.

Table 1 provides information about the data available on Kaggle. Figures 2 (a) and (b) illustrate the sample MRI data images of the tumor and healthy brains.

Table 1- BT data details

DATA	HEALTHY	TUMOR
Sample		
TOTAL	2087	2513
TRAIN	1600	1600
TEST	400	400



a) b)

Fig 2. MRI of (a) Healthy and (b) Tumor

A. IMAGE PREPROCESSING:

Almost every step of the BT detection method makes use of images from the Kaggle database. As a result, to build the model more effectively, the images must be faultless in every way. This can be accomplished using specific pre-processing techniques. Image resizing and noise removal are two of these techniques.

- **IMAGE RESIZING:**

The process of changing the dimensions of each image in a dataset to make them all the same size is known as "image resizing." Without cutting anything off, resizing enables to change the size of the image. Image scaling/ resizing is a crucial step in the pre-processing of computer vision [14]. DL algorithms are primarily faster at learning from small images. Another key advantage of image resizing is the ability to remove undesired image portions.

- **NOISE REMOVAL:**

An algorithm for noise removal is the process of decreasing or eliminating noise from an image. When eliminating noise, it's crucial to maintain image features so that the edges and corners of the objects are still clearly visible. For this proposed work we have used a median filter. Median filtering is one of the filters employed to eliminate noise in an image and it is used to remove the noise from the signals [15]. The advantage of using a median filter is to maintain edges while eliminating the noise. Impulse noise is effectively removed using a median filter.

B. DL MODEL

- CNN: A DL algorithm is a computer-generated classification system for images, text, and sounds. The CNN technique may identify images in several convolutional layers, requiring fewer DL models to complete a single task. The feature extraction and classification phases of a CNN classifier are separated by pooling layers, an activation function, and a few convolutional layers [16]. The classification component is made up of a few fully connected layers and a loss function. A feature map produced by the convolution process is then frequently employed in the next convolution step. The next stage is to create a vectorized, flattened feature map that will be used to do a fully linked layer procedure and yield an image classification.

● GLCM-CNN: Based on the number of pixels within every combination, statistics are categorized as 1st order, 2nd order, and higher order. The GLCM method can be used to extract characteristics of the second degree of complexity [17]. The technique has been used in numerous situations. Third and higher order consider the connections between three or more pixels. The number of grey levels, G, in the image is equal to the number of rows and columns in a GLCM matrix. GLCM features are used to compute the segmented tumor region's texture attributes. These GLCM characteristics were derived from the co-occurrence matrix as spatial features. To detect the tumor, these acquired features in the vector are applied to the CNN classifier's fully connected classification layer.

RESULTS AND DISCUSSION:

The proposed methodology is applied to a collection of MRI from the open-access dataset Kaggle. 4000 images of healthy and tumor MRIs were taken from the collection. The images are divided for training and testing purposes with the size of 3200 and 800. The two models including CNN and GLCM-CNN are constructed and evaluated. The outcome of both models in the training phase is detailed below.

The outcome of CNN in the training phase is shown with the help of a line graph. Figure 3 shows the CNN loss performance in the training phase. The graph illustrates the CNN loss performance with respect to Epochs. The CNN loss starts from the value of 1.6763 at the epoch of zero and reaches 0.2856 at 19th epoch.

