Section A-Research paper
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MRI based Brain Tumor Diagnosis using Convolution Neural Network

Divya D[a]*, Vanitha R [b], Prasanthi T [c], Nithya D[d] and Shenbagavall Bi[e]
[a]Associate Professor, Department of Computer Science and Engineering, Jerusalem College of Engineering, divya21cs@gmail.com
[b]Associate Professor, Department of Cyber Security, Jerusalem College of Engineering
[c]Assistant Professor, Department of Artificial Intelligence and Machine Learning, Jerusalem College of Engineering
[d]Assistant Professor, Department of Cyber Security, Jerusalem College of Engineering
[e]Assistant Professor, Department of Computer Science and Engineering, Jerusalem College of Engineering

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***Abstract*-The manual diagnosis of tumor is a time intensive process which may result in errors on the part of humans, leading to erroneous detection and classification of tumor types. The contributors provide a structure based on machine learning for recognizing different kinds of brain tumors, aimed at streamlining the diagnostic process for healthcare providers by integrating complex procedures related to medicine. The characteristics of the segmented tumor region are obtained, and the CNN classifier approach subsequently employs the tumor features to determine the tumor existence. In order to put the suggested model into action, pre-trained a Deep Convolutional Neural Networks (DCNN) are utilized. These designs are each coupled with a unique classifier. Using the architectures as transfer learning methodologies, the characteristics from the pre-trained DCNN framework are extracted, and then the Support Vector Machine (SVM) classifier is used to classify them. This process is carried out by deploying the models. The accuracy of the system that detects tumors automatically will be elevated as a result of utilizing this strategy. In the context of Magnetic Resonance Imaging (MRI), methods for augmenting data are utilized in order to stop the network from being overly fitted. When splitting MRI images, using several networks is examined by contrasting the outcomes with those obtained using just one network. The severity of the brain tumor is accessed by using the Convolutional Neural Network method, which yields trustworthy results.**

Keywords-Deep Convolution Neural Network, MRI Images, Automated diagnosis, Classifiers.

Nomenclature

Abbreviations	Descriptions
CNN	Convolutional Neural Network
D-CNN	Deep-Convolution Neural Network
MRI	Magnetic Resonance Imaging
FP	False Positive
BPNN	Back Propagation Neural Network
FAHS	Fully Automated Heterogeneous Segmentation
SVM	Support Vector Machines
FN	False Negative
ELM-LRF	Extreme Learning Machine Local Receptive Fields
BWT	Berkeley Wavelet Transformation
K-NN	K Nearest Neighbor
MSWA	Multilevel Segmentation by Weighted Aggregation
DNN	Deep Neural Network
DWA	Deep wavelet Auto Encoder
FrCN	Full resolution Convolutional Network
NN	Neural Network
RFA	Random Forest Algorithm
DT	Decision Trees
TN	True Negative
TP	True Positive

I INTRODUCTION

MRI has emerged as a key technique in clinical investigations on brain architecture [1]. Doctors can properly diagnose certain illnesses thanks to the soft tissue's great resolution, contrast, and distinct separation [2]. The sick and healthy tissues that make up the magnetic resonance picture must be precisely segmented in order to identify pathology, evaluate evolutionary tendencies, prepare, and choose the best surgical technique or alternatives [3]. By enabling automated volumetric analysis of the pathologic MRI signal and helping management with inconsistent levels of automation, automated segmentation approaches are a beneficial option [4A tumor anywhere else in the human organism is indicative of unregulated cell proliferation of malignancy, but a tumor in the brain is indicative of unchecked cell proliferation of brain tissue. There are two possible types of benign and malignant brain tumors [5]. Brain tumors that are benign share structural characteristics with malignant ones, despite the fact that benign brain tumors don't have actively cells [6]. Malignant tumors possess active cells. [7] Benign tumors include low-grade malignancies such as meningiomas and gliomas, whereas strong-grade cancers such as astrocytomas and glioblastomas are classified as malignant tumors. The most severe form of astrocytoma, or glioma, is called a glioblastoma [8]. Meningioma, glioma, and pituitary tumors are some of the most common types of brain tumors, and they are just three of the more than 120 different kinds of brain tumors that have been discovered and identified so far. Meningioma tumors belong to these three and may be one of the most frequent type of fundamental brain tumor. Meningiomas can damage both the brain and the spinal cord. Glioblastoma is distinguished from every other kind of tumors in its class [9] by the rapid growth of blood vessels, also known as angiogenesis, and the occurrence of necrosis, also known as cell death, across the bulk of the tumor. Glioblastoma is also the only type of tumor that can produce necrosis.

When conducting investigations into cancer, it is essential to differentiate between normally functioning and diseased brain tissues by using the distinct areas in Magnetic resonance imaging information pertaining to each. [10] This is done in order to develop effective curative options. All medical image processing methods still rely on the segmentation of pictures, which involves removing regions of interest from images [11]. Given the enormous quantities of information that each image contains, this technique is excessively time-consuming, boring, and occasionally difficult [12]. Typically, the radiologist takes into account all of these MRI methods at the same time when segmenting brain tumor pictures [13]. Although CNNs incorporate the processes of finding and categorizing features, they require minimal preliminary processing and extraction of features than traditional methods.

