JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A SURVEY ON EARLY DETECTION AND DIAGNOSIS OF BRAIN TUMOR

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Abstract**—**A brain tumor is considered as an uncontrolled growth of cells within the brain, resulting in a fatal condition that affects a large number of persons in their youth and adolescence. It is caused by unregulated and abnormal development within the brain or skull. Early discovery of a brain tumor at an early stage and the correct type of cancer would aid in determining accurate treatments, further study, and increasing patient survival rates. Manually analyzing a magnetic resonance image (MRI) is insufficient for a quick and accurate identification of a brain tumor. Current brain imaging philosophies have increased the percentage of brain cancers discovered. A lot of research has been done in the last couple of years to achieve 100% accuracy in computer-assisted analysis of human brain cancer. The focus of this investigation is on early detection of brain tumors by studying the various methodologies and proposed systems used by other researchers in the past and finding out which proposed system outperforms the rest and how.

Keywords— Segmentation, Brain Imaging, Feature Selection, Machine Learning, Magnetic Resonance Imaging, Gene Algorithm,

I.INTRODUCTION

The brain is considered as the most essential organ of the human body, as it regulates all other organ operations and also aids in decision-making. It is considered as the primary control centre of the central nervous system, and also in charge of conducting the body's daily voluntary and involuntary functions. The tumor is a fibrous web of aberrant tissue growth inside the brain that proliferates abnormally. The aberrant cells disrupt brain processes and have an impact on a patient's health.[1]

As brain tumors are fatal and cause a huge number of deaths in developed countries, brain image analysis is deemed crucial. For example, According to the National Brain Tumor Foundation, 29,000 people in the United States are diagnosed with brain tumors each year, with 13,000 of them dying (NBTF).[18]
Brain cancer can manifest itself in a variety of ways, mood swings, coordination problems, changes in speech, concentration problems, frequent headaches, seizures, and memory loss are just a few of the symptoms. The two forms of brain tumors that might occur are benign and malignant. Meningiomas, pituitary tumors, and astrocytomas are examples of benign brain tumors (WHO Grade-I), which seldom penetrate nearby healthy cells, have well-defined borders, and develop slowly.
The cells of malignant brain tumors (such as oligodendrogliomas and high-grade astrocytomas) attack neighboring brain or spinal cord cells quickly, have fuzzy borders, and proliferate quickly. Primary and secondary brain tumors are the 2 forms of brain cancers that can be classified depending on their origin.A primary brain tumor is the one that starts in the brain and grows from there. When a tumor spreads to the brain, it is called a secondary tumor.

II.OBJECTIVE

This paper aims at making a study and reviewing various research papers by publishers to understand the idea of brain cancer detection, analysis and segmentation in a detailed pattern. Studying of various algorithms and seeking results of those algorithms, study of various methods to detect a tumorous growth in the brain, and understanding effective solutions

III.LITERATURE REVIEW

Several publications were evaluated to lead an audit that demonstrates how deep learning approaches and machine learning techniques achieve cutting-edge execution in all aspects of clinical image analysis, particularly in the fields of brain tumor analysis, segmentation, and classification.

. *Brain Tumors Classification*:

Because of variations in the shape, size, position, and contrast of tumor tissue cells, classifying brain tumors is difficult. The Extreme Learning Machine Local Receptive Fields (ELM-LRF) methodology is also proposed, with three phases: noise removal using local and nonlocal methods, tumor segmentation using ELM-LRF, and classification. .This method is effective, and it achieves a 97.18 percent accuracy using cranial MR scans. [2]

According to the author, ANN has been used to construct Brain Cancer Detection and Classification Systems. Some of the strategies employed are data collection, data preprocessing, pre-modeling, model optimization, and hyper parameter adjustment.The model's generalizability was further assessed on the complete dataset using 10-fold cross validation. Radiologists frequently use magnetic resonance imaging (MRI) to assess the stages of brain cancer in order to avert and abort the tumor. [1]

. *The Intra-Operative HS Acquisition System:*

The Helicoid research team developed a custom intraoperative HS acquisition technology that was utilized to create an in-vivo HS human brain image collection. [32], [48], [49].
The HS camera collects 826 spectral bands and 1004 spatial pixels per line using a push broom approach, covering a spectral range of 400 to 1000 nm with a spectral resolution of 2–3 nm. [3].