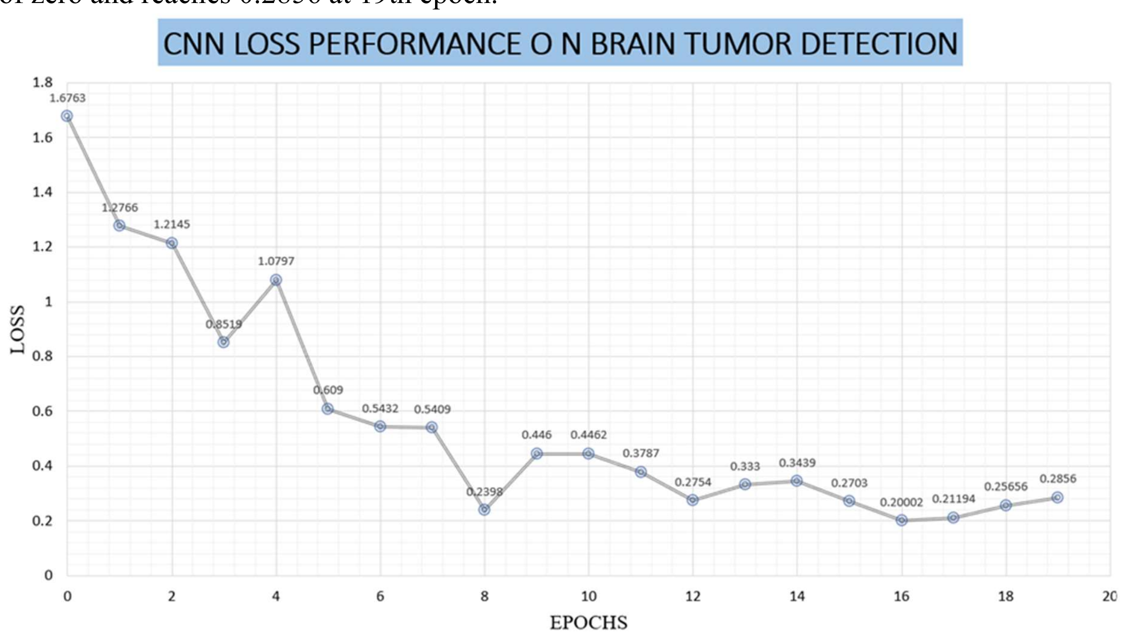


Figure 3 – CNN loss performance

The CNN Accuracy with respect to epochs on BT detection are 0.6458, 0.7945, 0.8656, ……., 0.9723. Figure 4 shows the accuracy performance of BT detection. The accuracy value increases as the epoch count rise.

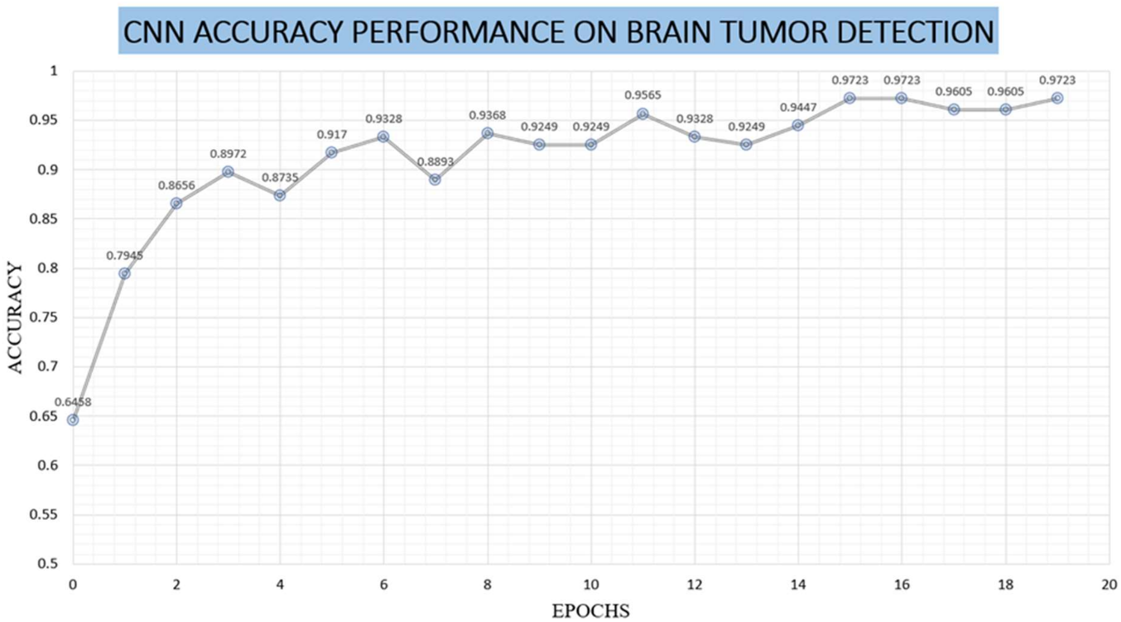


Figure 4- CNN accuracy performance

Whereas in GLCM- CNN there is a gradual increase in accuracy wave form and loss is also minimal compared to the CNN model. The outcome of the GLCM- CNN in training phase Loss with respect to Epochs performances gradually decreases as 0.7969, 0.4482, 0.3508, 0.106, ……., 0.0216. Figure 5 illustrates the loss performance of GLCM- CNN.