A CNN has the capability to autonomously gather from imagery relevant and linked properties. A CNN may however achieve good accuracy in identification regardless with a relatively modest amount of information used for training. Guidelines of the concepts currently do not need to be made, nor is prior understanding of qualities required. The utilization of the topographical data that is readily accessible in the input is the primary benefit of adopting a CNN framework for the purpose of achieving significant results. The outcomes of the recognition methods utilized by a CNN model are, for the most part, undisturbed by the rotation as well as translation of the source images.

The significant contribution of this paper is:

- To provide an efficient structure for enhancement, segmentation and classification of brain related tumors for early identification of brain tumor.
- To generate machine learning algorithm for classifying and extracting features from magnetic resonance images with the least error.
- The investigational consequences exhibit great correctness in early diagnosis of brain tumor identification and location using benchmark datasets.

The sequence that follows is the planned order of the research's contents: In Section II, the authors provide a literature assessment of current methods for detecting brain tumours, highlighting their strengths and weaknesses. In addition, the proposed paradigm for diagnosing brain tumours using MRI images is detailed in Section III. In Section IV, let will talk about the steps taken to effectively detect tumours. In Section V, represent the findings and explore them. The final section of the report, Section VI, discusses the implications of the findings.

II LITERATURE REVIEW

A Related Works

The Machine Learning-based Back propagation Neural Network (MLBPNN) approach for categorizing brain tumor systems was proposed by P.Mohamed Shakeel *et al.*, [11].This method can assist medical professionals in scanning an image by coloring the image cell with the results of computations based on order and package. The process of acquisition, grading and splitting, removal, and image representation in the workplace, characterization, and vital administration are just a few of the numerous stages that must be carried out in the production of the images from biopsy photographs in order to locate a disease. Other stages include: acquisition, upgrading and division, image accountability, evaluation, and vital maintenance. Analysis of MLBPNN is carried out with the use of infrared sensor imaging methodologies in this work. When some components of the overall structure are disrupted, the multidimensional machine's ability to produce distinct neurological evidence is significantly diminished. This image sensor is coupled to a Wireless Infrared Imaging Sensor, which transfers the heated tumor data to a medical practitioner for the purpose of evaluating the patient's health and to properly regulate the ultrasonic measurement level. This is particularly helpful in situations when there are elderly patients located in remote areas.

For the purpose of identifying and segmenting brain tumors, Zheshu ji, Deyun Chen, and their colleagues [12] suggested a Fully Automatic Heterogeneous Segmented employing the use of support vector machines (FAHS-SVM).The correctness of the computerized technique corresponds to the numbers for the variation among observers of the human separation technique. Through the use of an inherent image structure hierarchy in conjunction with quantitative categorizing information, regions of cancer can be located. The tumor regions presented are congruent with picture content, spatially compact, and provide a suitable and reliable guidance for the subsequent segmentation. The observations on utilize-parametric MRI scans show that the proposed method, when combined with a semi-supervised approach and both an individual and worldwide correctness system, can provide encouraging tumor separation. Our experimental findings suggest that the suggested strategy will aid in swiftly and precisely determining the precise location of the brain tumor.

Ali ARI and colleagues [13] created the ELM based LRF, which stands for "Extreme Leaning Model Local

Receptive Fields," in order to classify and diagnose different, types of brain cancers. To begin, sounds have been neglected by the utilization of non-local approaches and localized softening strategies. The second phase involved classifying the malignant or benign nature of cranial magnetic resonance (MR) images using ELM based LRF. The third phase involved segmenting the tumors. This study exclusively used cranial MR images with mass in order to achieve its goals. The results of the clinical studies indicate that the the cerebral magnetic resonance (MR) scans exhibit an accurate classification of 96.2%. The findings of the analysis indicated that the suggested approach was superior in efficacy compared to prior contemporary scholarly investigations. Clinical research suggests that utilizing this method can be successful in detecting brain tumor conditions with the aid of computers.

The Berkeley Wavelet Transform and Aided Vector Machine (BWT based SVM) was developed by Nilesh Bhaskarrao Bahadur and his colleagues [14] for the aim of recognizing and retrieving information from Magnetic Resonance imaging of brain tumors. They investigated texture- and histogram-based characteristics using a recognized MR brain tumor classification classifier. As opposed to the manually operated diagnostic performed by healthcare providers or radiologists entirely, the results of examinations for diagnosing brain tumors may be quickly and accurately evaluated from the numerous images. This allows for a faster and more accurate identification. When all of the metrics of performance, including as PSNR tests mean, the mean squared error precision, accuracy, recall, and coefficients of dice, are increased, the method that was suggested gives superior results.

The method of splitting brain tumors known as the Multilevel Segmentation by Weighted Aggregation (MSWA) was developed by Jason J. Corso *et al.,* [15]. In order to autonomously segment heterogeneous imaging data, it is necessary to connect the gap amongst appreciation-based, bottom-up, and top-down prototype-based strategies. The most important addition that this study makes is the development of a Bayesian method for introducing soft modeling assignments into the evaluation of affinities, which are normally free of models. The efficient computational approach outperforms existing methods by a factor of ten while providing outcomes that are equivalent to or better. Their qualitative results show how model similarities are incorporated into the separation algorithms used for the complex occurrence of brain tumors. This method combines the vital part of the graphical structure with the crucial component of each voxel to create the final product. The pictorial hierarchy is gathered, which results in the system being autonomous of each voxel and intuitively integrating data from the surrounding neighborhood.