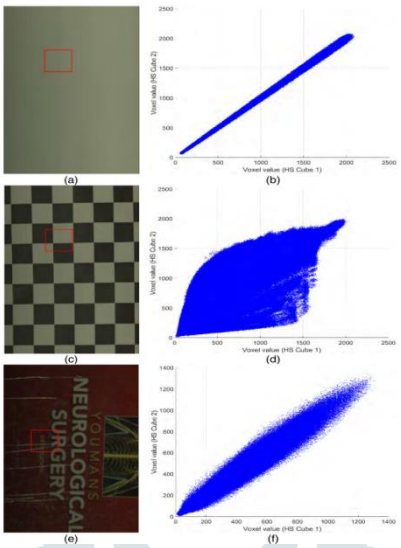

Figure 1. HS photos from the repeatable dataset and 200 x 200 pixel voxel values scatterplot example segment produced from the 2 HS cubes at a similar scene: White reference tile (a) and (b) ; Chessboard pattern (c) and (d); Book cover fragment (e) and (f).[3]

Three types of cancer-causing genes have been identified:

- Tumor suppressors are the first category, and they regulate the cell death loop.
- The second set of genes is responsible for the repair of DNA. DNA repair genes such as MGMT and the p53 protein are two examples. Any problem with them has the potential to lead to cancer.
- Proto-oncogenes, the third type of tumor suppressor gene, are involved in protein synthesis, cell division, and the suppression of normal cell death. They are tumor suppressor genes that work against them. [4]

If cancer develops in the body as a result of any aforementioned reasons, it is referred to as a primary tumor since other organs are directly invaded. Secondary tumor is referred to as spreading of cancer through blood vessels. [4]

. *Convolutional neural network:*

The visual cortex inspired CNN (Convolutional Neural Network) , which is a type of artificial neural network with multilayered feedforward (MLF). Convolution and pooling are two basic algorithms that are frequently practiced in image recognition applications. In comparison to older approaches, CNN has fewer specialized jobs and also learns extracting the features completely. [6]

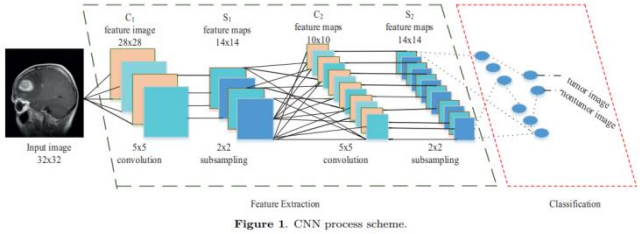

Figure 2. CNN process scheme [6]

Image-guided resection is used in modern neurosurgery for these tumors, although it requires expensive and/or invasive procedures like Neuronavigation, intraoperative Magnetic Resonance Imaging (MRI), injection of reactive for immunofluorescence, and so on. The purpose of this study is to use Hyperspectral imaging, a novel and non-invasive technological tool for image-guided brain tumor removal. This method of sensing is non-contact, non-ionizing, and non-invasive, making it perfect for medical applications.[7]

CNN has been widely employed to solve a variety of issues in a variety of fields, but its performance in image processing is exceptional when it comes to applications such as health segment. Only 160 photographs are employed to train and test the system, half of which would be negative and half of which would be positive.[8]

Hyperspectral imaging (HSI) is a method of capturing spatial and spectral information about an object by combining standard imaging with spectroscopy. In hyperspectral (HS) images, each pixel contains hundreds of spectral bands, providing a wealth of data. Each pixel has an essentially continuous spectrum (radiance, reflectance, or absorbance) that can be used to determine its chemical composition as a fingerprint (so-called spectral signature). This method is intriguing because it employs non-ionizing light in a non-contact manner, making the technology non-invasive.

The majority of existing conventional diagnosis procedures rely on human experience in reading MRI-scans for judgement, which raises the risk of false brain tumor detection and identification.