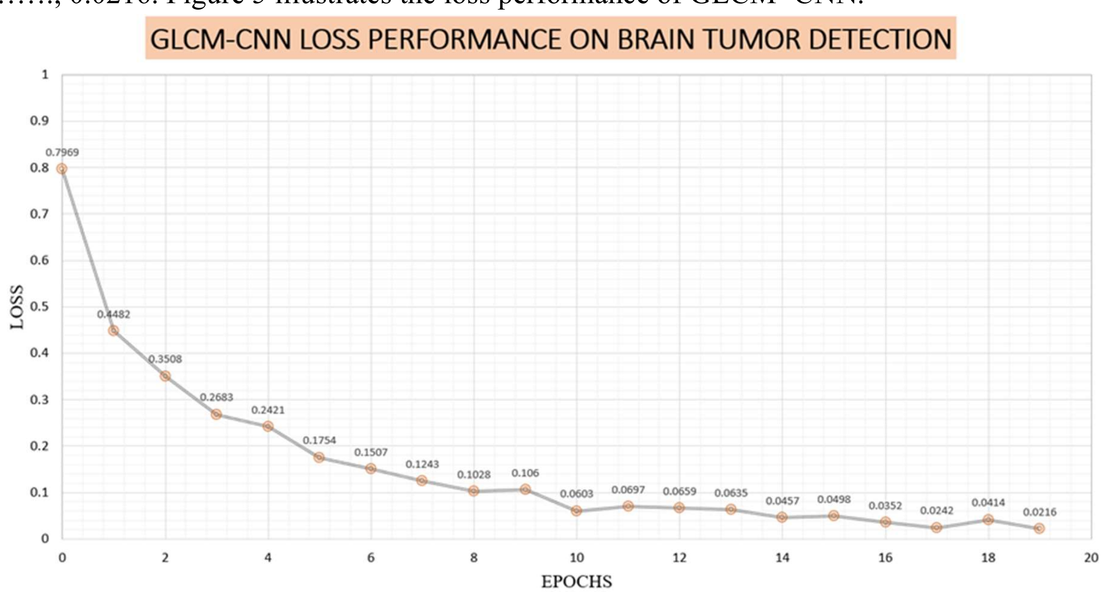


Figure 5 – GLCM – CNN loss performance

And the GLCM-CNN Accuracy with respect to epochs of the BT detection has a gradual increase in the graph, the values are 0.7275, 0.831, 0.8678, ………, 0.9877. Figure 6 illustrates the accuracy performance of GLCM-CNN in the training phase.

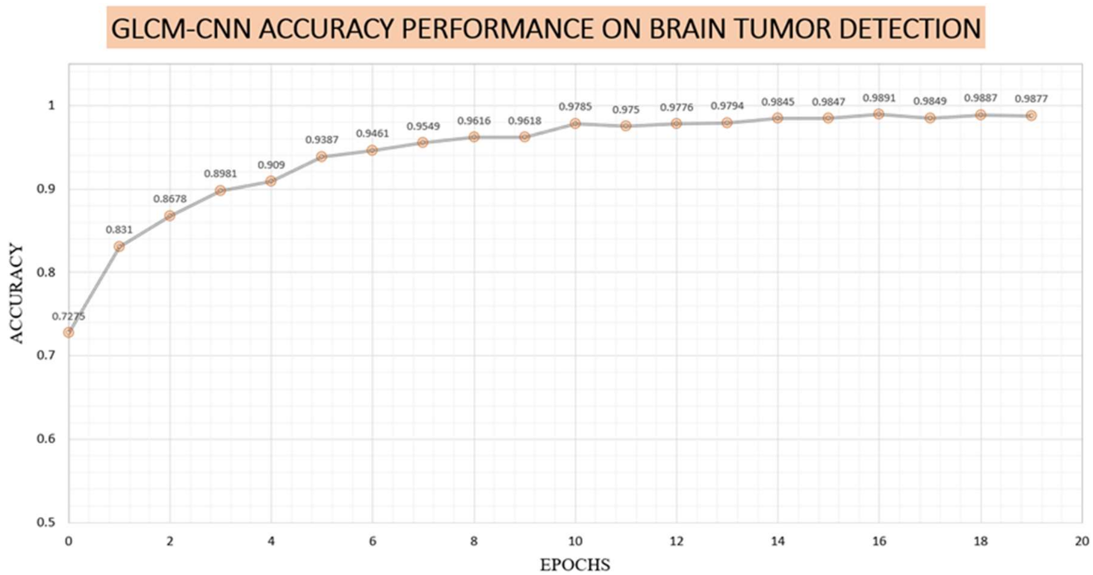


Figure 6. GLCM–CNN accuracy performance

After training, the model evaluation will be done. The test images are given to CNN and GLCM-CNN model, then calculate the metrics using a confusion matrix. The confusion matrix of both models is given in table 2. The four elements present in the matrix are detailed below.