Brain Magnetic Resonance image categorization for cancer detection was proposed by Pradeep Kumar Mallick et al. [16] using the Deep wavelet Auto Encoder and Deep Neural Network (DWA-DNN). In this research, we propose a Deep Wavelet Auto Encoder (DWA) as a means of compressing images. It combines the essential feature extraction capability of the Auto Encoder with the transform wavelet image decomposing method. The number of features required to sustain DNN identification is significantly impacted by the inclusion of both. The suggested DWA-DNN image classifier was tested on a database of brain images. The suggested method compiles the existing methods into a single summary and evaluates the DWA-DNN's effectiveness factor in comparison to those of other classifiers such as the Auto Encoder-DNN and DNN. Experimental results show that the DWA-DNN technique outperforms all other deep computing approaches in terms of accuracy and predictability. It would be much more interesting to find a technique to combine DNN with many further enhancements in the Auto Encoder so that the influence or results within the brain MRI dataset could be examined.

Three-dimensional MRI brain tumor identification using multimodal information fusion and convolutional neural networks was proposed by Ming Li *et al.,* [17]. It is recommended to use the improved multimodal 3D-CNNs in order to obtain the 3D properties of brain tumor lesions in different modalities. Find out what the specific distinctions are between the available settings. Second, to deal with the issues of slow network convergence and over-fitting, brain tumor characteristic data are normalized. Then, an entirely novel weighted loss function is built, considering both the tiny size of the lesion area and the enormous size of the non-focal area, to reduce the impact of the non-focal area on the identification of brain tumors. The identification of brain tumors in extraneous regions is therefore reduced by increasing the loss function. The results of the experiments show that the dice, SN, and SE evaluation indices may be optimized, and they also provide a comparison between the originally developed single-mode brain tumor detection technique and the two-dimensional brain tumor detection network.

Hasan Ucuzal *et al.,* [18] designed a web-based app that analyzes high-resolution T1 contrast MRI images to distinguish between glioma, meningioma, and pituitary tumors. The app makes use of a convolutional neural network trained with a deep learning algorithm. The experimental results show that all estimated performance metrics for brain tumor classification on the initial training dataset are higher than 98%. Similarly, with the possible exception of responsiveness and MCC performance metrics, all performance parameters for testing for meningioma brain tumors are above 91%. The study's developed system obtains considerable results and is effective for brain tumor multi-classification tasks, with the greatest overall correctness rates of 96.13% and 98.7% for the two datasets, respectively. Previous research has demonstrated that T1-weighted MRI can be used in conjunction with deep learning and machine learning methods to accurately detect and forecast brain tumors.

A new approach was developed by Sobhaninia et al.[19] that allows CNN to automatically segment the three forms of brain tumors that are diagnosed most frequently: gliomas, meningiomas, and pituitary tumors. According to the results of the study, the accuracy of segmentation can be improved by dividing images according to their respective angles. The accomplishment of this rather high score was made possible by the accurate segmentation of tumors in photographs taken from a sagittal angle. In sagittal views, other organs are not as easily discernible as they are in other photos, whereas the tumor stands out more than it does elsewhere. The photos taken from an axial perspective of the head were linked to the lowest Dice score achieved by the experimenters, which was 0.71. When compared to other views, the axial perspective lacks some features. It is anticipated that pre-processing on this set of photos would improve the categorization of tumor pixels and raise the Dice score. Their technology might be used as a quick and practical tool for clinicians to separate brain tumors in MR images.

B Review

Even though there has been significant progress made in detecting brain tumors over the past decade, there are still some challenges that need to be overcome in order to increase the accuracy of the process. The present skin cancer detection systems each have their own set of limitations and amenities, which are outlined in Table 1. A machine learning-based BPNN [11] with high accuracy, ultrasound measuring level of senior patients, which is effective for learning relevant features employing infrared sensor imaging methods, and it is capable of maintaining its potential to boost the performance of classifiers, has been developed. However, it does have certain flaws, such as the fact that it is rather slow and that it has a significant computational cost. The performance of the FAHS-based SVM[12] has been enhanced, and the time complexity of the algorithm has been reduced. Despite this, the number of outcomes divisions is greater than the number of classes that were desired. Even with unorganized data and partially structured information like images, ELM-based LRF [13] works very well and produces the best results. Nevertheless, it has a few flaws, such as the fact that it can be challenging to comprehend and that it requires a lot of time to train on huge data sets. In addition, the BWT-based SVM [15] increases the overall performance, and it is able to produce complete spatial resolution characteristics that employ texture and histogram-based classifiers for every pixel of the input images. This capability applies to the images as a whole. However, it does have certain drawbacks, such as the requirement of more training photos in order to improve the segmentation performance. MSWA [15] is effective when it comes to producing outcomes, and it has the ability to create new features from an existing collection of characteristics that are only partially represented in the dataset used for training. However, in order to give the results accurately, it demands a higher level of precision. DWA-DNN [16] is simple to comprehend as well as put into practice. However, there are certain limitations to the collection of characteristics that can be found in the training datasets that it supports. CNN [17] [18] [19] is effective in producing superior outcomes, and it has the ability to produce novel characteristics from a limited number of traits that have already been included in the dataset being used for training. Nevertheless, further training data is required for it. The danger of becoming too conformist is really remote. As a result, the obstacles outlined above need to be conquered, and an effective implementation strategy needs to be developed for the prompt identification of the presence of brain tumors in the future.