According to the colorectal cancer center's statistics, the people affected by brain cancer as well as the death rate caused by it continue to rise among people aged between 4 to 50. It is regarded as an extremely lethal disease, treatment of which may be extremely difficult. Brain Cancer, a result of progression of a malignant tumor is usually likely to metastasize to other regions of the anatomy, which may end up resulting in death. Quick detection may aid in decreasing the lethality of the condition by ensuring that the patient receives appropriate treatment to which his or her body responds.[12]

Hierarchical Self-Organizing Map with Fuzzy C-Means, the Genetic Algorithm with Fuzzy C-Means, and Ant Colony Optimization with Fuzzy C-Means are three strategies for detecting brain cancers. The performance of each of these approaches is evaluated using 120 MRI pictures, and then computation of the accuracy of pixel and position is performed.[14] Take a look at the image below:

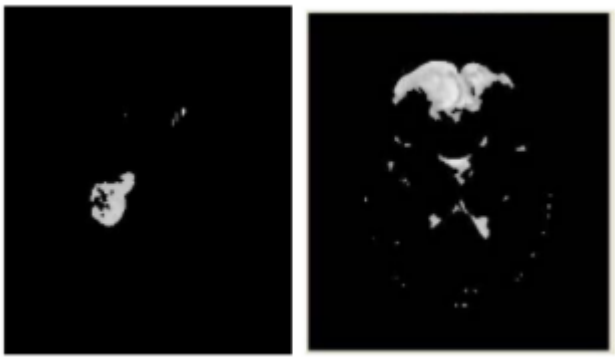
Figure 3 : PSO with FCM method and ACO with FCM segmented Pixel for Tumor Segmentation [14]

Performance assessments are often used to assess how well a system has met a specific given requirement. In any computer-assisted research, the execution time is one of the most important features for evaluating medical images. The number of pixels impacted by tumor cells was determined in these results, and the results were compared to earlier ones. Better results are obtained with the suggested PSO, which employs a fuzzy-based segmentation technique. When compared to existing methods, the accuracy of the brain tumor segmentation procedure is determined to be superior. In 98.87 percent of cases, tissues such as malignancies are found. [14]

First, the MRI picture must be segmented. The extent to which this subdivision is carried out is determined by the task at hand; for example, segmentation should finish when the tumor's edge is recognised. To put it another way, the major purpose is to isolate the tumor from its surroundings. The biggest problem with edge identification is that cancer cells near the MRI's surface are very fatty and hence appear very black on the MRI, which makes the process exceedingly confusing. [13]

Neural networks are a newly found technology. In domains such as cardiology, radiology, and oncology, neural networks are a "hot" study topic. Artificial neural networks may tackle extremely complicated problems by layering neurons together. Artificial neural networks (ANNs) are used to map an input into a desired output in medical applications, and neural networks are comparable to ANNs. It's a brand-new method for detecting brain cancers that delivers great results and precision. The "watershed approach" and the edge detection operation are merged. Color MRI images of the brain can be created using this method. The RGB image so obtained, is converted to an HSV color image, distinguished into three areas namely, hue, saturation, and intensity. In this case, the canny edge detector is applied to an output image for the edge reconstruction procedure. The three photos are then merged to create a segmented image of a brain tumor

.

On 20 brain MRI scans, this method produced great results. In an MRI scan, the very uneven borders of tumor tissues can be detected. Medical pictures are segmented using deformable modes and region base approaches. Undefined tumor location, unrecognized limits or data loss at boundaries, and a quiet edge that is not extended are the most common problems in MRI images. Using this approach, the silent edge is extended and the tumor site or area's boundary is determined, and the tumor boundary or location is clearly visible. The tumor can then be surgically removed. [15]

Segmentation is the split or separation of a picture into sections with similar properties. Many image processing systems have as their ultimate goal the extraction of essential elements from image data so that the computer may provide a description, interpretation, or comprehension of the scene. Brain tumors must be segmented from magnetic resonance pictures by medical professionals, which is an important yet time-consuming task. The digital image processing community has created numerous ad hoc segmentation algorithms. Four of the most prevalent approaches are as follows: 1) texture segmentation, 2) amplitude thresholding 3) template matching; 4) segmentation based on region growth It's essential for finding malignancies, oedema, and necrotic tissues. These algorithms separate brain images into three types: pixel-based, region-based, and structural-based. [18]

