

Brain Tumor Segmentation and Classification based on Deep Learning-Based Inception Networks

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Abstract:

Brain Tumor (BT) turns into a dangerous and deadliest sort of disease that happens altogether age bunches over the globe. Finding and characterization of BT is a significant issue in the plan of Computer Aided Diagnosis (CAD) device for therapeutic applications. Since the CAD model for BT finding is a dreary cycle, the coming of Deep Learning (DL) models prepare to plan an exact BT determination and order model. This paper centers around the plan of another SURF with DL based Inception networks for BT determination. The proposed model includes a bunch of cycles specifically preprocessing, division, highlight extraction, and order. The proposed model uses Fuzzy C Means (FCM) method to achieve a capable picture division measure. Likewise, Speed-Up Robust Features (SURF) and Inception v3 model is utilized to perform include extraction. Ultimately, Gaussian Naïve Bayes (GNB) and Logistic Regression (LR) classifiers are utilized to do the characterization measures. To evaluate the order aftereffects of the proposed model, a broad recreation was completed on the benchmark dataset. The recreation result guaranteed the unrivaled execution of the proposed technique with the greatest affectability of 100%, the explicitness of 97.41%, and exactness of 97.96%.

KeyWords: *Brain tumor, Deep Learning, Feature Extraction, Fuzzy C Means*

I. INTRODUCTION

In the human body, the mind is an essential organ that goes about as a focal sensory system. It controls and guides the body to work appropriately. Since the mind is a significant organ, it must be covered from damage and diseases. Not many of the BT are Meningioma, Glioma, and Pituitary. Initially, Meningiomas are noticeable infections; be that as it may, it is a non-harmful sort of tumors created in restricted dividers around the mind tissues and cells [1]. BTs are viewed as the most horrendous sickness which mitigates the lifetime of an individual inside a brief period. Prior expectation of BT is exceptionally fundamental and important to expand the patient's life expectancy. This is cultivated by utilizing Magnetic Resonance Imaging

(MRI) filtering model which is applied broadly by radiologists to look at the BT. At long last; the output report shows whether the cerebrum is sound or undesirable. Followed by, it additionally finds the class of tumors when it is influenced by a problem. Under the use of Machine Learning (ML), MRI reports ought to have a précised picture for foreseeing BT. At first, the designer's expected 3 segments in particular, Pre-handling of MRI, Feature age, and extraction just as Classification.

Eventually, the Median Filter (MF) has been applied to upgrade the prevalence of pictures and over save the edges in the pre-preparing stage [2]. At that point, picture division is performed with the assistance of K-Means, FCM, etc. offers more worthwhile highlights from applied pictures. It is one of the reasonable and significant stages which helps in picture assessment and translation. Likewise, it is utilized widely in cerebrum imaging capacities like tissue arrangement, tumor position, assessing the volume of the tumor, platelet tendency, careful plans, and coordinating. In [3], BT division was used by Convolutional Neural Networks (CNN) to 3D MRI. Computerized forecast of the mind's anatomical construction by utilizing Deep Neural Network (DNN) was projected in [4]. In [5], a democratic plan for a gathering of straightforward designs like power and versatile shape modes happens with the joining of discrete gaussian just as higher-request designs like Markov-Gibbs irregular field grouping was created. The hybridization of profound auto-encoder related to the Bayesian fluffy grouping depended division component has been set up in [6].

In [7], 2D MRI is partitioned as the left and right side of the equator alongside some factual properties that were assessed for the SVM grouping approach. As there are gigantic highlights, include extraction is performed with substantial information under the use of Principal Component Analysis (PCA), Scale Invariant Feature Transform (SIFT), and SURF descriptors. In [8], subsequent to processing cross breed include extraction and covariance network, a regularized outrageous learning has been utilized for grouping the cerebrum problem.