TABLE 1 FEATURES AND CHALLENGES OF THE EXISTING SKIN CANCER DETECTION MODELS

Author [citation]	Methodology	Features	Challenges
P.Mohamed Shakeel et al. [11]	MLBPNN	• Analyzing MLBPNN using Infrared sensor imaging technology to effectively manage the ultrasound measurement level of the elderly patients.	• It is relatively slow.
Zheshu ji, Deyun Chen et al.[12]	FAHS-SVM	• Combining a quasi-supervised method with division of tumors yields encouraging results. • Its time complexity is low.	• This method is only appropriate for a preliminary diagnosis.
Ali ARI et al. [13]	ELM-LRF	• Noises have been ignored using non-local means to classify the malignant images. • It has high accuracy.	• The only aggregate magnetic resonance (MR) images of the brain were used for analysis in this investigation.
Nilesh Bhaskarrao Bahadur et al.[14]	BWT- SVM	• Using texture and histogram-based classifier to recognize a brain tumour.	• Statistics like PSNR tests mean, the mean squared error precision, degree of specificity, sensitivity, and coefficient of dice all improve as a

			result. • Training huge data sets is a time-consuming process.
Jason J. Corso et al. [15]	MSWA	• The ability to assess correlations through the completion of softer modeled chores.	• Classification accuracy need to be increased.
Pradeep Kumar Mallick et al. [16]	DWA-DNN	• Effective at producing excellent outcomes. • Make use of a small subset of attributes from your training databases in order to produce distinctive characteristics.	• Additional training data is needed.
Ming Li et al. [17]	CNN associated with three-class classification	• For Use with Rare Medical Images, the use of transferable learning strategies is a powerful tactic.	• Over-fitting due to inadequate training information size. • The repercussions are difficult to imagine.
Hasan Ucuzal et al.[18]	CNN-based DL model	• Machine learning is surpassed by AI-based transfer learning for classifying brain tumors.	• Classification accuracy need to be increased.
Sobhaninia et al.[19]	CNN	• Segmentation accuracy is increased by separating pictures depending on the angles.	• Axial view shows fewer details than other photos. • It is computationally high cost.

III PROPOSED BRAIN TUMOR DIAGNOSIS: AN EFFECT OF CT IMAGES

A. *IMAGE DESCRIPTION*

The primary application of cerebral MRI images is to look for the modeling of the tumor and its progression. The most important applications of this information are in the detection and management of cancerous growths. When compared to an ultrasound picture or an MRI image, an MRI examination offers a greater amount of information regarding a particular medical imaging process. MRI scans provide a wealth of information on both the structure of the brain and the detection of anomalies in its tissue, in contrast to computerized methods to the discovery and classification of brain cancers utilizing brain MRI images. This is due to the fact that they were designed prior to the time when it was possible to scan and upload medical images to a computer.

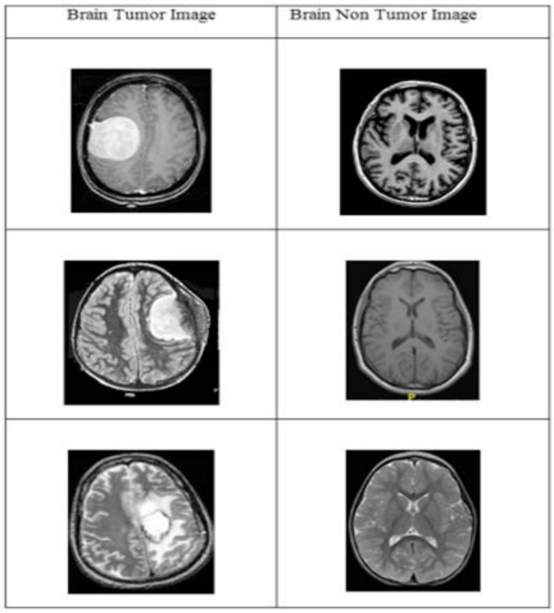

Fig. 1 Sample of Tumor and Non-Tumor images

The classification system for cancers and non-tumors based on imaging of the brain Fig 1 shows a block

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representation of a brain tumor. The classification process illustrated in Fig. 2 makes use of a neural network composed of convolutional neurons. The tumor in the brain that was reported by CNN. The steps of training and testing are both divisions that go into the categorizing process. The amount of photographs has been organized into a variety of groups by affixing labels to each one, some of which are titled "tumor and non-tumor brain images" and alternative images. During the training phase, tasks including as prior processing, extraction of features and categorization utilizing the loss function are being carried out. These tasks are necessary for the creation of a prediction model. First, label the photo collection used for training. In order to modify the dimensions of an image before it is processed, image resizing is performed.

The automated categorization of brain tumors uses a convolutional neural network. The brain image collection was made available through the ImageNet website. One of the models that can be learned is referred to as the image net. As a result, a significant amount of time is required. There will be repercussions for the execution. In order to circumvent problems of this nature during the classification stages, a pre-trained model that is derived from a brain dataset is utilized. Train the last layer in Python for the proposed CNN. Not all of the layers should be trained. In the suggested automated brain tumor classification technique, calculation time is therefore short while performance is excellent.