The median filter is a noise reduction technique that uses non-linear filtering. To remove salt and pepper noise from the converted grey scale image, median filtering is applied. It substitutes the median of the intensity values in the pixel's immediate vicinity for the value of the centre pixel.Median filters are highly effective in the presence of impulsive noise. Because of the white and black specks that cover the image, impulse noise is also known as salt and pepper noise. The median filter is illustrated, which is used to minimise salt and pepper noise in MRI images.[16]

Figure 4. MRI imaging with salt and pepper noise (left) vs after applying Median Filter (right) [16]

. ***TensorFlow***

Google released TensorFlow in 2015 as an open-source software library to make it easier for developers to design, build, and train deep learning models. It originated as an internal library used by Google developers to create models in-house, with more capabilities likely to be added to the open source version as the internal version is tested. The name TensorFlow stems from the computations that such neural networks perform only on multidimensional data arrays called tensors. [17]

TensorFlow is a Python package that lets you define any computation as a high-level network of data flows. The edges in this graph represent data transported from one node to the next, while the nodes represent mathematical processes. Tensors, which are multidimensional arrays, are used to represent data in TensorFlow. TensorFlow is primarily utilized in practise and research for deep learning, despite the fact that this framework is very valuable in a range of domains for thinking about the computations. [17]

IV. METHODOLOGY

1. *The ANN model:*
   The ANN model, has seven layers. The first layer is the flatten layer, which converts the 256x256x3 images into a single dimensional array. The dense layers, with relu as the activation function and 128, 256, 512, 256, and 128 neurons in each layer, are the next five levels. The output layer is the last dense layer with a sigmoid activation function, with one neuron representing each of the two classes, and these five levels are the hidden layers. The Adam optimization technique and the binary cross entropy loss function are used to construct the model. By giving the training and validation photos, the model is created and trained. After the model has been trained, it is put to the test.

1. *The CNN Model:*
   Different layers are used to construct the CNN sequential model. The image is resized to 256x256 pixels. With ReLU (Rectified linear Unit) as the activation function and padding equal to the input picture, the convolve layer is applied to the input image, resulting in an output image that is similar to the input image. There are 32,32,64,128,256 filters for distinct convolve layers. With 20% dropout, the max pooling method is used with a 2x2 window size and the dropout function. The Flatten method is used to flatten the features into a one-dimensional array. The dense approach with 256 units and ReLU as the activation function is used to build a totally linked layer. The two classes and the output layer are represented by a single unit.

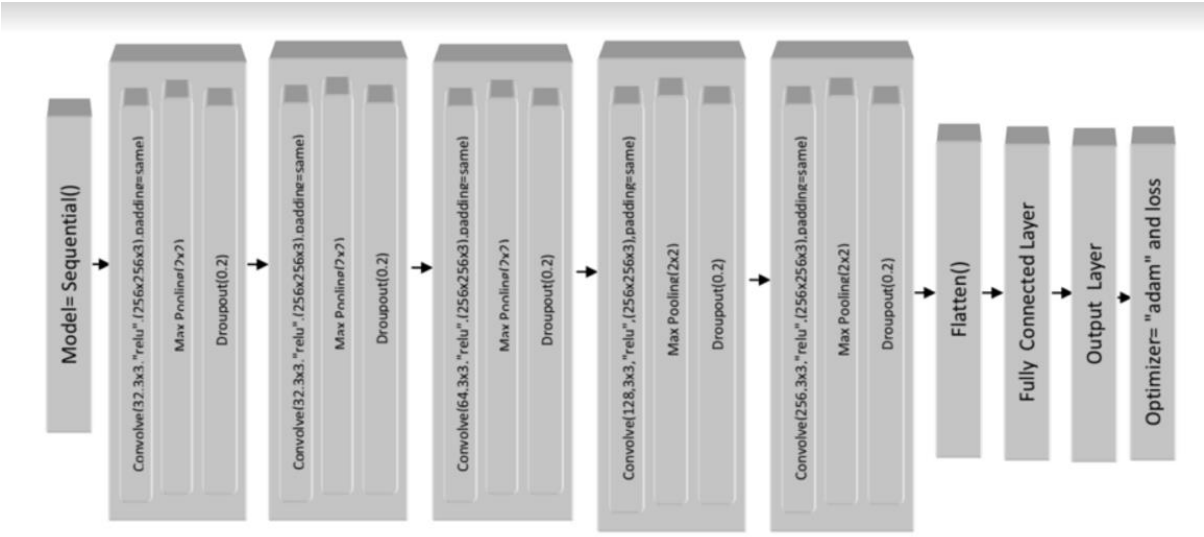

Figure 5. Architecture of CNN model [1]