II. LITERATURE REVIEW

This segment plays out a short study of various ML and DL based BT conclusion models accessible in the writing. In [10], highlight extraction was applied where the mind framework interface which goes through order utilizing Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). Lately, CNN is one of the well known instruments concerning highlight extraction under different investigations like clinical pictures, video assessment, and Natural Language Processing (NLP). The vital target of CNN is to estimate the central examples and information from preparing pictures. For instance, VGGNet, GoogleNet, and AlexNet are a portion of the viable constructions applied in picture grouping which are additionally utilized for BT forecast.

In [11], pre-handling just as information planning utilizing 3D-channels and CNN with

multipath and fell designs has been introduced. In pixel, the CNN structure was used for creating different pictures of similar individual with particular stances. In [12], a pretrained CNN was utilized for BT grouping with DNN and SVM. At that point, in [13], course CNN delivered a room embellishment. As CNN is costly, designers focused on creating savvy techniques with accurate tumor arrangement. The normal method is to apply an outfit of small synergistic students as opposed to utilizing a chaotic framework, to manage hearty preparing execution just as intermingling. Accordingly, the learning interaction of companion organizations could be self-sufficient.

In [14], a KullbackLeibler difference has been applied for coordinating with the likelihood appraisals of friends in regulated learning. Additionally, in [15], multipath students are engaged with the yields of shared layers. The fundamental point of this model is to identify the issue powerfully and keeps up tumor improvement somewhat. A significant test in the ML model is to assess the information circulation. For example, hardcoded relationship between each picture pixel and the neighbors are muddled to relate to no high level information. Also, autoregressive methodologies are information driven assessors used to distinguish these relationship with normal data. Then, the created results have improved pictures with restricted commotion and exception. The thickness assessor attempts to determine different characterizations, relapse, missing information, and issues. In [16], a quantum variety Auto Encoder (AE) was introduced where the inert generative calculation which goes about as a quantum Boltzmann machine. By the assessment of BT from MRI, little preparing inputs, different states of tumors, and unpredictable data could be distinguished for each class.

