Brain Tumor Segmentation and Classification using hybrid Deep CNN with LuNet Classifier

T. Balamurugan (✉ balamurugan.thiyagu@gcedpi.edu.in)
GOVERNMENT COLLEGE OF ENGINEERING,DHARAMPURI,TAMILNADU
E. Gnanamanoharan
Annamalai University

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Brain Tumor Segmentation and Classification using hybrid Deep CNN with LuNet Classifier

T. Balamurugan[1], E.Gnanamanoharan[2]

[1]Assistant professor, Department of ECE, Government college of Engineering, Dharmapuri, Tamilnadu,

[2]Assistant Professor, Department of ECE, Annamalai University, Chidambaram, Tamilnadu

balamurugan.thiyagu@gcedpi.edu.in, gnanamanohar@gmail.com

Corresponding Author: T. Balamurugan

ABSTRACT:

The early diagnosis of brain tumors is critical to enhancing patient survival and prospects. The magnetic resonance imaging (MRI) brain tumor images must be physically analyzed in this work. As a result, computerized approaches for more precise tumor diagnostics are required. However, evaluating shape, volume, borders, Tumor detection, size, segmentation, and classification remains challenging. This work proposes a hybrid Deep Convolutional Neural Network (DCNN) classifier using an enhanced LuNet classifier algorithm in this proposed work. The primary intention of this work is to determine the area of the tumor site and classify brain tumors as benign or malignant. Initially, we split the data using the extended LuNet algorithm. Grey-level co-occurrence matrix (GLCM) and VGG16 extracted the features, yielding 13 classification features. For pretreatment, the Laplacian of Gaussian filter (LOG) is used. Overall, the proposed approach tries to increase the performance of non-deep learning classifiers. Traditional classifiers are superior deep learning methods because they require fewer training data sets, have lower computing complexity, lower user costs, and are easier to use by people with less training experience. The proposed algorithm achieves a better accuracy rate of 99.7%. Compared to the existing algorithm, the proposed approach outperforms them.

Keywords: Segmentation, Brain Tumor, Deep Learning, Deep Convolutional Neural Network, LuNet, VGG-16, GLCM.

1. INTRODUCTION

Brain tumor segmentation is a challenging problem in medical imaging. Brain tumor segmentation aims to accurately describe brain Tumor regions using appropriately placed masks. In recent years, deep learning methods have illustrated auspicious performance in solving a wide range of problems in computer vision, including image classification, object recognition, and classification techniques. Many different types of deep learning have been used to separate brain Tumors with excellent system performance [1]. Deep Learning (DL) computational models are made up of several processing layers that represent data at different levels of abstraction. Deep learning is used in almost every field, especially medical imaging and biostatistics. As a result, deep learning has significantly improved identification, prediction, and diagnostic testing methods in various medical fields, including pathology, brain Tumors, lung disease, the stomach, cardiovascular system, and retina [2]. The problem of forecasting brain Tumors and patient survival remains unsolved for researchers. MRI allows for new research tools in brain cancers, such as prediction, segmentation, and segmentation analysis. There are two types of brain Tumors: benign and malignant. MRI data should be used to differentiate and categorize Tumor types (gliomas, meningiomas, pituitary Tumors) to assist physicians and avoid risky histology procedures. At the same time, improving the quality and precision of the diagnostic is a challenging task. For this objective, various approaches have been presented [3].

The advancement of artificial intelligence and new deep learning-based technologies has had a significant impact on medical imaging, specifically in illness diagnoses. The CNN model is the most extensively used deep learning model in neural networks. Extraction of features and segmentation are the two aspects of a standard CNN model. An input layer, a folding layer, a pooling layer, a fully connected layer, and a classification layer are the five layers of CNN architecture [4-6]. The most commonly used and highly accurate algorithms are SVM, KNN, and ANN. At the same time, improving brain Tumor classification will require growing the available data in the field and developing a new artificial neural network-based technique known as deep learning. The most notable distinction between these three Tumors is that meningioma is typically benign, whereas gliomas are generally malignant. CNNs are a neural network that helps you visualize, interpret, and explore enormous volumes of data in medical imaging. The suggested autonomous computer diagnostic system's performance is evaluated using parameter accuracy.

The application of CNN's integrated feature extraction and classification to recognize and identify brain Tumors is suggested in the paper [7-9]. This work proposed a completely automated brain Tumor segmentation and classification model using deep convolutional neural networks and multiscale approaches [10]. The input image is processed in three different spatial scales with varying processing paths, which is one of the contrasts between our proposal and past work. It has a multi-task classification system based on CNN for Tumor identification and prediction.

The segmentation of Tumors in a CNN-based model is used to localize brain cancers. Rather than creating a separate model for each classification assignment, the method employs a model to categorize a range of brain MRI classification data. Instead of using a new model for each classification, this brain tumor classification model employs a multi-task classifier [11]. Machine learning methods for classifying brain Tumors require many extracted functions to be effective. As a result, various machine learning approaches classify Tumors on normal brain MRI images using individual function extraction methods. These approaches for extracting functions and organizing them are not automated.

The proposed LuNet model for developing a new way to solve the problem of automatically classifying brain tumors based on magnetic resonance imaging (MRI) [12]. ANN, Fuzzy Cluster Mean (FCM), Expectation-Maximization (EM), Finite Element Method (FEM), SVM, CNN, DLN, LSTM-based segmentation, and other techniques have been utilized to diagnose brain Tumors from MRI images in recent years. The detection, segmentation, and classification of brain tumors using MRI images are the subject of extensive research. The use of a novel CNN for brain tumor categorization has been proposed in this research work.

The main limitations of these diagnostic procedures are that they are intrusive, time-consuming, and prone to sampling errors. Clinics and radiologists are computer-aided auto-detection and diagnostics to assist professionals in making rapid and accurate judgments to increase diagnostic capabilities and save diagnostic time. [3–4]. For medical image analysis, machine learning algorithms make detection and classification processes more accessible and accurate. For the detection and classification of meningioma, CNN deep network-based image analysis approaches with excellent accuracy and classification speed have been developed. This research uses common medical imaging sub-modules such as pretreatment, extraction of features, categorization, and segmentation [5]. The capabilities of a brain Tumor detection system based on a hybrid machine learning algorithm are presented in this research work.

1.2 Problem Statement

After reviewing several research articles on reinforcement learning to detect brain MRI tumors, it was discovered that deep models had many layers. Conventional algorithm complicates the training parameters, mainly when dealing with small data as the model's complexity grows, which increases simulation time. As a result, we propose a solution to the issue of reduced data set complexity. The proposed model has a few layers, does not require more iteration, and takes very little running time. Furthermore, the proposed LuNet model produces better results for all the test parameters in the test data set.

1.3 Major Contribution

A four-layer deep LuNet model is used for classification. Moreover, traditional methods are incapable of achieving locational inheritance and authenticity. As a result, we propose a fully automatic classification method based on a hybrid DCNN with LuNet classifier. The proposed method was used to preprocess, classify, and segment adult primary brain Tumors. The proposed hybrid architecture extracts feature from augmented images and classify them as normal or abnormal Tumor images on the inside. FCM and GMM use local morphological and functional approaches to classify Tumor regions.

The proposed rating system employs a hybrid classification approach for quantitative and qualitative evaluation. Measurements like sensitivity and specificity show that segmentation and classification accuracy and rate are 99.4% and 99.5%, respectively. They also show that the accuracy and F-score for authentic images show that this is true. The deep LuNet model is easier for Tumor diagnosis than the computationally expensive deep learning model.

The remaining proposed work has been organized as follows; Section 2 provides a literature overview. Sections 3 describe the proposed work. Sections 4 discuss the analysis of the results and finally conclude the work in section 5.

2. LITERATURE SURVEY

The proposed strategy is highly reliant on brain Tumor classification. Deep learning and machine learning (ML) techniques have become popular for classification in recent years. Previous processes and methods for segmentation and ML-based categorization of brain Tumors on MRI are described in this part. Ginny Garg et al. [13] proposed a hybrid emblem technique employing random forest (RF), K-nearest neighbour method, and decision tree (DT) based on a majority rule (KNN-RF-DT). Our goal is to determine the size of the Tumor and categorize it as benign or malignant. Otsu's threshold approach was used to divide the data at first. For function extraction, Stable Wavelet Transform (SWT), Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM) were utilized, yielding 13 types of functions. For classification, the Hybrid Ensemble Classifier (KNN-RF-DT) uses majority voting. Rather than using deep learning, researchers strive to increase the performance of existing classifiers. In terms of training data set size and computational complexity, traditional classifiers are superior methods for deep learning.