The brain of a human being, which is considered to be one of the most significant structures in the human organism, is composed of billions of cells. Uncontrolled cell division results in the formation of an aberrant cell group, commonly known as a tumor. There is a distinction between lower-quality and strong-grade brain tumors. The most common types of brain tumors are those of a low grade. In a manner not dissimilar to this, a strong-grade tumor is often referred to as a malignant tumor. Tumors that are malignant are not the same as tumors that are benign. Because of this, it is unable to propagate to other parts of the brain. On the other hand, the tumor that has cancer is a malignant tumor. As a direct consequence of this, it is able to rapidly expand to unrestricted areas of the human organism and easily spread to other parts of the body. On the other hand, during the course of the last few years, Neural Networks (NN) and Support Vector Machines (SVM) have emerged as the most preferred methodologies for their successful implementation.

However, computational models of learning are currently representing a fascinating trend in the field of machine learning. This is due to the fact that the underground building designs are capable of communicating complex connections without the need for a large number of nodes. This is in contrast to surface-level architectures such as the Support Vector Machine (SVM) and the K-Nearest Neighbor (KNN). In contrast to the other subfields of health informatics, such as imaging analysis for medicine, medical information systems, and bio-informatics, they progressed more rapidly to the point where they are now considered the state of the art. Fig. 2 presents the proposed model, which includes a suggestion for an automated technique of brain tumor segmentation that is based on convolutional neural networks.

B. ARCHITECTURAL VIEW

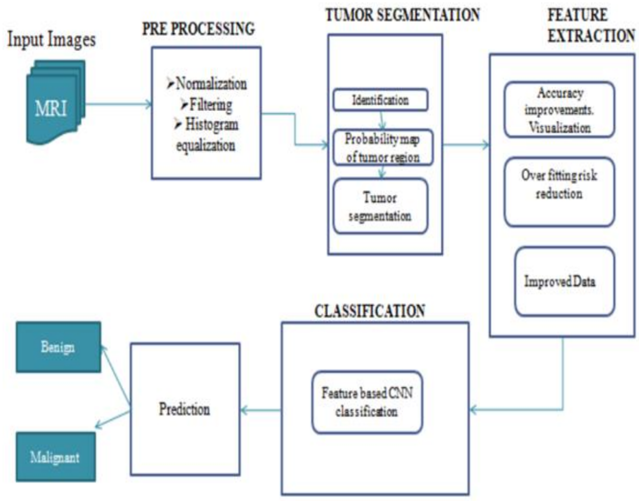

Fig. 2 Proposed Framework of Brain Tumor Identification

The following stages are involved in the earliest diagnosis of brain tumor.

- Pre-processing
- Segmentation
- Feature Characterization
- Classification

The manual investigation of brain tumor categorization is a time-intensive process that is susceptible to potential human error. The expeditious and precise execution of analysis is of utmost importance. The present study introduces a convolutional neural network (CNN) methodology-based a computerized system for brain tumor classification, which exhibits a high degree of accuracy. The utilization of the Alex Net transfer learning structure in CNN is exploited.

IV STEPS ADOPTED FOR PERFORMING EFFECTUAL BRAIN TUMOR IDENTIFICATION

The pre-processing of images is done for developed brain tumor detection involves the following process.

A. PRE-PROCESSING

The images obtained from the MRI of the brain are used. MRI scans of the body are used rather than MRI scans of the brain because they are considered to be safer and more accurate. When considering the quantity of characteristics found in older works. If there are more training data samples than there are data points, the support vector machine, or SVM, will not function very well. One deep learning technique that uses a series of feed-forward layers is CNN. The segmented tumor region's characteristics are retrieved, and the CNN classifier technique then uses the tumor features to confirm the presence of the tumor. The automated tumor identification system will become more accurate thanks to this technique. Convolutional neural networks are capable, given the right sets of training data, of distinguishing between aberrant and normal tumor areas and correctly classifying them as benign tumors, malignant tumors, or healthy brain tissue. This ability is dependent on the quality of the training data. The IOT is kept up to date based on the observed output of the brain cells. The pre-processing of data is an important step in the whole procedure of data mining. In many cases, the procedures that are used to collect data are not adequately controlled, which results in figures that are outside of their normal range, impossible data combinations, missing information, and so on. An inaccurate picture of the situation may emerge from a data analysis that has not been examined adequately for these flaws. Because of this, it is essential, prior to carrying out an analysis, to take into consideration the representation and quality of the data. Data pre-processing is typically considered to be the most important stage of a machine learning project, particularly in the field of computational biology.

Train phase acquiring knowledge is made more difficult by the presence of unnecessary, insignificant, or noisy data. Processing time for data preparation and filtering procedures might be somewhat long. Thus, data pre-processing include activities such as cleansing, sorting, feature extraction, normalization, and transformation. The end outcome of the data pre-processing is the training set. Image When both the input and output images are intensity images (the most basic form of picture), the technique is referred to as pre-processing. Typically, a matrix of image function values is used to depict an intensity picture; such iconic images are of the same type as the raw data acquired by the sensor. The purpose of pre-processing is to improve the image data by suppressing unintentional distortions or enhancing some image features crucial for further processing, so geometric transformations of images are included in this category because similar techniques are used.