III.THE PROPOSED METHOD

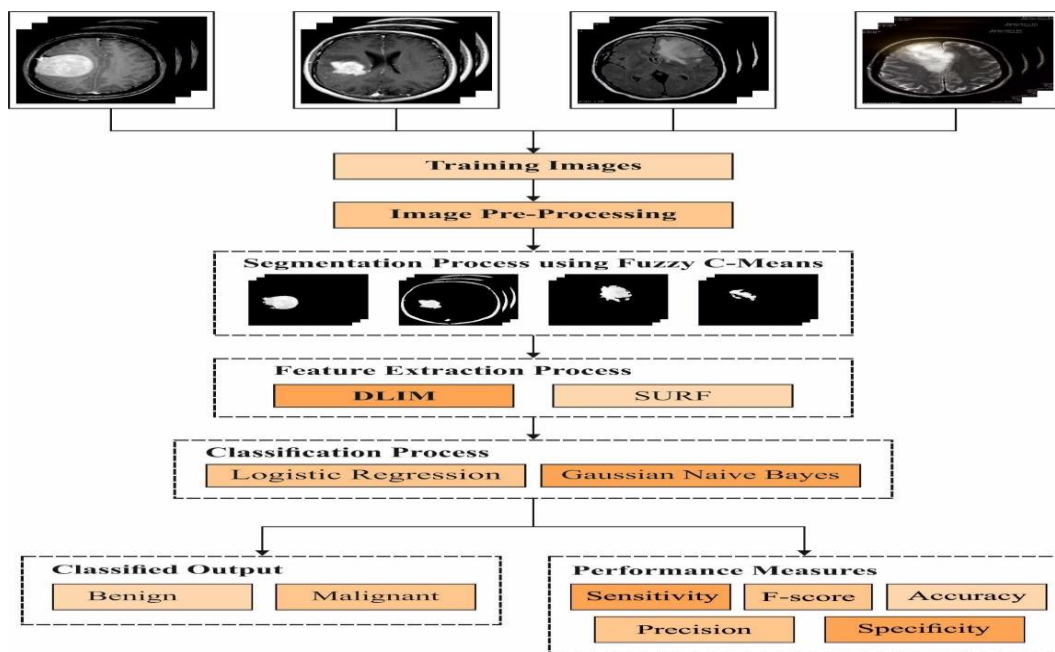


Fig 1:Proposed System

Figure 1 portrays the square graph of the introduced model, including its distinctive subprocesses. Principally, the information picture is pre-prepared for stripping the skull, eliminate the clamor, and increment the difference level. At that point, the FCM based division strategy is utilized to recognize the infected bits in the picture. Thereafter, the SURF and Inception v3 models are applied to remove a valuable arrangement of highlight vectors. Finally, GNB and LR models are used in arrangement measures.

A. Image Pre-handling

At first, the pre-handling of info pictures happens in three distinct manners: skull stripping, clamor expulsion utilizing Bilateral Filtering (BF), and Contrast Limited Adaptive Histogram Equalization (CLAHE) based differentiation upgrade. Close to picture preprocessing, a division task is done to recognize the influenced tumor districts.

B. FCM based Segmentation

The FCM method is applied to section the pre-handled picture. FCM is a notable methodology developed from the unaided ML technique that is widely utilized for picture division. Fluffy grouping guarantees to be more adaptable to conquer the error of topographical information with distant detecting information. It is essentially applied in huge information examination, Data Mining (DM), Vector Quantization (VQ), picture division, and example discovery with continuous and hypothetical qualities.

C. Feature extraction

This section explains the two main feature extraction techniques namely SURF and Inceptionv3 model.

(i)SURF model:

It is a local feature extraction technique, which makes use of a local invariant fast keypoint detection process to extract the key points of the image features. The SURF is composed of 4 main phases namely, scale-space feature extraction by robust Hessian detector, extraction of keypoint, orientation schedule, as well as key point descriptor. It exploits Lowe's suggestion named as Best-Bin-First approach, which has a distance ratio from 0.6–0.8 among closest features which is a standard matching attribute

SURF feature point prediction model depends upon scale-space theory where it applies the determinant of Hessian matrix in the form of discriminant to seek higher measures.

$$H(P, \sigma) = [L_{xx}(P, \sigma)L_{xy}(P, \sigma) \\ L_{xy}(P, \sigma)L_{yy}(P, \sigma)]$$

(ii)Inception v3 model:

CNN is developed as a multi-layer interconnected NN, where powerful low-, intermediate-, and high-level features were extracted hierarchically. A common CNN model

is composed of 2 layers namely, convolutional and pooling layers which are jointly named as convolutional bases of a system [19]. Few modules like AlexNet and VGG are implanted with Fully Connected (FC) layers. First, the convolutional layer is applied to extract the spatial characteristics from the images. Typically, initial convolutional layers filter out the low-level features like edges and corners whereas the final convolutional layers filter the high-level features like image structures. It is recommended by its maximum efficiency of CNNs to learn the spatial hierarchical patterns. Also, it is operated on 2 elements namely, convolution patch size as well as and depth of the last feature map which represents the filter count.

D. Image Classification

Finally, the extricated include subsets are taken care of as contribution to the GNB and LR models to play out the grouping cycle.

(i)GNB Model:

A Naive Bayes (NB) grouping model estimates the feasibility of the applied examples which has a place with a particular class . A portion of the case X is characterized by the relating highlight vector (x_1, \dots, x_n) just as class target y , restrictive likelihood $P(y|X)$ is portrayed as a blend of basic probabilities under the use of Naive autonomy presumption dependent on the Bayes' theorem in Equation 9.

$$P(y|X) = P(y)/P(X|y)$$
$$P(X) = P(y)\prod_{i=1}^n P(x_i |y)/ P(X)$$

(ii)LR Classifier:

LR is defined as a commonly employed classifier, which is used to predict a binary related parameter. The dependent variable ranges from 0 or 1 values. Hence, the conditional probability for the dependent attribute is provided in the following as shown in Equation

$$P(Y = 1|X) = \pi(X) = e^{\beta'X} / 1 + e^{\beta'X}$$

IV PERFORMANCE VALIDATION

In this section, the simulation result analysis of the presented model is discussed. The simulation takes place on GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The simulation tool used is Python - 3.6.5 with different python packages namely TensorFlow (GPU-CUDA Enabled), Keras, NumPy, pickle, matplotlib, sklearn, pillow, and OpenCV-python. The dataset involved, measures, and the results are discussed in the subsequent sections.