Yilam Shazadi et al. [14] developed a CNN cascade with a long-term memory (LSTM) network to identify 3D brain Tumor MR Images of HG and LG gliomas. For identifying HG and LG gliomas, pre-trained VGG-16 functions are extracted and passed to an LSTM network to learn high-level functional representations of 3D brain Tumor volumes. According to the results, the parts recovered from VGG-16 have greater classification accuracy than those extracted from AlexNet and ResNet.

Wu Wentao et al. [15] Suggested a support vector machine approach based on deep convolutional neural networks (DCNN-F-SVM). There are three essential processes in the proposed brain Tumor segmentation model. First, a deep convolutional neural network must be trained to learn a mapping from picture space to Tumor marker space. In the second stage, the test image is mixed with the deep convolutional neural network training prediction label, and the input is fed into the support vector machine classifier. The third step is to cascade a deep convolutional neural network and an ensemble support vector machine to train a deep classifier. To segment brain Tumors, run each model on custom datasets. Outperforms deep convolutional neural networks and ensemble SVM classifiers in terms of how well it can separate things into groups.

Javaria Amin et al. [16] suggested a weiner filter with multiple wavelet frequency bands to remove and improve input slice noise. A portion of Tumor pixels can be clustered using PF (potential field) clustering. In addition, Tumor areas were isolated from FLAIR and T2MRI using global thresholds and different mathematical processes. The LBP (Local Binary Pattern) and GWT (Gabor Wavelet Transform) functions work together to get a good classification. To classify Tumor / non-Tumor MR slices, multiple classifiers use the proposed mixed texture feature for each segmented portion. We discovered that functional fusion and KNN outperformed other classifiers based on a thorough performance evaluation. The results demonstrate the advantages of the proposed method. This paper suggests and develops a novel Genetic Algorithm based on the Seed Corrected Region Growing (GFSMRG) approach and a Back Propagation Neural Network (BPNN) based on fuzzy initialization. The proposed system has four stages: preprocessing, segmentation, feature extraction, and classification [17]. It also specifies the accuracy and temporal complexity of the GFSMRG algorithm. Performance indicators such as the similarity index, jacquard index, sensitivity, specificity, and accuracy have been used to statistically and qualitatively validate the method's performance.

Jaeyong Kang et al. [18] applied the transfer learning principle and some pre-trained deep convolutional neural networks to extract deep properties from the brain's magnetic resonance (MR) pictures. Several machine learning classifiers assess the extracted depth functions. Select the top three deep parts that operate well with various machine learning classifiers, connect them to a collection of deep functions, feed them to various machine classification models, and predict the final result. Different types of pre-training for brain Tumor classification using three different sets of magnetic resonance imaging (MRI) (deep feature extractor, machine learning classifier, and deep feature set) published on the web evaluate the finished model's validity. By collecting in-depth features, experimental results can significantly improve performance. In most cases, Support Vector Machines (SVMs) with long-term base function cores outperform other machine learning rating containers.

Shanka Ramesh Gunase karatal et al. [19] proposed the triple deep learning architecture. The classifier is first implemented as a deep folded Convolutional Neural Network (CNN), and then on the classified images, a Region-based folded CNN is used to identify Tumor regions for decision making. As the third and final step in the segmentation process, the segmentation algorithm delineated the focused Tumor boundaries. Because traditional edge detection algorithms based on pixel intensity slope frequently fail during medical image segmentation, we propose an active contour algorithm defined as a smooth function. The proposal's final output, the border area, divided by the gold standard, and the boundary area divided by the targeted expert are used to determine the noise ratio (PSNR).

Baza et al. [20] developed a new CNN architecture to classify three types of brain Tumors. T1-weighted contrast-enhanced magnetic resonance imaging was used to test the new network, which is less complicated than a network that has been pre-trained. Hari Mohan Rai et al. [21] demonstrated a new deep neural network tailored for Tumor identification with U-Net (LuNet). It is simpler and has fewer layers. From a data set of 253 high-pixel images, this assignment required identifying MRI scans of the brain as normal or pathological. MRI pictures are resized, cropped, pre-treated, and scaled for the first time to swiftly and adequately train deep neural models. The suggested LuNet deep CNN model for detecting brain Tumors on MRI images is straightforward, fast, and efficient. For this task, we created an efficient CNN architecture dubbed "LuNet for medical picture segmentation." The proposed approach is a hybrid of Le-Net and U-Net with many tweaks. Because of its minimal design complexity, few layers, and use of Le-Net and U-Net and the new CNN architecture, it has been named LuNet. Downsampling and upsampling are the two main components of the design. Five statistical evaluation scales were used to evaluate and compare the performance of the LuNet models: precision, recall, specificity, F-score, and accuracy. Le-Net and VGG-16 are the other two models.

Chong Zhang et al. [22] denoise and remove brain tissue using adaptive wiener filtering and morphological manipulation. This significantly lowers the method's susceptibility to denoising. A fuzzy C-means algorithm and K-means ++ clustering are used to break up the image. This clustering enhances the algorithm's stability while simultaneously lowering the sensitivity of the clustering settings. Finally, the retrieved images were post-processed using morphological manipulation and median filtering to picture the brain Tumor accurately. In addition, the suggested technique will be compared to various segmentation algorithms that are currently in use. The results show that the algorithm is better than the other algorithms in accuracy, sensitivity, specificity, and recall.

Huseyin Kutlu et al. [23] presented a hybrid CNN-DWT-LSTM technique for classifying CT pictures of a Tumor-bearing liver and magnetic resonance (MR) images of a Tumor-bearing brain. The suggested method divides liver Tumor images into benign and malignant categories before dividing brain Tumor images into meningioma, glioma, and pituitary tumors. The hybrid CNN-DWT-LSTM approach is utilized to extract the feature vectors of the pictures using the pre-trained AlexNet-CNN architecture. It reduces feature vectors but improves them before training and classifying them in an LSTM network using a single-stage 1D discrete wavelet transform (1-D DWT). The photos of 56 benign and malignant liver Tumors from Frat University Research Hospital and published brain Tumor databases were used in this work. The suggested method outperforms classifiers like the K-nearest neighbour method (KNN) and SVM in terms of performance.

The Fuzzy Cluster Means (FCM) partitioning methodology was created by Aneza and Rawat et al. [24]. Cluster validation power, processing time, and convergence speed evaluate segmentation performance. An error rate of 0.537 % was achieved using the FCM approach. Wasule and P. Sonar et al. [25] have demonstrated this. The characteristics of this article were extracted using the GLCM method. The method uses SVMs and K-nearest neighbours to categorize malignant gliomas, positive gliomas, low-grade gliomas, and high-grade gliomas (KNN). The clinical dataset distinguishes between malignant and benign gliomas, whereas the BRATS 2012 dataset distinguishes between high- and low-grade gliomas.

Salle k et al. [26] proposed a reliable and accurate FCM splitting technique. From the MRI, the malignant mass was excised. The suggested method avoids troublesome estimation by utilizing FCM clusters as input data. To identify the optimal threshold for splitting pixels into groups other than the selected group, GLCM is used to extract texture properties. This has a significant bearing on precision. M. Rashid et al. [27] looked into techniques to improve the sharpness of MRI pictures and Tumor location. The technology uses MRI brain scans as input. This method removes noise from brain MRIs with an anisotropic filter and then uses SVMs to make changes to the morphology of the fragments after they have been broken up.

T. Len et al. [28] created a classification system for brain cancers. Histogram smoothing removes unnecessary information from the image in the first place. We developed three categorization methods through research and development: FCM, Core-based FCM and weighted fuzzy kernel clustering. It has a 2.36% lower misclassification rate than other algorithms. According to Mohamed Tallow [29], deep transmission learning algorithms should be used to separate MRI brain images into normal and pathological categories. The ResNet34 technique is used in the pre-trained CNN model. A data expansion technique is used to extend the database. This method has been proven by looking at MRI data from Harvard Medical School [13]. It can look for autism, stroke, Parkinson's disease and Alzheimer's disease.