B. SEGMENTATION

Image segmentation is a method for breaking up a digital picture into smaller pieces [24]. Segmentation is performed on images to simplify their representation or to make it more meaningful and easily understood. Segmenting an image is a common practice for extracting features (points, lines, curves, etc.) from a photo. Segmenting an image involves labeling each pixel so that pixels with the same label share common characteristics. Segmentation of an image can produce a set of regions that together make up the entire image, or it can produce a set of retrieved contours in the case of edge detection. When it comes to a given characteristic or computational quality, like color, intensity, or texture, every pixel in a given area is roughly equivalent to every other pixel in that space. In terms of the same factor, neighboring regions vary widely from one another [25]. When applied to a stack of photos, as is common in medical imaging, the contours obtained after picture segmentation can be used to produce 3D reconstructions via interpolation methods like marching cubes.

For the purpose of generating medical image segmentation in which various structures have differing intensities or other experimental properties, thresholding is a procedure that is not only straightforward but also effective. A binary division of the picture intensities is used to construct the images in this method of image creation. During the thresholding process, an attempt is made to find an intensity value that will serve as the threshold for separating the classes of interest. After that, the segmentation is accomplished by placing all of the pixels into one class if they have an intensity that is higher than the threshold and placing all of the other pixels into another class. In other words, the threshold image is signified as $G(x_a, y_a)$ of image $f(x_a, y_a)$ is represented as,

$$g(x_a, y_a) = \begin{cases} 1, & if\ f(x_a, y_a) \geq Th \\ 0, & if (x_a, y_a) < Th \end{cases}$$

Where the variable 'Th' represents the threshold to be determined. The thresholding procedure is frequently performed as the first stage in a series of actions pertaining to image processing. The method, despite being straightforward, has a number of drawbacks, the most significant of which is that it generates just two classes and cannot be used with multi-channel photographs. Therefore, it is sensitive to the noise as well as the intensity homogeneities that can appear in magnetic resonance images.

C. FEATURE CHARACTERIZATION

A significant volume of unprocessed data is broken up into more manageable chunks by a method known as feature extraction, which is a type of dimensionality reduction technique. Because these massive data sets contain a large number of different variables, the processing of them requires a significant amount of computer power. The phrase "feature extraction" refers to the processes of selecting or combining variables into features. This greatly minimizes the quantity of data that needs to be processed while still accurately and completely characterizing the initial data set.

D. CLASSIFICATION

In the classification process, a test sample is given a class based on the knowledge the classifier learned during training. The following algorithms are only a few of the machine learning types employed in this research proposal. When performing classification tasks, the data are frequently need to be partitioned into training and test sets. Every single instance that makes up the training set is assigned a goal value, which is represented by the class labels, in addition to a variety of attributes. Fig 3 provides a visual representation of how well the classification process worked.

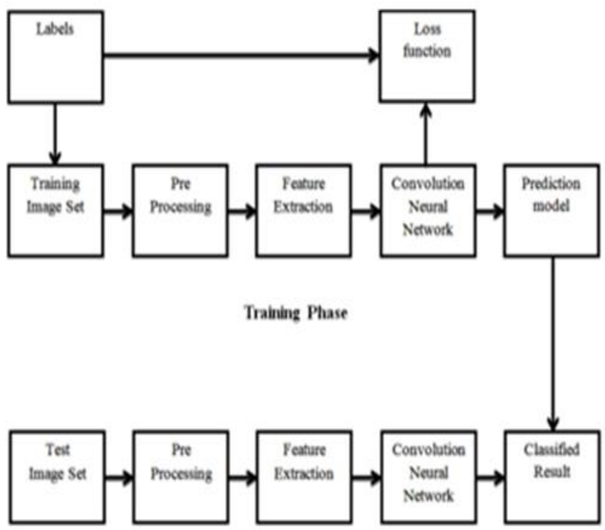

Fig. 3 Illustration of Classification Performance

- **The K-Nearest Neighbor**

K-NN is the simplest algorithm among all the other machine learning approaches. It is an instant- based learning and the final decision of classification depends on the nearest neighbor decision rule, according to which the class of a test sample depends on a group of already classified samples [21][22]. It assigns a class to the unknown test sample by voting of its neighbors. By a majority vote for the most prevalent class among the KNN, the item is categorized by its neighbors. By utilizing Bayesian optimization (fitcknn), k is set to 1 in the suggested study. Between two locations, i and j, having k dimensions, the used distance is determined as follows: m is the total number of characteristics present in objects i and j. KNN's benefits include ease of use, rapid training, and applicability in situations when a sample has a large number of class labels. 29 Cons: It requires a lot of storage space.

- **Random Forest**

The aforementioned is an algorithm for ensemble learning. An ensemble refers to a collection of heterogeneous classification algorithms that are combined to create a more robust and effective model. This algorithm is typically designed utilizing the bagging approach, a statistical methodology that involves creating multiple training sets from a single set. Each classifier constructs a Random Forest on its respective training set by implementing a subset of random attributes. Decision trees exhibit instability. The development of algorithms on heterogeneous training sets with stochastic attributes results in the generation of multiple classification algorithms. Thus, the correlation between the models is reduced, resulting in the optimization of overall performance. A voting system merges all decision trees to classify a record. Every tree votes for a class for the record, and RF chooses the class with the most votes [23]. The voting mechanism averages DT (decision tree) forecasts with substantial volatility. Even with massive data sets, accuracy is improved. Since it averages tree predictions and produces more robust outcomes, the random forest is less likely to over fit than a single decision tree. For desirable construction, this algorithm has few parameters. When the number of trees increases, this approach's computing time is maximized.