1. For brain cancer tumor characterisation, a hybrid system combining two machine learning methods has been developed. In this study, a total of 70 brain MRI pictures (60 aberrant, 10 normal) were used. DWT [20] was used to extract the features from the photos. PCA [22] was used to minimise the overall number of features. Two classifiers were applied to the reduced features separately after feature extraction namely, FP-ANN and KNN. FP-ANN is referred to as the back-propagation learning approach for updating weights [19]. Similar traits cluster together, according to the KNN classification. The KNN assigns the most common label among an unknown instance's K closest neighbours to an unknown instance. The suggested method's process model is depicted in figure 6. [4]

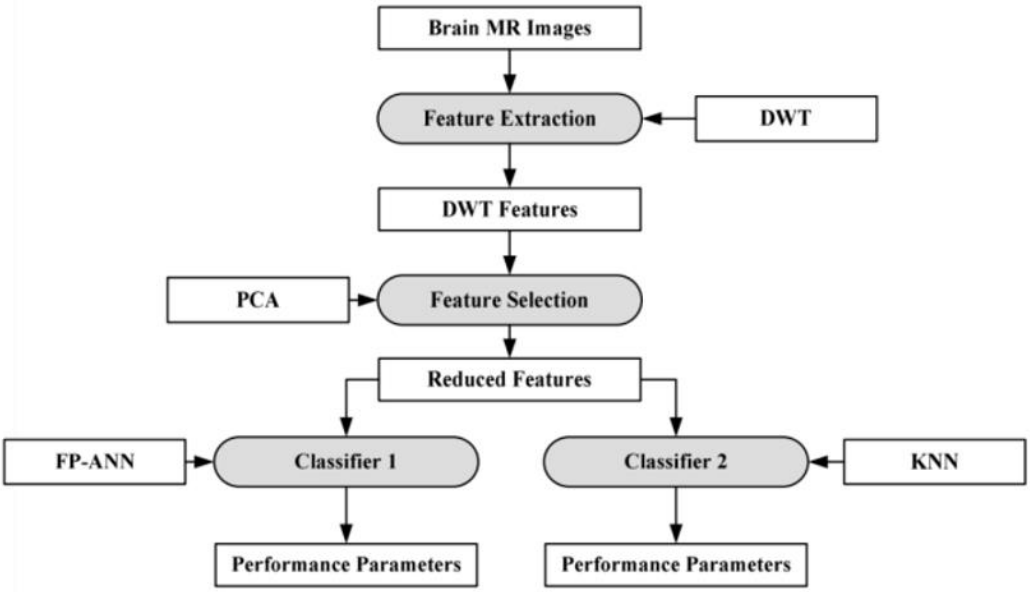

Figure 6. KNN- based classification model process.[4]

1. The K-means method, unlike the other hyperspectral brain cancer detection techniques, does not have a predefined number of steps to follow. Because no prior understanding of the data is required, it employs unsupervised and unguided learning. The programme divides the information into K clusters, each with its own K value. Data is grouped together based on similarity of features. The approach begins with the definition of K centroids, one for each cluster. Based on the distance between each location and the centroids, an initial grouping is created using those centroids. The cluster indicated by the nearest centroid is associated with a point. At this time, each k centroid is modified to represent the group's barycenter. This procedure repeats until the difference in centroids between two successive iterations is smaller than a threshold limit, or until the maximum number of repetitions is reached. [5]

1. The three key stages of the proposed strategy were preprocessing, image categorization with ELM-LRF, and tumor resection using image processing algorithms. In the preprocessing stage, denoising and normalising algorithms were utilised to prepare input images for the next stage. In the classification stage, the ELM-LRF was used. There are two types of brain tumors: benign and malignant. Convolution and pooling algorithms were used to the images in the input layer. The input layer weights were determined at random. The weights between the hidden and output layers were calculated analytically using the least square approach. Watershed segmentation was used to detect tumors. [6]