A Google Net-based brain Tumor classification technique was proposed by S. Deepak et al. [30]. There are three forms of brain cancers: gliomas (meningiomas), meningiomas, and pituitary Tumors. Because brain Tumor classification is difficult, substantial changes in size and shape frequently occur, affecting classification. When employing typical machine learning algorithms, this problem is especially perplexing. We use migration learning to solve this problem and obtain higher learning accuracy than earlier models. Even with tiny datasets, significant improvement has been accomplished. This method recommends Google Net, a Tumor classification system that has been updated for various Tumor types and is commonly utilized at the softmax level. The CNN-centric Google Net technique improves accuracy from 92.3% to 97.8% on multiclass SVMs.

3. PROPOSED METHODOLOGY

This proposed work proposed a hybrid DCNN classifier using enhanced LuNet classifier technology. Our goal is to determine the Tumor site and categorize it as benign or malignant. The enhanced LuNet method is used to divide the data first. The (GLCM) and VGG16 are being used to extract functions, which are then divided into 13 categories. For pretreatment, the Laplacian Gaussian filter is used. Overall, it tries to increase the performance of non-deep learning classifiers. Traditional classifiers are superior to deep learning methods because they require fewer training data sets and have lower computational complexity. On MRI scans, a CNN deep network was used to diagnose and classify meningioma cancers. Modify all database images having a resolution of 512 * 512 pixels to 256 *256 pixels to reach the same size. The suggested CNN deep network classifier was applied to evaluate if the preprocessed brain MRI pictures were normal or pathological. The global threshold approach is used with the linked component method to split the Tumor region. This work proposed the combining GLCM and CNN classifiers to diagnose segmented regions. Figure.1 shows the proposed brain tumor classification process model.

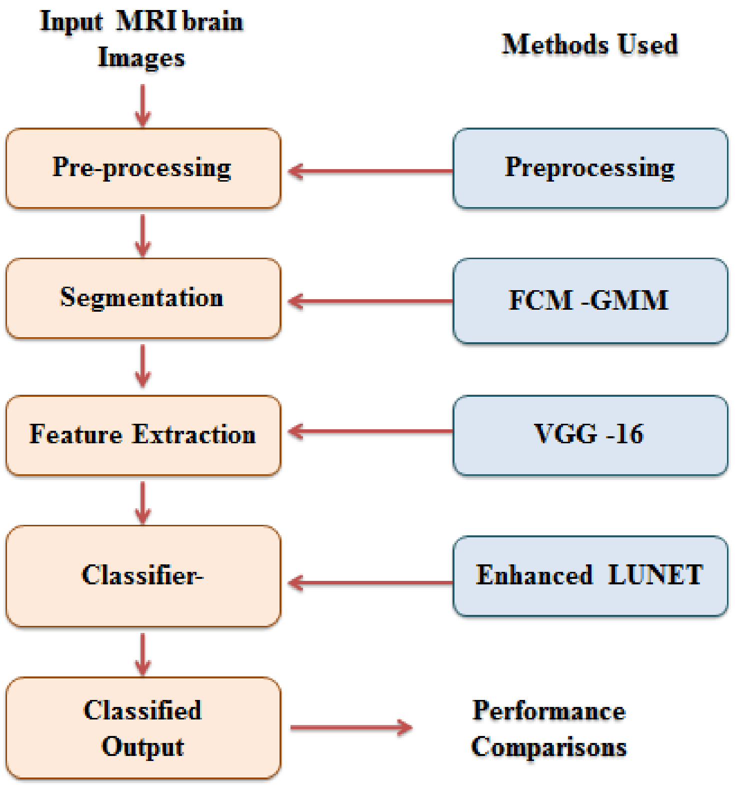


Figure 1.Block diagram of proposed work

3.1 DATASETS

The suggested Deep CNN performs effectively with MRI brain images from BRATS open access data sets. The proposed method was tested and assessed using actual images received from experienced radiologists and a brain Tumor database maintained at SRM Hospital [12]. This essay uses 600 brain photos from a data collection of 340 brain images that include both normal and pathological brain images (260 brain images). The data set is split into two sections: training and testing.

There are 90 normal photos and 75 deviant images in the training dataset. There were 250 "normal" MR images and 185 "deviant" MR images during the test. In addition, Tumor and non-Tumor data are separated in these training, test, and validation datasets. The training data contains 64 non-Tumor photos and 109 Tumor images; the test set contains 15 non-Tumor images, and the validation set contains 19 non-Tumor images and 31 Tumor images. It demonstrates that there are photos of individual Tumors.

3.2 Preprocessing

The preprocessing phase aims to improve the features of the specific necessary image and eliminate undesired distortion in preparation for later processing. Image enhancement is a preprocessing technique for transforming a less-than-ideal image into a better one. The following measures should be adopted during the pretreatment stage: Combine the original image with the sharpened image for extra impact. The MRI scan image is transformed into a greyscale image with a resolution of 255 x 255 when it is stored in the system. These photos have been noise-reduced, which harms image quality. Images with excellent resolution and no noise are produced by the high-pass filter used for feature extraction and sharpening. Data expansion is one of the preprocessing approaches used to turn the brain's visual source into a homogeneous three-dimensional image by vertically rotating and tilting the image. As a result, data expansion assists the suggested hybrid DCNN-LuNet architecture in achieving high accuracy and precision in evaluation. Figure 2 depicts the better outcomes of MRI brain scans. MRI was improved using Laplace Gaussian (LOG) filtering and contrast-limited adaptive histogram smoothing.

3.3 Segmentation using hybrid FCM-GMM

To further classify and predict brain Tumors, use brain Tumor segmentation to extract Tumor regions from pictures. Various mechanical ML/DL approaches have been developed for segmenting Tumor cells. Some of these machine learning algorithms are trained using manually segmented photos. This is an expensive, time-consuming procedure that necessitates medical competence. The deep neural network model was used to determine where the Tumor was on an MRI using hybrid FCM-GMM. Figure 3 depicts the Segmented Output –Dataset I & II.

3.3.1 ROI Segmentation:

A region of interest (ROI) is a portion of an image or dataset that has been selected for a specific purpose from a raw sample. On T1-weighted MRI, the limit of brain Tumors on the intervertebral disc in this situation is ROI. Annotation masks for Tumors may be found in the Brain Tumor Dataset. The Tumor area in this database has a "1" designation, while everything else has a "0" label. Using a mask that corresponded to the pixels, the specific Tumor was retrieved from the MRI sample of the brain. Because Tumor sizes differed between samples, the Tumor ROI image shrunk and gave zero padding to meet the proposed model's input geometry. After ROI segmentation, each image is 256 x 256 pixels in size.

Hybrid procedures relate to using several methods or techniques to attain high accuracy, emphasizing the method's benefits while minimizing its drawbacks. Studies that combine FCM and GMM, for example, have been proposed to segment brain-related disorders. FCM is utilized in the first approach to identify sick areas in the brain, while the second method is used to classify them. To extract features, the authors used a gray scale length matrix. According to the study's authors, the FCM approach can categorize Tumor tissue more accurately than the K-means method, while the latter can complete the task faster. As a result, each classifier in this study can take advantage of this advantage to perform classification in less time and produce better results [7].

3.3.2 FCM-GMM

When splitting an image into various pieces, segmentation is crucial. Only the valuable bits can be considered in this scenario. This step should be completed to reduce the work required in the following steps. If only the Tumor area needs to extract its features throughout the entire image, feature extraction is easy. K-means is an unsupervised, repetitive clustering algorithm. The centres of gravity of all clusters are distributed at random. K-means converges by finding the local minimum of the cost function. The distance between the centre of gravity and the data points is calculated using the Euclidean distance. Because K-means is a complex cluster technology, data points can belong to any cluster.

The distance between randomly picked data points and the centre of gravity is solely used to allocate data points to each cluster. The proposed approach employs a Gaussian mixture model (GMM) segmentation technique [12]. GMM is a more advanced algorithm than the K-means algorithm. GMM also use expectation maximization (EM) approaches to divide the brain into distinct areas and decrease data. Only the brightest pixels were gathered in Figure (8), and the Tumor region was removed.