- True Positive (TP): The predicted and real outcome are the same. Actual images contain tumor, and the model forecast is the same.
- True Negative (TN): The predicted and real outcome is the same. Actual images have no tumor, and the model forecast is the same.
- False Positive (FP): The predicted and real outcome is different. The actual outcome is normal whereas the predicted outcome shows the BT.
- False Negative (FN): The predicted and real outcome is different. The actual outcome is a tumor whereas the predicted outcome shows the brain is healthy.

Table 2 – Confusion Matrix

MODEL	TP	TF	FP	FN
CNN	382	383	21	14
GLCM-CNN	393	386	12	9

Performance comparisons of different metrics in percentage for CNN and GLCM-CNN are given in table 3. The accuracy of CNN and GLCM-CNN on test data is 95.625 and 97.375, Similarly, the score of other metrics like True Negative Rate (TNR), True Positive Rate (TPR), False Negative Rate (FNR), False Positive Reading (FPR), F1 score, and Precision are detailed in the table. By analysing the table, the GLCM-CNN performance will be higher than the CNN in all metrics.

Table 3- Performance Comparison

METRICS	CNN	GLCM-CNN
ACCURACY	95.625	97.375

TNR	94.802	96.9849
TPR	96.4646	97.7612
FNR	3.53535	2.23881
FPR	5.19802	3.01508
PRECISION	94.7891	97.037
F1-SCORE	95.6195	97.3978

The GLCM-CNN model is finalized, and the User Interface is created. The outcome of the user interface for tumor and healthy MRI is shown in figure 7. The figure illustrates the healthy and affected images with confidence value in percentage. This confidence level helps the user to know how much the model result will be approximate. If the confidence level is low, then the user can go for a second opinion.

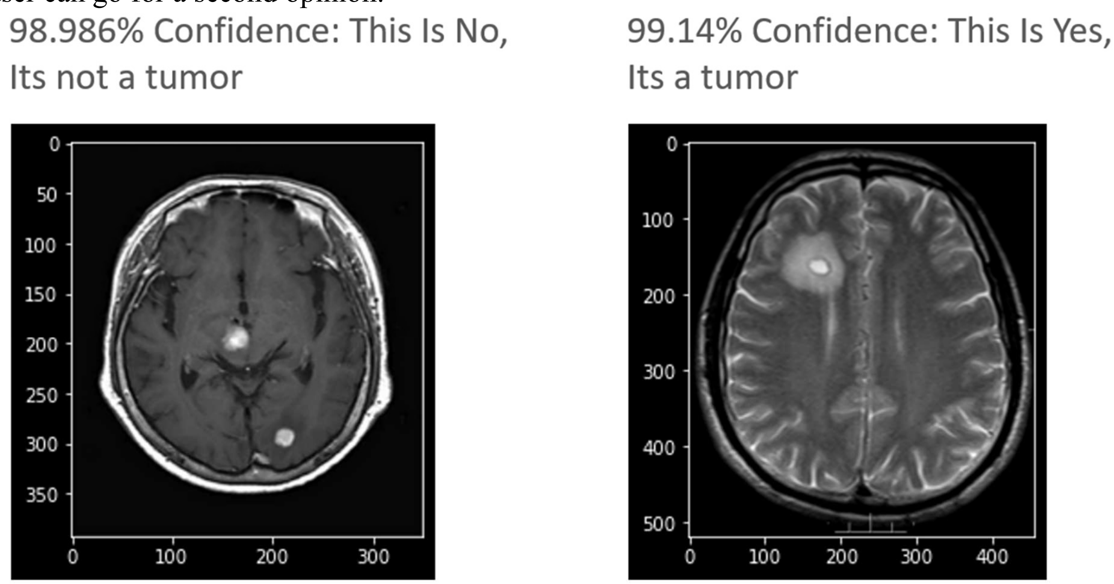


Figure 7- Outcome of GLCM-CNN for tumor and healthy images

CONCLUSION:

BT is extremely dangerous. Greater than ten billion active brain cells can be found in the human brain. Defective cells self-diagnose by dividing to produce new ones. This regeneration is governed by strict protocols. Uncontrollable cell division and regeneration can lead to a lump of abnormal tissue known as a tumor. In MRI scans, locating the infected region and identifying the BT is a laborious and time-consuming process. An image-processing approach can be used to illustrate the human body's anatomical structures. The analysis of aberrant human brain regions using conventional imaging methods is a significant challenge. This article offers a solution, by developing a GLCM-CNN model. Kaggle's raw healthy and tumor images are obtained and processed. The processed image is fed into two models: conventional CNN and the recommended GLCM-CNN. Both models use identical values for the hyperparameters such as batch size, epoch, and others. After that, we train and verify both models. Validation makes use of seven metrics, including accuracy, TPR, TNR, FPR, and FNR, precision and F1-score. A high GLCM-CNN score across all seven parameters demonstrates the effectiveness of the proposed framework. Plans include implementing the GLCM-CNN recommendation on a website, allowing people all over the world to experience the benefits of DL in the medical area at a lower financial expense.