- **Support Vector Machines**

With better accuracy and mathematical advantages over some other traditional classification methods, SVM [20] is one of the most recent technologies used in classification. It is a supervised learning technique for applications like classification and regression analysis. In SVM, instances are partitioned into classes using hyper-planes constructed in a dimensional space defined by the selected kernel function. The linear, polynomial, radial basis and sigmoid functions are examples of kernel functions that are frequently used in SVM. A polynomial kernel was used in the suggested study. P is the polynomial's degree, where 1 and 2 are vectors in the input space. The SVM kernel function reduces complexity, which is a benefit.

Within the literature, convolutional neural networks are an emerging field. The approach considered each stage of the segmentation process will be covered in a portion of this review. The key conclusions will be presented. An illustration segmentation strategy will be proposed using literature-based data. The Sorensen-Dice coefficient (DSC), which is derived, serves as the primary output metric.

$$Dice = \frac{2|P \cap Q|}{|P + Q|}$$

The Q characterizes the second set, which is often the manually seperated set that the automated segmentation set is checked in contradiction of, and the P indicates the cardinal elements in the first set. The point where the segmentations converge is indicated by the symbol "∩" The accuracy will be used in cases where the DSC is not reported. The automation of quantitative picture analysis is greatly aided by machine learning. This dataset requires fixed parameters because it is trained by extracting features from a training dataset. Standard voxel-based manipulation methods may not be as precise as machine learning through repeated repetitions. In a study of 9 different machine learning models, ensemble learning showed a moderate accuracy of up to 57.8% for survival prediction for classification into short-, medium-, and long-term survival. More research is needed to determine which machine learning models are the most predictive of patient survival; this can be accomplished by adapting techniques used in segmentation feature extraction and modeling for use in radiomics.

V EXPERIMENTAL RESULT AND DISCUSSION

The proposed Brain Tumor detection was executed in MATLAB 2020a and presentation evaluation was done, and the sample datasets is illustrated in Fig. 4. The MRI scans of the brain are used as the dataset for this study. There are a total of 153 photos in the dataset, 155 of which depict brain tumors and the remaining 108 depicting normal tissues in the brain.

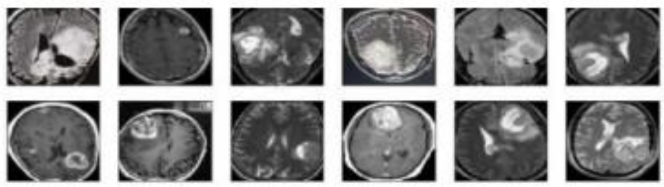

Fig. 4 Benchmark Dataset of Brain Tumor Images

A. PERFORMANCE MEASURES

A representation of the precision and recall metric may be found in Fig. 5 shows that the term "True Positive" (TP) relates to the amount number of correctly retrieved data, also known as "relevant data," that was retrieved in response to a user's request, whereas the term "False Positive" (FP) refers to the overall amount of incorrectly retrieved data, also known as "irrelevant data," that was retrieved in response to the user's request. The data that was collected is equal to True Positive plus False Negative added together.

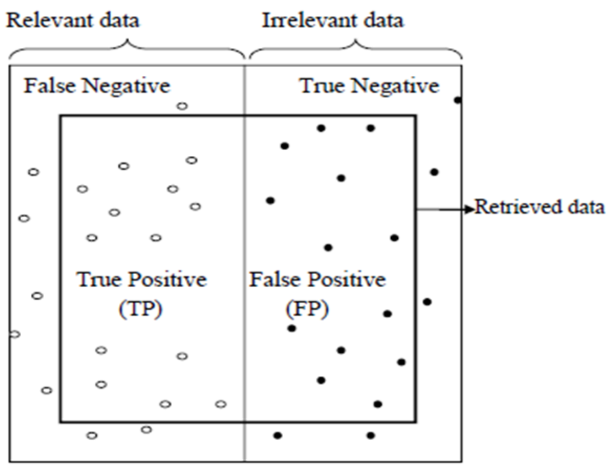

Fig. 5 Representation of Sensitivity and Specificity

Performance evaluation criteria, such as True Positive and True Negative, have been used to evaluate the suggested algorithm. The first measures how often the proposed approach correctly identifies a damaged region as impaired, while the second measures how often it correctly identifies a non-damaged section as non-damaged. The FP and FN indicators represent the number of instances that the proposed technique either over- or underestimates the extent of the harm. Table 2 provides further explanation of the many performance indicators used for assessing the system's efficacy.

Table 2. Evaluation Metrics

Metrics	Expression	Description
Accuracy	$\frac{TrP + TrN}{TrP + TrN + FaP + FaN}$	Rate of exactly predicted observations
Sensitivity	$\frac{TrP}{TrP + FaN}$	Number of true positive recall identified exactly
Specificity	$\frac{TrN}{TrN + FaP}$	Proportion of anticipated positive observations to be true as a percentage of all predicted positives.

B SEGMENTED RESULTS

The findings of the constructed model for diagnosing brain tumor are depicted in Fig. 7 after being preprocessed and segmented.