(i)Dataset used:

To test the classifier results analysis, a benchmark MRI brain image dataset is utilized[23] that comprises an entire of 147 tumor images. A set of 34 and 113 images comes under benign and malignant classes respectively. The image size varies between 630*630 and 192*192 pixels. Few of the sample benign and malignant class images are shown in Figure 2.

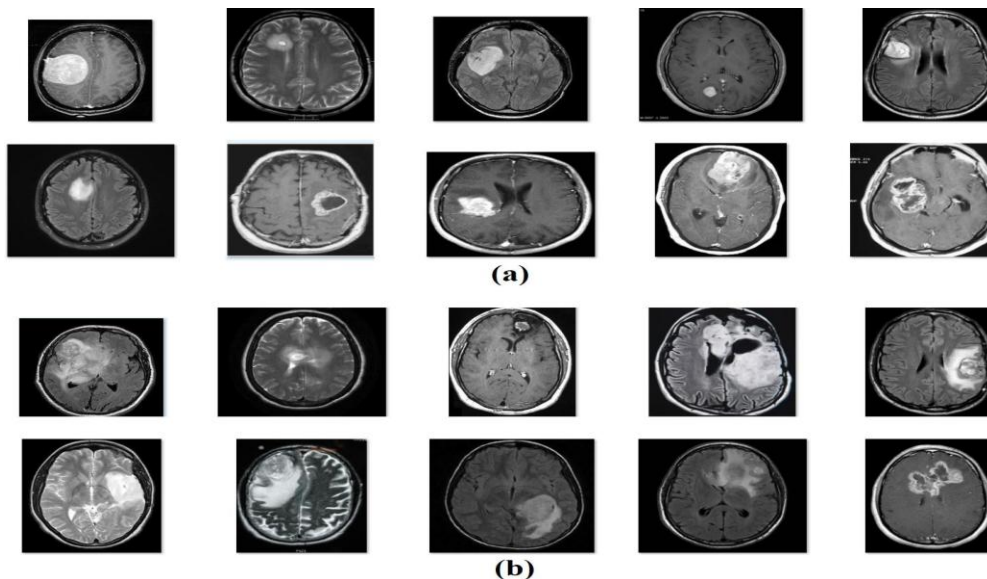


Fig2. Sample Images a) Benign b) Malignant

A visualization of the results attained by the presented model is revealed in Figure 3a. The input original image is depicted in Fig. 3a, the resultant preprocessed and segmented images are displayed in Figures 3b and 3c respectively. The figures showed that the presented model effectively preprocesses and identifies the tumor regions properly.