REFERENCE:

1) https://www.cancer.net/cancer-types/brain-tumor/statistics

2) https://braintumor.org/brain-tumor-information/treatment-options/clinical-trials/ [Feb 2020]

3) Hashemzehi, Raheleh, Seyyed Javad Seyyed Mahdavi, Maryam Kheirabadi, and Seyed Reza Kamel, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE", Biocybernetics and Biomedical Engineering, vol. 40, no. 3, pp. 1225-1232, 2020.

4) Nalbalwar, Rajeshwar, Umakant Majhi, R. Patil, and Sudhanshu Gonge. "Detection of brain tumor by using ANN." International Journal of Research in Advent Technology, Vol.2, No.4, April 2014, 2014.

5) G. Karayeğen and M. F. Akşahin, "Brain Tumor Prediction with Deep Learning and Tumor Volume Calculation," 2021 Medical Technologies Congress (TIPTEKNO), Antalya, Turkey, 2021, pp. 1-4, doi: 10.1109/TIPTEKNO53239.2021.9632861.

6) G. J. Ferdous, K. A. Sathi, and M. A. Hossain, "Application of Hybrid Classifier for Multi-class Classification of MRI Brain Tumor Images," 2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ICEEICT53905.2021.9667829.

7) S. Shanjida, M. S. Islam and M. Mohiuddin, "MRI-Image based Brain Tumor Detection and Classification using CNN-KNN," 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), Arad, Romania, 2022, pp. 900-905, doi: 10.1109/GlobConET53749.2022.9872168.

8) S. Prusty, R. Panda, L. Dora, and S. Agrawal, "A Study on Brain Tumor Analysis Using Deep Learning Methods," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2022, pp. 1106-1111, doi: 10.1109/ICCMC53470.2022.9753979.

9) M. C. Xenya and Z. Wang, "Brain Tumour Detection and Classification using Multi-level Ensemble Transfer Learning in MRI Dataset," 2021 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), Durban, South Africa, 2021, pp. 1-7, doi: 10.1109/icABCD51485.2021.9519361.

10) S. Arora and M. Sharma, "Deep Learning for Brain Tumor Classification from MRI Images," 2021 Sixth International Conference on Image Information Processing (ICIIP), Shimla, India, 2021, pp. 409-412, doi: 10.1109/ICIIP53038.2021.9702609.

11) M. Qiao et al., "Breast Tumor Classification Based on MRI-US Images by Disentangling Modality Features," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 7, pp. 3059-3067, July 2022, doi: 10.1109/JBHI.2022.3140236.

12) H. A. Shah, F. Saeed, S. Yun, J. -H. Park, A. Paul and J. -M. Kang, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet," in IEEE Access, vol. 10, pp. 65426-65438, 2022, doi: 10.1109/ACCESS.2022.3184113.

13) S. A. Sony, T. Zaman, M. K. Islam, J. A. Ovi, and M. A. Islam, "eLearn++: An effective Incremental Learning Approach for Brain Tumor Detection," 2021 2nd International Conference for Emerging Technology (INCET), Belagavi, India, 2021, pp. 1-8, doi: 10.1109/INCET51464.2021.9456395.

14) Saponara, S., Elhanashi, A, “Impact of Image Resizing on Deep Learning Detectors for Training Time and Model Performance”, In: Saponara, S., De Gloria, A. (eds) Applications in Electronics Pervading Industry, Environment and Society. ApplePies 2021. Lecture Notes in Electrical Engineering, vol 866. Springer, Cham, 2022¸ doi: 10.1007/978-3-030-95498-7_2

15) Zhu, Youlian & Huang, Cheng, “An Improved Median Filtering Algorithm for Image Noise Reduction”, Physics Procedia, vol. 25, pp. 609-616, 2012¸doi: 10.1016/j.phpro.2012.03.133.

16) Tripathi, Milan, “Analysis of Convolutional Neural Network based Image Classification Techniques”, Journal of Innovative Image Processing, vol. 3, pp. 100-117, 2021, doi: 10.36548/jiip.2021.2.003.

17) P.S, Shijin & Vs, Dharun, “Extraction of Texture Features using GLCM and Shape Features using Connected Regions”, International Journal of Engineering and Technology, vol. 8, pp. 2926-2930, 2016, doi: 10.21817/ijet/2016/v8i6/160806254.