Fuzzy C – means algorithm Fuzzy C: A pixel set with the algorithm X =X_1, X_2 ,... X_N indicates that it has been divided into C fuzzy clusters. Each point is part of a cluster. Based on their membership value, points can belong to multiple clusters. This is an iterative process in cluster-centred C that minimizes the objective function associated with the fuzzy member set U.

$$j = \sum_{i=1}^{N} \sum_{j=1}^{C} U_{ij}^{m} \left(X_i - C_j\right)^2 \tag{1}$$

Where, U_{ij} is the membership table, m is a cluster fuzziness factor and $(X_i - C_j)$ is Euclidean distance. Data points towards the cluster's centre have a higher degree of membership than data points around the edges [27]. FCM calculates the centre for each cluster and assigns a membership ranking to each cluster for each point. The cluster's centre is then moved to the correct place by repeatedly updating the data set's centre. The membership defines the ambiguity of the image and the information contained within it.

Image segmentation in the classic sense FCM clusters the pixel sample set directly. However, it has the drawback of being computationally intensive. As a result, selecting an appropriate first cluster centre is essential. The technique can swiftly converge to the actual cluster centre by selecting a better initial cluster centre. Many real-world problems, such as astronomy, geology, medical imaging, measurement detection, and picture segmentation, have been effectively solved using FCM algorithms. Because it can retain more information from the original image, the FCM segmentation approach has significant advantages over the complex segmentation method. The FCM algorithm consists of the steps in equations 1-3. Iteratively optimizing the aforesaid goal function and updating the member U_{ij} and the cluster centre Cj as follows achieves unclear segmentation:

Step 1 : $\mathit{Initialise} \quad U = \left[U_{ij}\right] \mathit{matrix},\ U^{(0)}$ (1)

Step 2 : At k-step : calculate the centres vectors $c^{(k)} = [C_j]\ \mathit{with}\ U^{(k)}$

$$U_{ij} = \frac{1}{\sum_{k-1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|}\right)^{\frac{2}{m-1}}} \tag{2}$$

Step 3: update $U^{(k)}\ \mathit{and}\ U^{(k+1)}$

$$c_j = \frac{\sum_{i-1}^{N} U_{ij}^{m} x_i}{\sum_{i-1}^{N} U_{ij}^{m}} \tag{3}$$

Step 4 **:** $\mathit{if}\ \left\| U^{(k+1)} - U^{(k)} \right\| < \in \quad \mathit{then\ STOP}\ ;\ \mathit{otherwise\ go\ back\ to\ step}\ 2$

The term "k" refers to an iterative step. This process eventually leads to a local minimum or saddle point of j_m.

3.4 Feature Extraction using VGG-16

The VGG16 extract characteristics into 13 different categories. Many CNN models now have more excellent performance and a more profound architecture. On the other hand, deeper networks are challenging to train since they necessitate a significant amount of data and millions of parameters. Including an extensive, well-labelled dataset is critical for more accurate and generalized models. Large labelled datasets are not available for medical imaging challenges. In order to solve this problem, transfer learning techniques are used, in which the model is first pre-trained on a substantial raw image dataset like ImageNet, and then fine-tuned to solve the specific problem at hand [28].

For feature extraction, a VGG-16 network pre-trained with ImageNet is used. These characteristics are used as the LSTM's input signal. VGG-Net comprises 16 convolutional layers and a 3x3 filter with one convolutional layer stride and three fully connected (FC) layers. The VGG-16 network comprises multiple stacked tiny kernels with filters that improve the network's depth, allowing it to extract more complicated features at a lower cost. In this work, the feature extractor VGG-16 is compared to AlexNet [28] and ResNet [29].

3.5 Classification using Enhanced LUNET

The LuNet network receives VGG-16 features that have been pre-trained. By freeing memory, LuNet can solve the degradation problem. LuNet is a more advanced version of CNN with three gates: entry, exit, and forget. There are two hidden layers in the neural network, each with 100 nodes. LuNet uses these gates in order to learn long-term dependencies over time. This suggested that deep CNN with LuNet for detecting brain Tumors from MRI images is straightforward, quick, and effective. This project will create the LuNet, a very efficient CNN architecture for medical picture classification. The proposed concept is a hybrid of LuNet and U-Net with numerous modifications. The new CNN architecture is built as LuNet, which is less complex and has very few layers, which is a benefit over Le-Net and U-Net.

Downsampling and upsampling are two components of its overall architecture. There are only two layers in the downsampling section, and there is also a Maxpooling procedure. The dimensions of the input image are 224 × 224 x 3. Two ConvNets plus a max-pooling layer with a 3x3 filter size of 32 make up the first layer of the LuNet. Figure 2 depicts the overview of proposed brain tumor classification process. The LuNet second layer network comprises two 64-digit ConvNets and a pooling layer with a 3x3 filter size. Up sampling is a two-layer process in the second half. A transposition layer and two convNets are used to do sampling. The preceding part's high-resolution functions are merged with sampled data during the sampling step to find picture data.

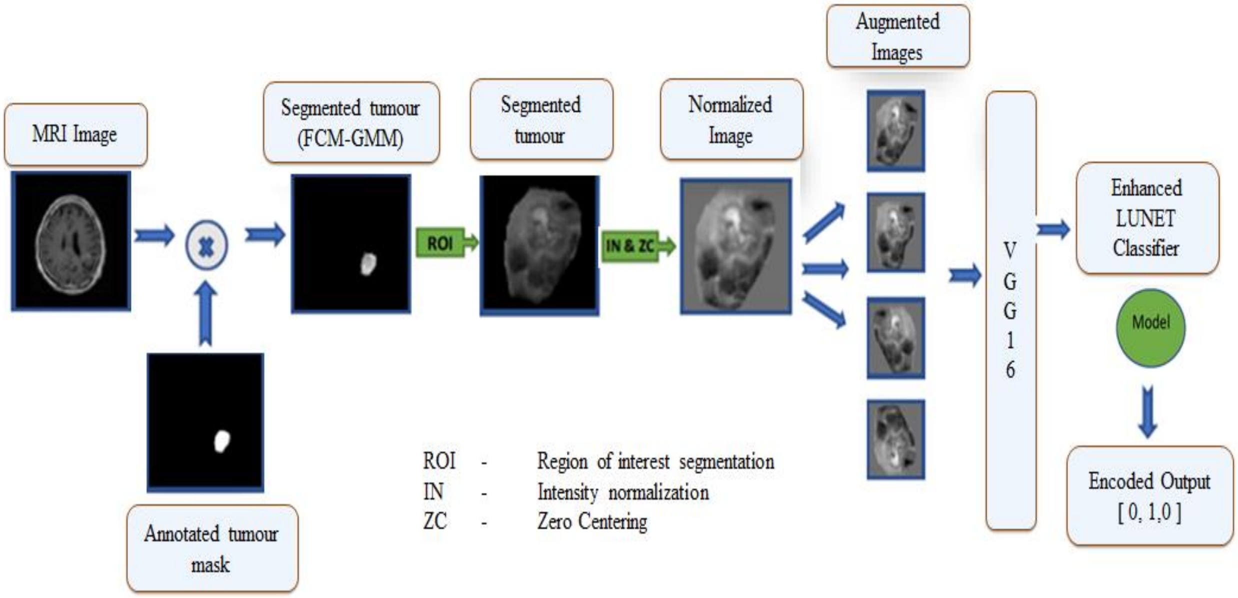


Figure.2 Overview of Proposed work

A continuous ConvNet with transposed layers' function is to learn an extremely accurate output data composition (Ronneberger, Fischer, and Brox, 2015). The upsampling section of the LuNet has a transpose layer and two convolutional layers, and the first transpose layer has a filter size of 2x2, 64 digits in two stages, and the two ConvNets have the same size of 3x3 64 numbers. Second transposition layer with a 2x2 filter, 32 digits for two steps, and two ConvNets of the same number. As a result, after applying the sample layer, the output data will have the exact resolution as the input image. Because the LuNet model does not discard negative pixels, each layer has an "eLU" activation characteristic.