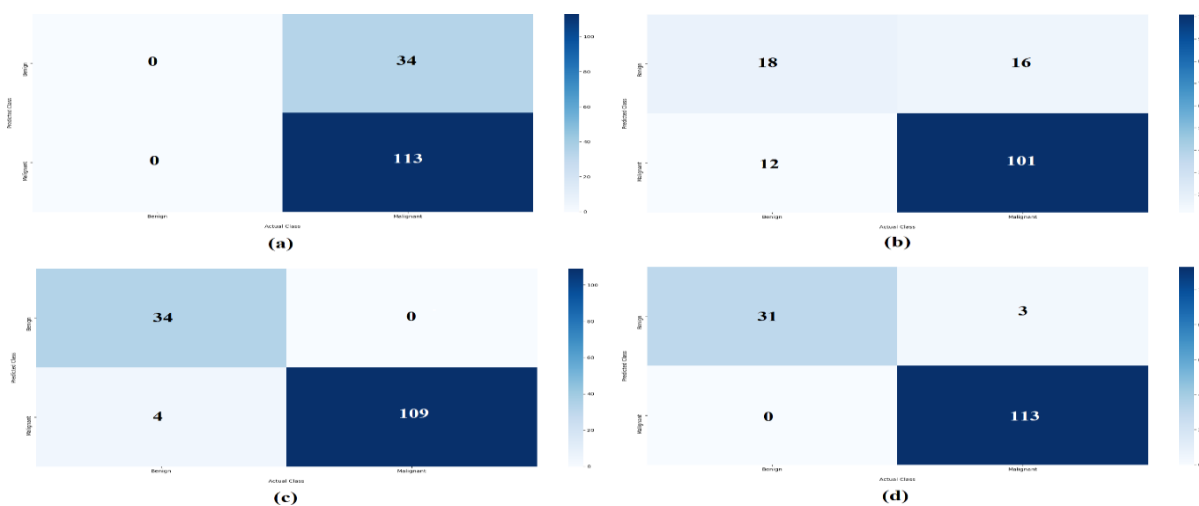


Fig 3 Confusion Matrix a) SURF-LR b) SURF-GNB c) DLIM-GNB d) DLIM-LR

The confusion matrices produced by the different sets of proposed models are shown in Figure 3. Figure 3a exhibits that the SURF-LR model has effectively classified no images as benign and 113 images as malignant. Similarly, Figure 3b showcased that the SURF-GNB model has proficiently classified a total of 18 images as benign and 101 images as malignant. Followed, Figure 3c depicted the near-optimal results of the DLIM-GNB model by classifying a total of 34 images as benign and 109 images as malignant. At last, Figure 3d demonstrated that the DLIM-LR model has resulted in the classification of 31 images as benign and 113 images as malignant.

Table 1 and Figure 4 summarize the classifier results analysis of the four proposed models in terms of distinct evaluation parameters. On looking into the table, it is observed that the SURF-LR model has led to the least specificity of 76.87% and a sensitivity of 76.87%. Also, the SURF-GNB model has surpassed the SURF-LR model with the certainly higher sensitivity of 60%, the specificity of 86.32%, the accuracy of 80.95%, precision of 52.94%, and accuracy of 53.25%. Though the DLIM-GNB model has exhibited satisfactory classification outcome with a high sensitivity of 89.47%, the specificity of 100%, the accuracy of 97.28%, the precision of 100%, and an F-score of 94.44%. But the DLIM-LR model has shown proficient performance with the maximum sensitivity of 100%, the specificity of 97.41%, the accuracy of 97.96%, precision of 91.18%, and an F-score of 95.38%.

| Methods | Sens | Spec. | Accu. | Prec. | F-score |
|----------------|-------------|--------------|--------------|--------------|----------------|
| DLIM-LR | 100 | 97.41 | 97.96 | 91.18 | 95.38 |
| DLIM-GNB | 89.47 | 100 | 97.28 | 100 | 94.44 |
| SURF-GNB | 60.00 | 86.32 | 80.95 | 52.94 | 56.25 |
| SURF-LR | - | 76.87 | 76.87 | 0 | 0 |