1. The data mining algorithm chosen for classifying data in this research paper is Random Forest (RF). This approach has already been applied to hyperspectral data classification. Random Forest is a collection of Decision Trees (DTs), each of which was trained with the same data set but grows using distinct random vectors. A single Decision Tree is capable of handling high-dimensional input, ignoring unnecessary aspects, and providing a simple model interpretation. DT, on the other hand, has a low prediction accuracy. Many efforts to increase DT's prediction accuracy have been proposed as a result of its benefits. Using ensembles of DT, such as the Random Forest classifier, has been discovered to be one of the best ways to increase the performance of Decision Tree-based algorithms. The most popular class voted by the trees is calculated as the output of the RF classifier.[7]

1. The outcomes of this investigation were analysed using an SVM classifier and a data partitioning technique that included a leave-one-patient-out cross-validation. The test group includes all of the patients' samples save those that will be tested, whereas the training group includes all of the patients' samples except those that will be tested. Every patient in the test database uses the same procedure. The SVM classifier was selected to compare the findings to previous published work.

1. The paper presents a neuro fuzzy logic recognition system for MRI. It works on an efficient system for the detection of cancer from a given brain MRI and recognizes the extracted data for further applications. Data Sets, Image Segmentation, Histogram Equalization, Thresholding, Image Enhancement, Sharpening Filter, Morphological operation, Feature Extraction, Feature Selection, Neuro-Fuzzy Classifier are the 10 steps used in the proposed method. [13]

1. Particle Swarm Optimization (PSO) is a novel heuristic search technique whose mechanics are inspired by the swarming or collaborative behaviour of biological populations. Particle creation, positions, and velocities are split into three phases in the PSO method: (1) velocity update, (2) position update, and (3) velocity update. A particle in this example is a kernel in the full brain picture that changes location based on velocity updates from iteration to iteration. [14]

1. The median filter is a non-linear filtering technique used to reduce noise. To eliminate salt and pepper noise from the converted grayscale image, median filtering is utilised. It replaces the value of the centre pixel with the median of the intensity values in the pixel's immediate vicinity. The median filter is shown below, which is used to reduce salt and pepper noise from MRI images:

Fig. 2 (a) Salt and pepper Noise apply **(b)** Median filter

Figure 7. a)salt and pepper noise b) median filter[16]

1. The suggested method generates intuitive hyper-parameters with intuitive interpretations that may be fine-tuned to handle non-stationary objectives and problems with very noisy and sparse gradients. Adam is effective in practice and comparable to other stochastic optimization approaches, according to recent empirical results. [17]

V. RESULT

The graphic shows the accuracy and loss obtained using the ANN model on the training and validation datasets. The training accuracy is 97.13 percent and the validation accuracy is 71.51 percent when the ANN model is run for fifty epochs on the training data. When applied to testing data, it yields an accuracy of 80.77 percent.[1].