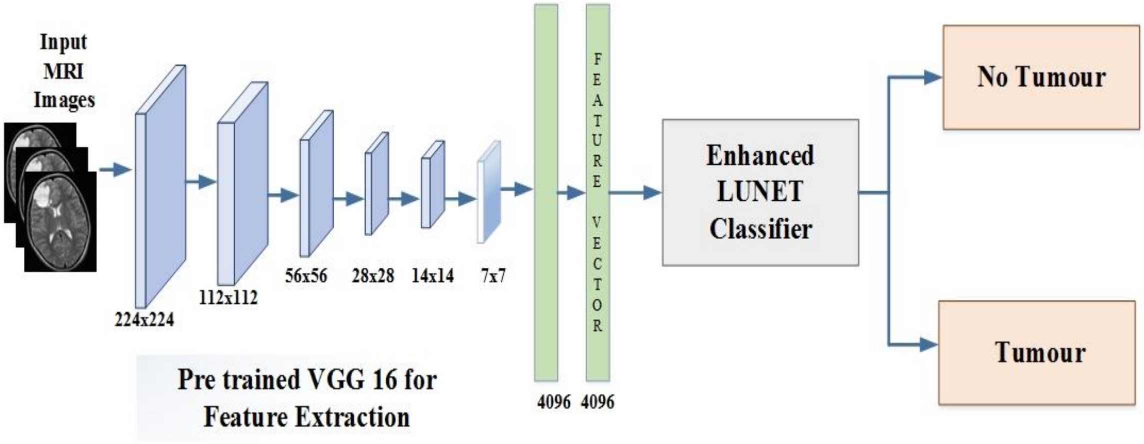


Figure 3 Proposed hybrids DCNN with LUNET classifier architecture

In the final section, two ultimately linked layers are coupled with up sampled data and a sigmoid activation function. Figure 3 depicts the proposed model's graph and table structure for each tier (LuNet). Because the suggested LuNet model can be viewed, it only has two layers for the encoder, two layers for the decoder, two ultimately linked layers, and four layers for the sigmoid activation function. The proposed model structure is based on the U-Net model, but the model is unique, simple, and fast because it only has six layers. Large datasets may not produce very promising findings, which is a shortcoming of this model.

4. RESULT ANALYSIS

The qualitative and quantitative analysis of the proposed system is presented in this section. This system makes use of the 64-bit MATLAB 2019a software. Subjective and objective classification and segmentation comparisons are well described in terms of sensitivity, specificity, precision, accuracy, F-score, DSI, etc. The proposed hybrid DCNN with LuNet analysis employs classification rates, which are numerical ratios. The percentage of correctly classified objects concerning the total number of objects used in the method. The proposed hybrid system DCNN- LuNet brain Tumor detection also considers the following performance metrics: Sensitivity and specificity are good representations of correlation between correctly categorized pixels. In segmented brain MRI images, accuracy refers to the percentage of accurately recognized pixels by identifying and illustrating healthy pixels free of malignancies. These variables are expressed in % and range from 0 to 100. Precision, recall, F-number, and precision measurements are all evaluated using quantitative analysis, which is expressed mathematically as:

$$Sensitivity\ (Sen) \quad = \quad TP/(TP+FN))$$

$$Specificity\ (Sp) \quad = \quad TN\ /\ (TN+FP)$$

$$Accuracy\ (ACC) \quad = \quad (TP+TN)\ /\ (TP+FN+TN+FP))$$

$$\text{Precision(Pr)} \quad = \quad TP\ /\ (TP+FP)$$

$$F-score \quad = \quad 2*Sen*Pr/(Pr+Sen)$$

$$Dice\ Similarity\ (DSI) = \quad 2*TP/(TP+TN+FP+FN)$$

A confusion matrix with values TP and TN represents the evaluation scale for the proposed method's performance analysis, giving correctly recognized Tumor and detected non-Tumor pixels, FP and FN. It gives Tumors and non-Tumor pixels that were mistakenly recognized as Tumors. True positives (TP) are referred to as benign (or glioma identification). A true negative (TN) Tumor has been recognized as malignant.

When a benign condition is misdiagnosed as malignant, it is called a false positive (FP) or when a glioma is identified as a meningioma. False-negative (FN) are malignant Tumors that have been misdiagnosed as benign (or meningioma's identified as gliomas). The simulation was run on a 253-image brain Tumor MRI data set for Tumor detection. Figure.4 shows the sample input brain tumor datasets for proposed classifier algorithm

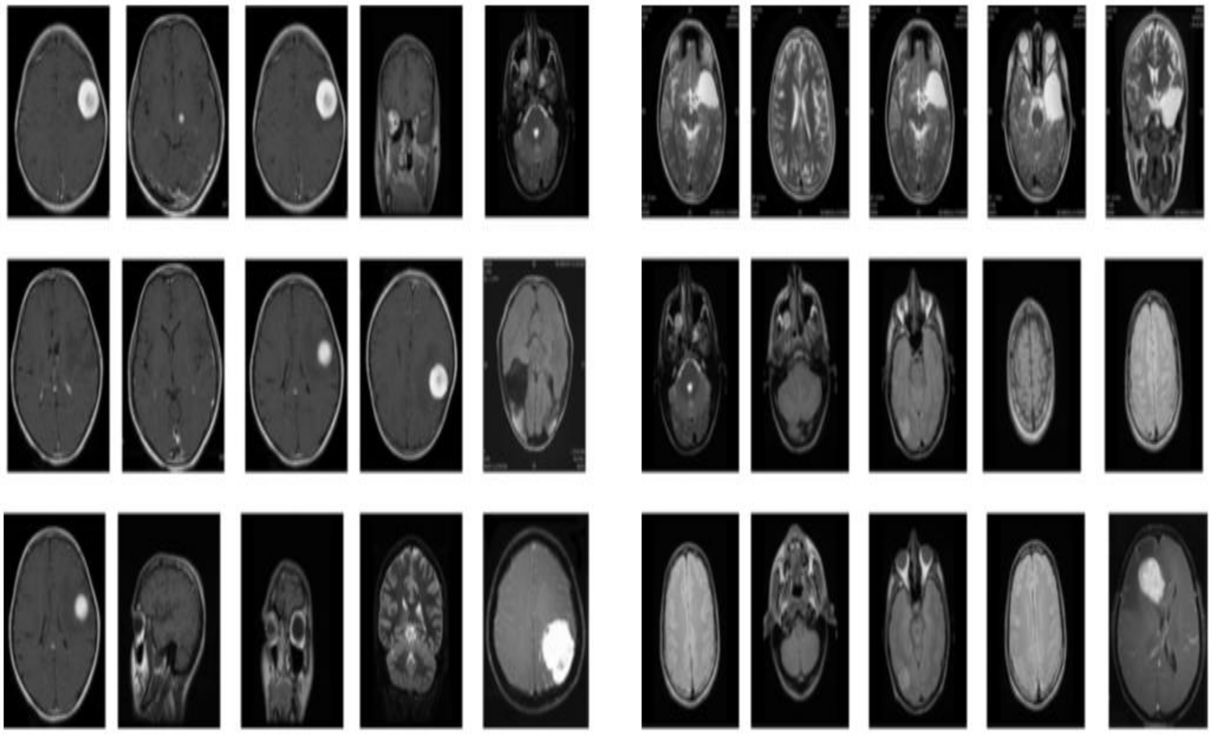
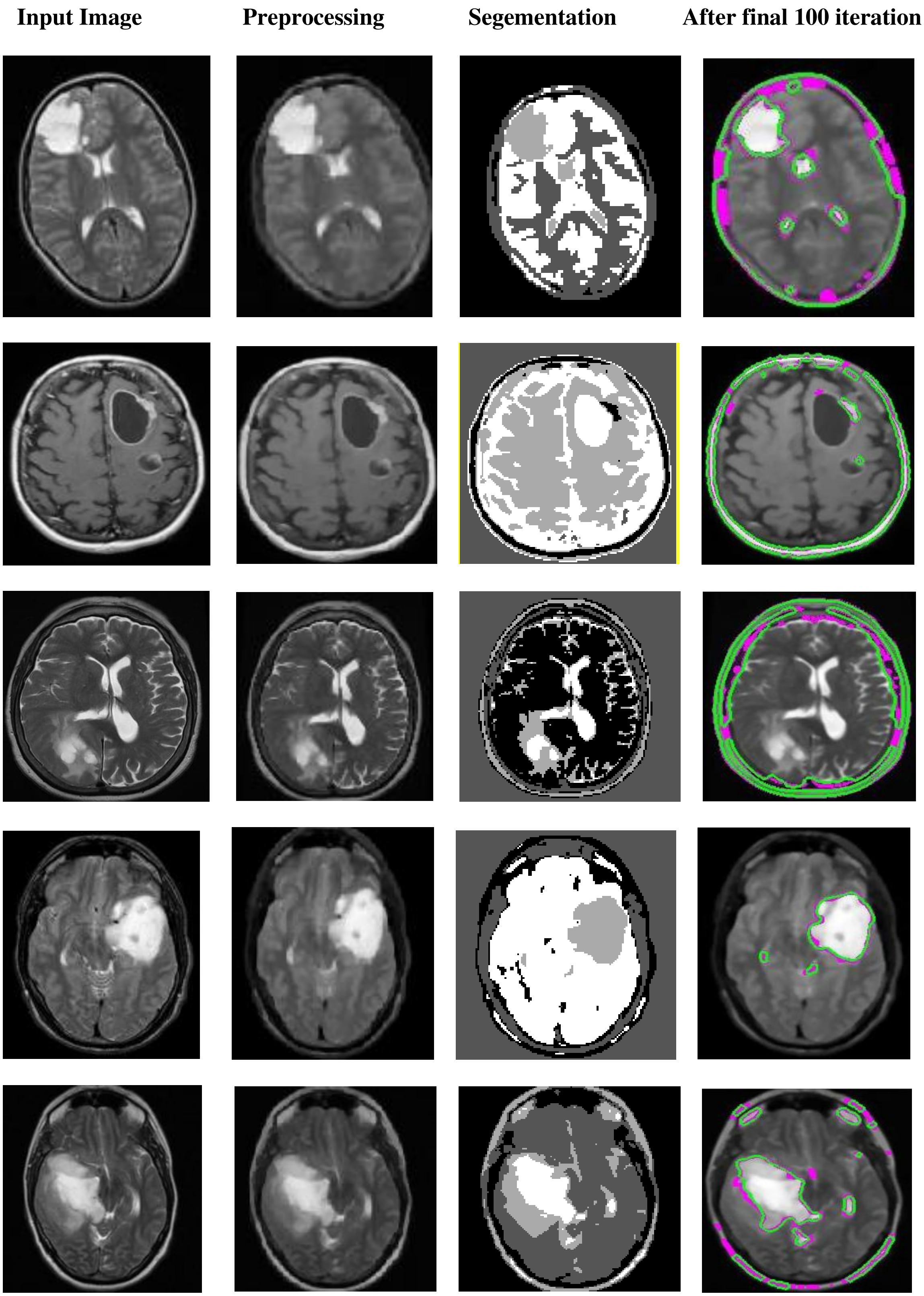