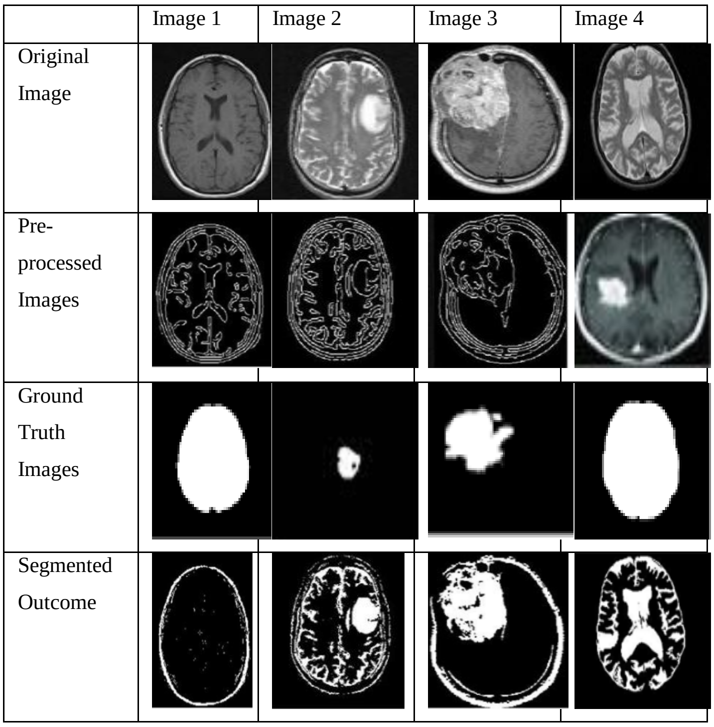

Fig. 7 Segmented Results of Proposed Brain Tumor Diagnosis

C COMPARISON ANALYSIS WITH STATE OF ART CLSSIFIERS

The evaluation measures that have been stated are utilized for the evaluation. The following Table 3 provides a description of the other classifiers that was utilized in the testing of the system, as well as the respective values for accuracy, sensitivity, and specificity for each of the methods .

Table 3 Statistical Evaluation of Proposed Vs Existing Classifiers

Evaluation Parameters	**SVM**	**Random Forest**	**K-NN**	**Deep CNN**
Accuracy (%)	79.31	80.95	83.32	89.33
Sensitivity (%)	81.23	83.81	89.43	94.82
Specificity (%)	63.36	59.11	42.51	73.32

The SVM performs superior in terms of sensitivity but inferior in terms of specificity. This indicates that this method will accurately predict the numerous other predictions in the brain tumor; however, it will fail to recognize all of them accurately, which is what leads to the extremely precise value of 50% and the low sensitivity value of 29%. Comparatively speaking, Random Forest and k-NN have superior performance when measured against the SVM metrics. However, Deep CNN has the highest accuracy than other evaluation matrices due to their ability to produce higher sensitivity value, which demonstrates that Deep CNN performs better. This is because other evaluation matrices cannot produce higher recall value. Lastly, when compared to the current methods, the model that was suggested is superior in effectiveness.

The comparison of proposed Deep CNN is done with other classifiers such as K-NN, Random forest, Vector Machine concerning the different parameters such as accuracy, precision and recall. Fig 8 shows the detailed analysis of comparison among classifiers in terms of different performance measures. The Deep CNN give accuracy of 89.33 percent, precision value of 73.32 percent and recall value of 94.82 percent. This depicted that Deep CNN performed more effectively and has improved the process of brain tumor detection in comparison with other classifiers.

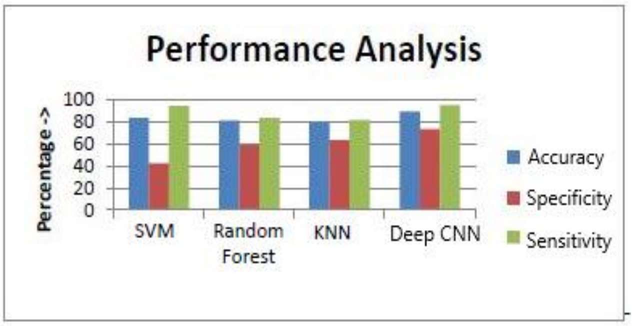

Fig. 8 Graphical Representation of Performance Analysis

VI CONCLUSION

The present study presents a novel system for detecting brain tumors, consisting of four stages: (a) Pre-processing, (b) Segmentation, (c) Feature Extraction, and (d) Classification. The MRI images were utilized as the input for pre-processing procedures. The pre-processing stage consisted of two steps, namely image enhancement utilizing filtering techniques. During the stage of image enhancement, the processes of image scaling and contrast enhancement were performed. Subsequently, during the segmentation stage, the tumors were delimited through the utilization of interpolation regions. Furthermore, during the feature extraction phase, various features were extracted including color morphology features, local features, and morphological transformation-based features. The features that were extracted underwent analysis using a Deep Convolutional Neural Network (CNN). Based on the experimental findings, it can be concluded that the Deep CNN classifier exhibits a higher level of accuracy compared to the other classifiers. In conclusion, it has been determined that the Deep CNN that was developed exhibits superiority over current methods in terms of implementing effective segmentation and classification for the purpose of diagnosing brain tumors. Future research endeavors may involve the utilization of deep learning methodologies to address image processing challenges across varying image dimensions.

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