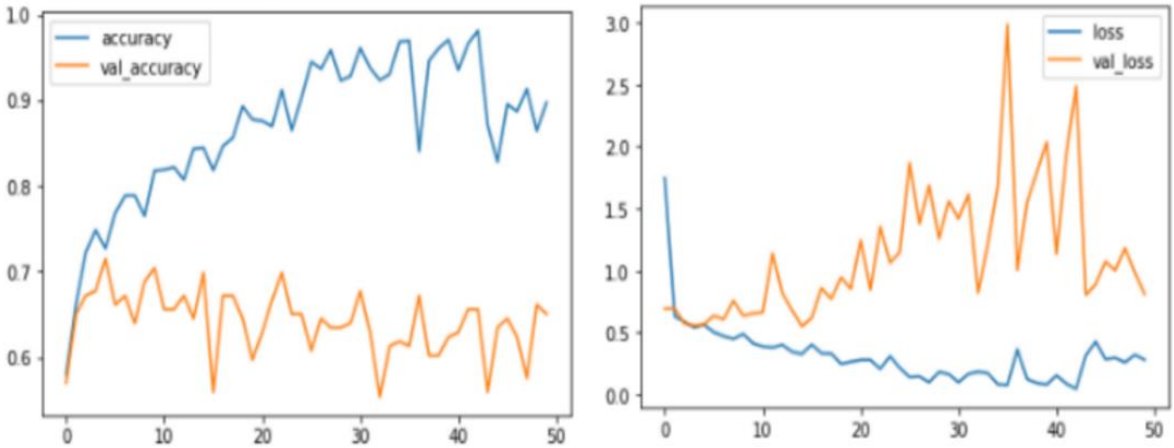

Figure 8. A comparison of ANN model training/validation accuracy and loss

When the CNN model is applied to the training dataset for 200 epochs, the maximum validation accuracy is 94.00 percent. The ratio of training accuracy to validation accuracy, as well as training loss and validation loss, are plotted in the following figure.[1]

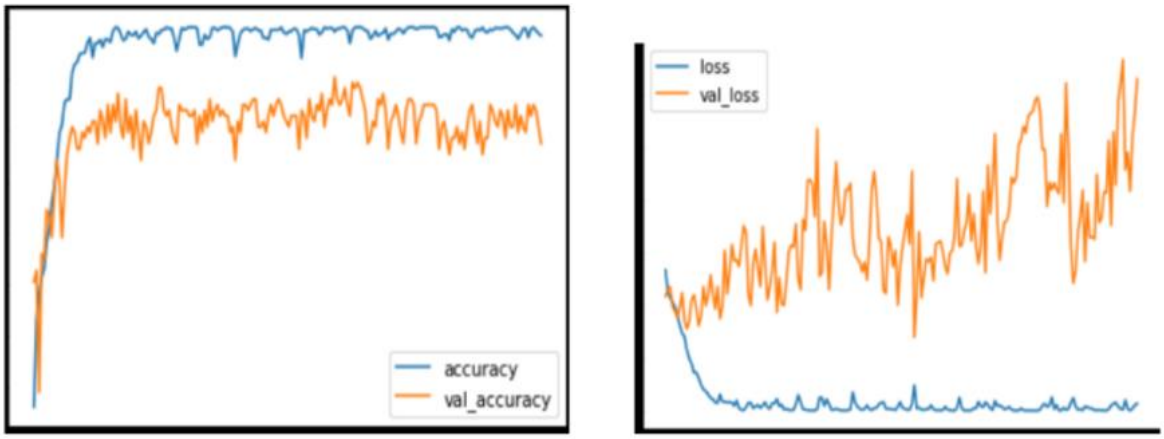

Figure 9. A comparison of CNN model training/validation accuracy and loss

Using the FP-ANN and KNN methods 97% and 98% accuracy, respectively can be achieved [4].

The sensitivity and specificity scores were 96.80% and 97.12%, respectively.
The ELM-LRF method was calculated.[6]

In tests, our supervised classification method was able to discriminate between normal and malignant tissues with an accuracy of over 99 percent. [7]

With an average of 20% increase in accuracy in the tumor class, the reduced dataset offered superior accuracy results in SVM than the original dataset. [9]

When the spread value is 1, the LVQ-based PNN system handles MRI image classification with 100 percent accuracy. When compared to traditional PNN, it also reduced processing time by over 79 percent. [10]
In comparison to the current neural classifier, the significant iteration time and recognition accuracy level is found to be around 50-60% better. [13]

Particle Swarm Optimization (PSO) was discovered to have a 92.3 percent total tumor pixel accuracy.[14]

With 35 epochs, this was accomplished, resulting in good training and validation accuracy. The machine learning technique used to detect cancer tumors in MRIs is extremely effective. After 35 epochs, a validation loss of 0.000 was discovered with 99% training accuracy and 98.6% of validation accuracy. [17]

VI.CONCLUSION

The study of brain tumors using medical imaging is a difficult and time-consuming process that can be divided into three stages: pre-processing, classification, and post-processing. The research demonstrates various methods for detecting and segmenting brain cancers using MRI data. All in all, CNN is considered one of the most successful algorithms for assessing image information.It predictions by shrinking the image without sacrificing the necessary information to make the prediction.. The testing accuracy of the ANN model created here is 65.21 percent, which can be increased by providing more image data. For hyperspectral medical picture clustering, there are several concurrent implementations of the K-means algorithm.

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