Figure 4. MRI images of Brain Tumor dataset- I & II

Table 1 Distribution of glioma and meningioma classifications in the database.

Types of tumor	**Total images**	**Training**	**Testing**
Glioma MRI	271	218	53
Meningioma MRI	98	79	19

Before training the model, divide the data into three components: training data, test data, and validation data. The input data for all three models is divided into 173 training data sets, 30 testing data sets, and 50 validation data sets. The data will then be resized to width 224, height 224, and channel three as the next step (RGB). To test the full CNN model, standard parameters are employed. The MR image's input size is 224 × 224 x 3. Figure 5 represents the proposed preprocessing; segmentation of proposed algorithm.Table.1 represents the distribution of types of tumor classification.



Input Image Preprocessing Segementation After final 100 iteration

Figure 5. Segmented Output –Dataset I & II

Table 2. Analysis of the proposed method in comparison to the conventional method

Approach	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Measure
SVM	96.21	94.6	96.1	97.52	95.76	96.9
Decision tree	92.98	92.4	93.3	92.79	91.5	94.7
Random Forest	94.1	95.5	96.0	96.2	95.8	96.4
Genetic algorithm	93.4	91.4	92.2	92.9	93.3	94.2
CNN	96.5	96.1	92.1	95.7	96.4	97.1
ResNet 50	95.1	94.6	95.5	88.63	90.69	89.65
AlexNet	96.87	95.8	94.3	96.63	93.5	97.85
Google Lenet	97.50	96.2	97.1	97.0	95.5	97.93
Proposed hybrid DCNN-LUNET	**99.7**	**98.2**	**98.6**	**99.4**	**99.8**	**98.82**

Table 2 compares the suggested simulation results with those of other standard methods for the same data set image. These comparisons show that the suggested technique employs CNN's deep network rating and delivers higher simulated values on brain MRI images of the same data set than other methods [4]. Figure 6 and 7 contains all the measurement data Accuracy, Sensitivity, Specificity, Precision and recall for all CNN models. According to the table data, the accuracy of the proposed hybrid DCNN with LuNet classifier has improved by 99.7%, Google Lenet is in second place with 97.50 % accuracy, and the SVM model has the lowest performance at 96.21 %. The enhanced LuNet models have Accuracy, Sensitivity, Specificity, Precision and recall of (99.7, 98.2, 98.6, 99.4, 99.8 and 98.82) respectively.

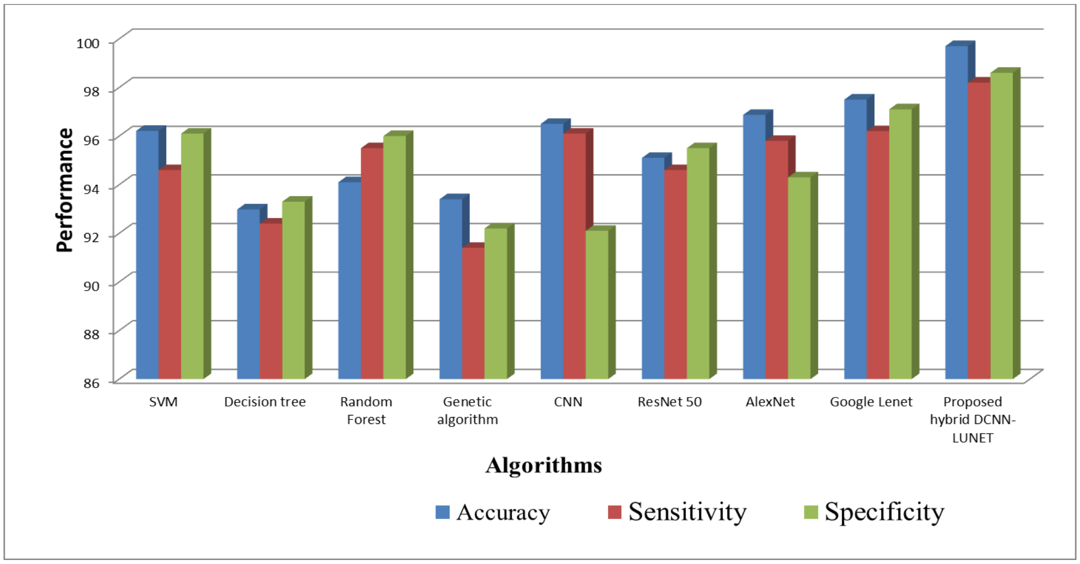


Figure 6. Comparison of proposed algorithm

Hence, the proposed hybrid algorithm provides the best performance in terms of all evaluation parameters. Our proposed model achieved the highest accuracy of 99.7% among all state of art methods, which shows the model's superiority. The proposed hybrid model DCNN-LuNet is used in the final experiments, and it performs admirably on both training and testing data. The LuNet model performed admirably on both training and test data in terms of accuracy and loss.