Table 1 Result Analysis of Proposed Methods in terms of distinct measures

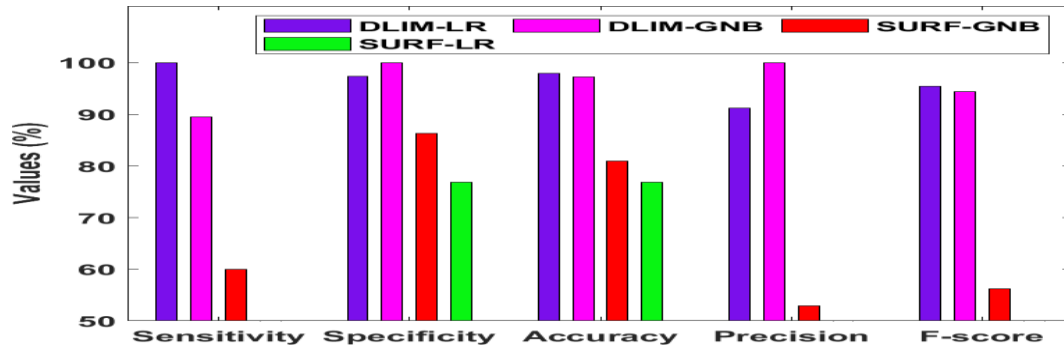


Figure 4. Result analysis of DLIM-LR model with a different model

| Methods | Sens | Spec. | Accu. | Prec. | F-score |
|---------------|-------|-------|-------|-------|---------|
| DLIM-LR | 100 | 97.41 | 97.96 | 91.18 | 95.38 |
| CNN-VGG16 | 81.25 | 88.46 | 89.66 | 84.48 | 85.25 |
| ResNet-50 | 89.74 | 96.40 | 92.54 | - | 93.33 |
| CART | 88.00 | 80.00 | 84.00 | - | - |
| Random Forest | 90.00 | 80.00 | 88.00 | - | - |
| k-NN | 80.00 | 80.00 | 80.00 | - | - |
| Linear SVM | 91.20 | 80.00 | 88.00 | - | - |
| ANFIS | 96.20 | 95.10 | 96.40 | - | - |
| CNN-CA | 91.20 | 93.40 | 93.30 | - | - |
| CNN | 94.20 | 94.40 | 94.60 | - | - |
| DCNN-CA | 92.60 | 93.00 | 93.30 | - | - |
| MABA | 94.30 | 95.10 | 95.90 | - | - |

Table 2 Result Analysis of Existing with Proposed Methods in terms of different measure

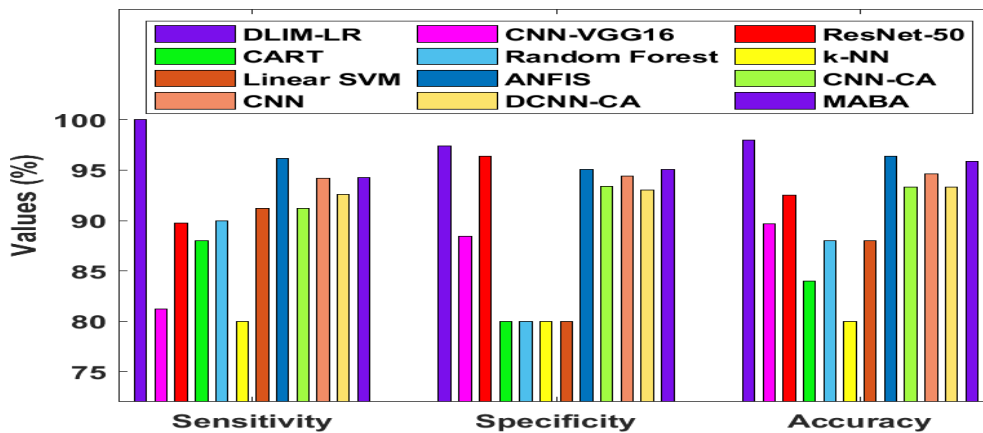


Figure 5. Comparative analysis of DLIM-LR model

Table 2 and Figures 5 implies the analysis of the comparative results of the DLIM-LR method with previous approaches [24-27] using various metrics.

V CONCLUSION

This study has introduced a new BT diagnosis model using the SURF and Inception network. Primarily, the input image is pre-processed to strip the skull, remove the noise, and increase the contrast level. Then, the FCM based segmentation technique is employed to identify the diseased portions in the image. Afterward, the SURF and Inception v3 models are applied to extract a useful set of feature vectors. At last, GNB and LR models are utilized in classification processes. To validate the analysis of the results of the presented technique, a series of experiments take place on the benchmark dataset. The simulation outcome verified the supremacy of the proposed DLIM-LR model on the diagnosis of BT with the maximum sensitivity of 100%, a specificity of 97.41%, and an accuracy of 97.96%.

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