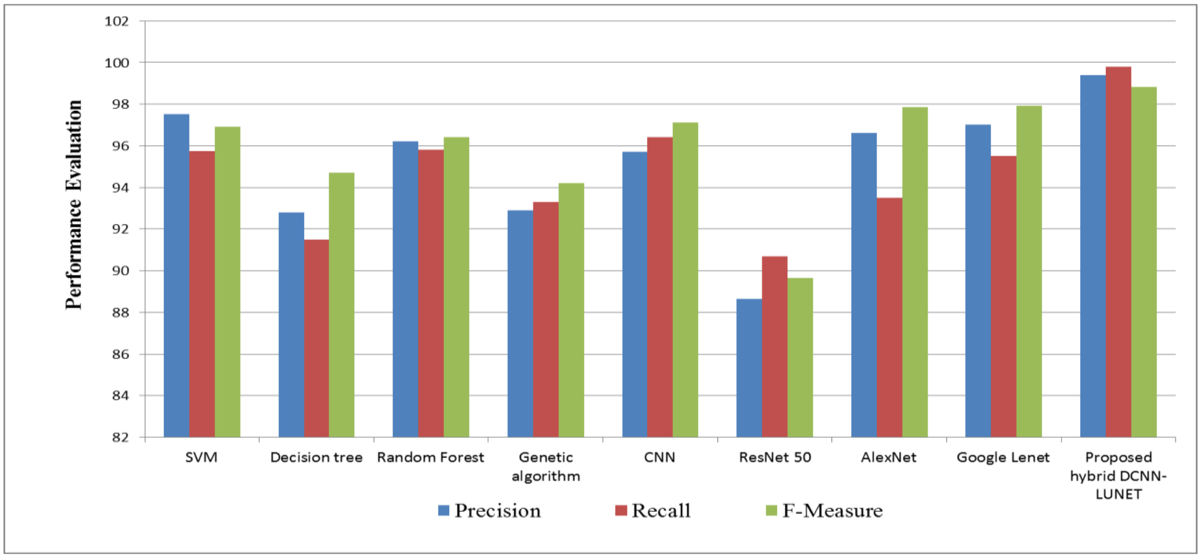


Figure 7. Comparison of proposed algorithm

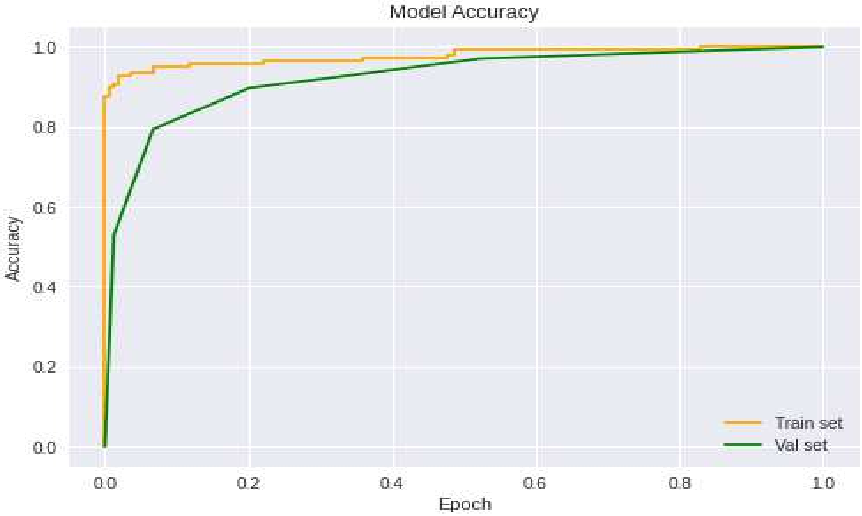


Figure 8 Accuracy with cropped MR images using the LuNet Model

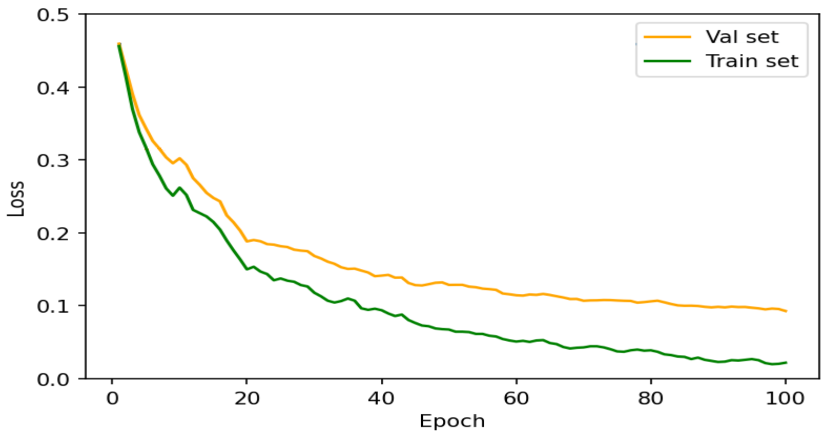


Figure 9. Loss variations with cropped MR images using the LuNet Model

The proposed hybrid DCNN with LuNet classifier model, which has very good performance on training and testing data, is used in the final experiments. On training and testing data, the LuNet model outperforms in terms of accuracy and loss is shown in Figure 8 and 9. Figure 10 depicts the LuNet model's training and test accuracy performance, with training and validation dropouts. When 340 standard MRI images and 206 were affected, Tumor MRI images were classified using this method. The classification rate between normal and affected Tumor images was 99.5%. As a result, the proposed method has an average classification rate of 99.5 % and a verification accuracy of 99.4%.

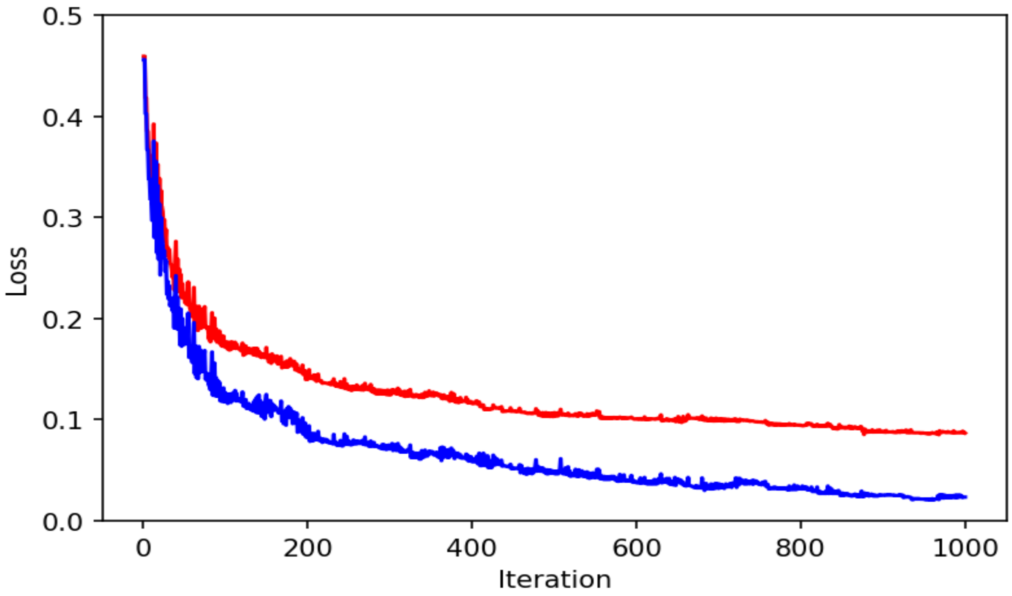


Fig. 10 Losses curves for classification

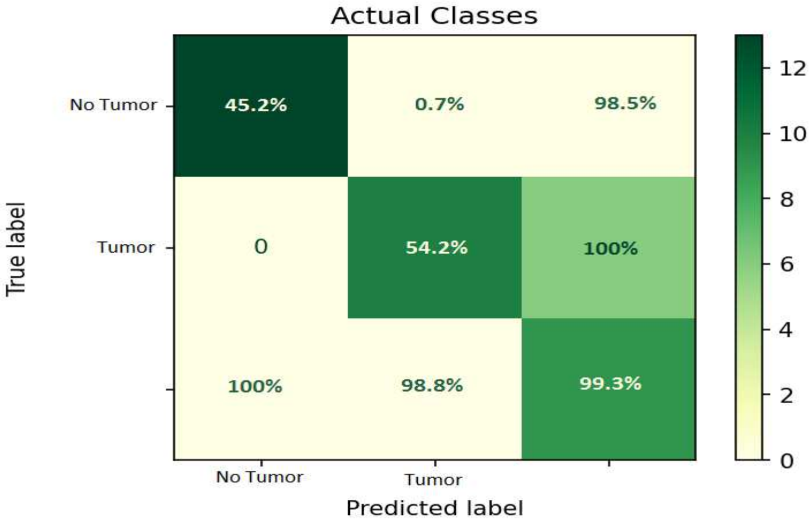


Figure. 11 Confusion Matrix for classification

The suggested CNN deep network's sensitivity, specificity, accuracy, and F-score metrics outperform existing machine learning methods. There are 1249 benign and 29 malignant Tumors among the 1278 benign Tumors. Furthermore, 1239 of the 1278 Tumors are classified as malignant, whereas 39 are benign. Overall, the proposed technique achieves a high level of accuracy of 99.705%. The proposed method performs better for the various evaluation parameters given above than existing methods. As a result, the proposed method for classifying benign and malignant brain tumors is both new and effective. Figure 11 shows the confusion matrix for classifications. A confusion matrix is presented as an example of the performance of the ground truth classification model.

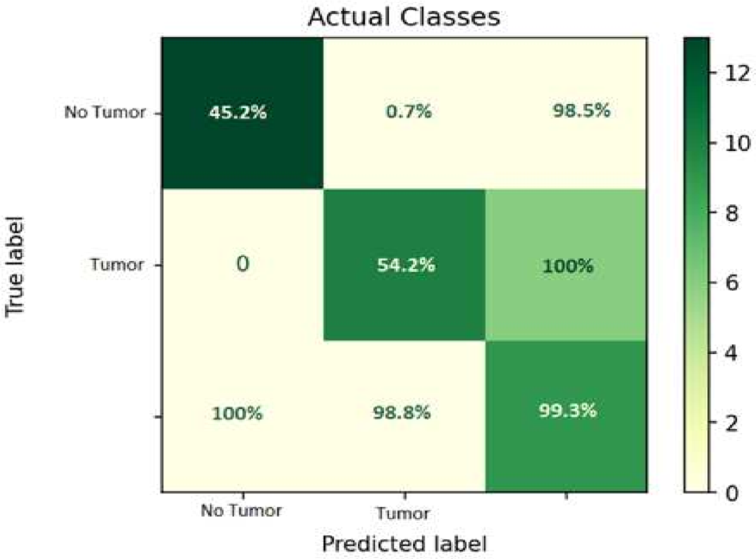


Figure 12 Confusion Matrix for testing

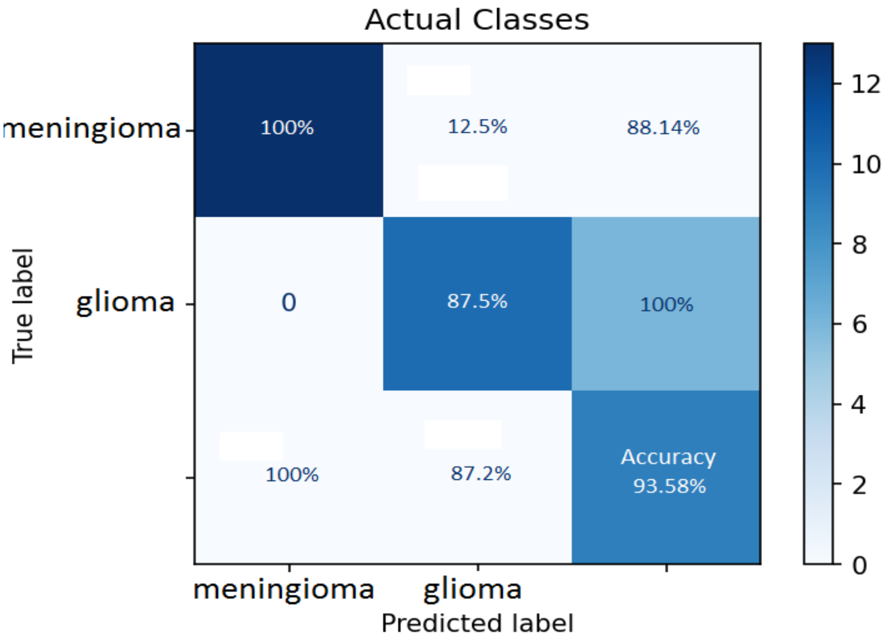


Figure 13. Confusion Matrix for training

Figures 12 and 13 show confusion matrixes for testing confusion matrix for training. For the training dataset and test samples, green squares indicate TP and TN values in each confusion matrix, bright orange squares represent FP and FN values in each confusion matrix, and blue squares represent positive anticipated values in each confusion matrix. Positive predictive value (PPV), negative predictive value (NPV), specificity (Sp), and sensitivity (Sn) are shown clockwise from upper right to lower left, respectively. The purple square represents the total rate of proper classification (accuracy rate). The classification errors for the electronic training and test sets were 7.69% and 6.42%, respectively. The classification process is summarized in Table 3.

Table 3. Comparative analysis of simulation time for all CNN models

CNN MODEL	Simulation times (s)
CNN	421.6
ResNet 50	398.2
AlexNet	321.4
Google Lenet	253.6
Proposed DCNN- LUNET	225.9

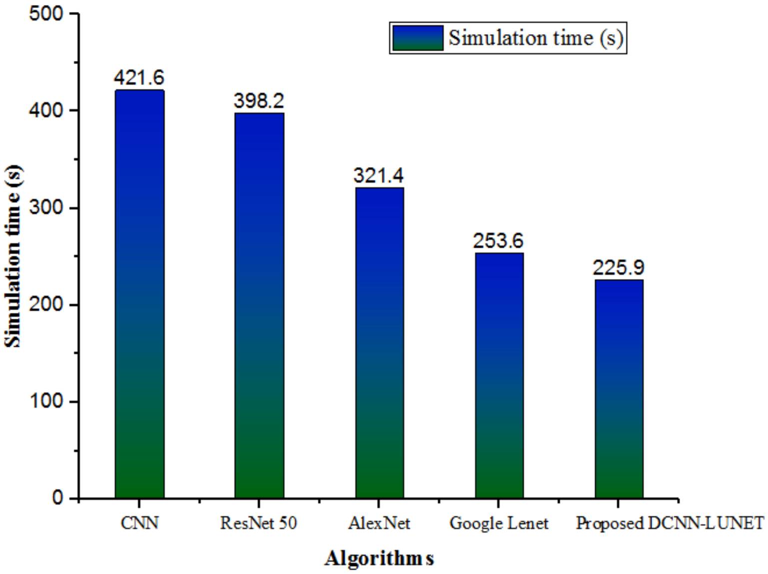


Figure 14. Comparative Analysis of proposed method to conventional method

Based on simulation time, computational and structural complexities are also compared. Table 3 and Figure 14 compares each model's simulation time (in seconds) to the same data set and the number of parameters. In addition, the table shows that the CNN model has the longest simulation time of 421.6 seconds, the Google Lenet model has the shortest simulation time of 253.6 seconds, and the proposed DCNN- LuNet model has the shortest simulation time of 225.9 seconds. The classification accuracy of the state-of-the-art model and the simulation time of the model used in this paper demonstrate that the proposed model is efficient, accurate in classification, and computational and structurally complex.

5. CONCLUSION

The procedures for detecting brain Tumors and classifying malignant brain MRIs into malignant and benign tumors and glioma and meningioma's using MRI are described in this research work. Preprocessing procedures are used to detect brain Tumors, followed by skull dissection and brain Tumor segmentation. This algorithm could be used to segment brain Tumors from MRI images. This research presents a hybrid DCNN classifier with a LuNet classifier using the MATLAB tool. The performance metrics such as recall, F-score, specificity, and total accuracy are used to evaluate the performance of all CNN models. Experiments show that the proposed algorithm outperforms other CNN models, with an overall accuracy of 99.7%. The experimental outcomes show that DCNN with LuNet classifier correctly diagnoses both high- and low-grade Tumors compared to previous techniques. The proposed algorithm models have accuracy (99.7%), sensitivity (98.2%), specificity (98.6%), precision (99.4), F-Score (98.2) and recall (99.8%), respectively. In future work, novel hybrid Deep learning with bio-inspired optimization will be proposed to improve the performance of brain tumor segmentation and classification process.

Conflict of interest:

The authors declare that they have no conflict of interest.

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