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RESEARCH ARTILE

DEEP LEARNING MODEL FOR ACCURATE BRAIN TUMOR DETECTION USING CT AND MRI IMAGING

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Abstract – Brain tumors (BT) are a very common, deadly condition with a very poor prognosis at the most aggressive grade. BT represent a prevalent and fatal condition with particularly poor prognosis at advanced stages. Accurate diagnosis and classification are critical for effective treatment planning and patient care. This study introduces a novel deep learning-based algorithm for early BT detection using CT and MRI images. The proposed model enhances image quality using Adaptive Trilateral filtering, extracts feature via the MobileNet model, selects relevant features through the Tyrannosaurus optimization algorithm, and classifies brain tumors with a Deep Belief Network (DBN). The model categorizes tumors into three classes: pituitary tumor, no tumor, and glioma tumor. In comparison to conventional deep learning networks, the model performs better in experiments using the BRATS2020 dataset, reaching a 99.3% accuracy rate and great dependability. This paper offers significant improvements in automated brain tumor detection, promising better patient outcomes through early and precise diagnosis.

Keywords *– Brain Tumor, Deep Learning, Deep Belief Network, Mobile Net.*

1. INTRODUCTION

Worldwide, the frequency of brain tumors is rising quickly, and millions of people die from them every year [1]. For brain cancers to be effectively treated, proper diagnosis and categorization are crucial. Appropriate patient care and the development of a effective treatment plan depend on a timely diagnosis [2]. In order to manually classify brain tumor MR images with comparable structures or features, radiologists must be capable of reliably identifying and classifying brain cancers. In addition to acting as the administrative hub, the human brain is a vital component of the nervous system that handles daily activities [3,4]. The human body's sensory organs send impulses or signals to the brain, which then receives, interprets, and makes a decision about them before sending the data to the muscles [5]. One of the most serious conditions affecting the human brain, BTs, is characterized by abnormal brain cell development that is irregular [6,7]. There are two main kinds of BT: primary and secondary metastatic.

Brain tumors can be identified and their progression monitored during the diagnosis and therapy phases using brain MRI and CT scans [8]. Automated medical image analysis is heavily influenced by the high-resolution images obtained from MRIs and CT scans, which provide extensive insights into brain disorders and structure [9,10]. Brain tumor classification, data analysis, and professional diagnosis are the main uses of image processing and deep learning algorithms [11,12]. Deep neural networks have made it possible to segment brain tumors successfully thanks to recent developments in medical imaging [13]. This article proposes a deep learning-based algorithm for early BT detection using CT and MRI images. The main contribution of the proposed model is organized as follows.

- Initially, the input images are pre-processed utilizing Adaptive Trilateral filter to expand the quality of the image.
- Then, Mobile Net model is employed for extracting the features in the pre-processed brain image.
- The extracted image features are selected using Tyrannosaurus optimization Algorithm.
- Afterward, the selected features are fed into the DBN model to classify the Three cases of brain tumour.

The remaining sections of the research paper adhere to the following structure: Chapter 2 provides detailed summaries of relevant works, while Chapter 3 offers a comprehensive explanation of the proposed model for early recognition of brain tumors. Chapter 4 encompasses the experimental outcomes and discussion, and lastly, Chapter 5 contains the conclusion and outlines future work.

2. LITERATURE SURVEY

In 2022, Ottom, M.A., et al., [14] developed a Dl model for 2D BT subdivision in MR images and conveying the intrinsic commonalities of a more narrowly defined collection of tumors via Znet and deep neural networks (DNN). The experiment's accuracy rate was 99.6%. The disadvantages of Znet include that it requires a large number of annotated ground truths (labels), which adds time to the process and necessitates rigorous testing.

In 2022, Gaur, et al., [15] introduced an explanation-driven DL model for the use of an MRI image collection in the prediction of different types of brain cancer utilizing CNN, LIME, and Shapley additive explanation (SHAP). Even if the model in use has an accuracy of 94.64%, the reliability rate is still insufficient for the classification.

In 2022, Haq, et al., [16] developed a hybrid, thorough method that uses CNN to accurately classify brain MRI cancers. The intended CNN and SVM-RBF classifier yielded a 98.30% reliability rate. The recommended model has noticeably superior performance than state-of-the-art methods, as exposed by the segmentation and classification results. The time-consuming aspect of this strategy is a disadvantage.

In 2023, Mostafa, et al., [17] suggested an automatic technique to categorize brain cancers using MRI pictures. The BT segmentation dataset, which was developed as a standard for emerging and accessing systems for BT division and analysis, includes the suggested MRI pictures of BTs. Image feature extraction using DCNN with a U-Net model is used to accomplish this aim. Through training on the BraTS dataset, a 98% overall accuracy model was created.

In 2024, Geetha, et al., [18] presented a new SCAOA to categorize the brain tumor. It extracts the aspects involving statistics and texturing. The Archimedes Optimization Algorithm (AOA) and the Sine Cosine Algorithm (SCA) are combined to create the suggested SCAOA. Even though the suggested SCAOA-based Dense Net achieves the maximum accuracy of 93%, the dependability rate is insufficient for BT detection.

In 2024, Sharif, et al., [19] recommended that an end-to-end optimized DL system be used to construct a multimodal brain tumor classification system. A CNN model is trained and the contrast along the ant colony optimization strategy is improved using hybrid division histogram equalization. An MC-SVM receives the fused result after it has been combined using a matrix length technique. In the research investigation, the suggested method had a 99.06% accuracy rate.

In 2024, Akter, et al., [20] suggested a deep CNN-based architecture and a U-Net-based segmentation model for the automatic classification of brain pictures into four classifications. Two classification techniques are also assessed according to AUC, accuracy, recall, and precision. The top correctness of 98.7% was attained by the classification model with the assistance of the segmentation approach, according to the results.

3. PROPOSED METHOD

In this section, a novel deep learning-based method has been proposed for early BT recognition from CT and MRI images. To progress the image quality, the input images are first pre-processed using an Adaptive Trilateral filter. The features in the previously processed brain image are then extracted using the Mobile Net model. Tyrannosaurus optimization algorithm is used to choose the features from the retrieved image. The three brain tumor cases are then classified using the features that were chosen and supplied into the Deep Belief Network model. Figure 1 shows the proposed architecture.

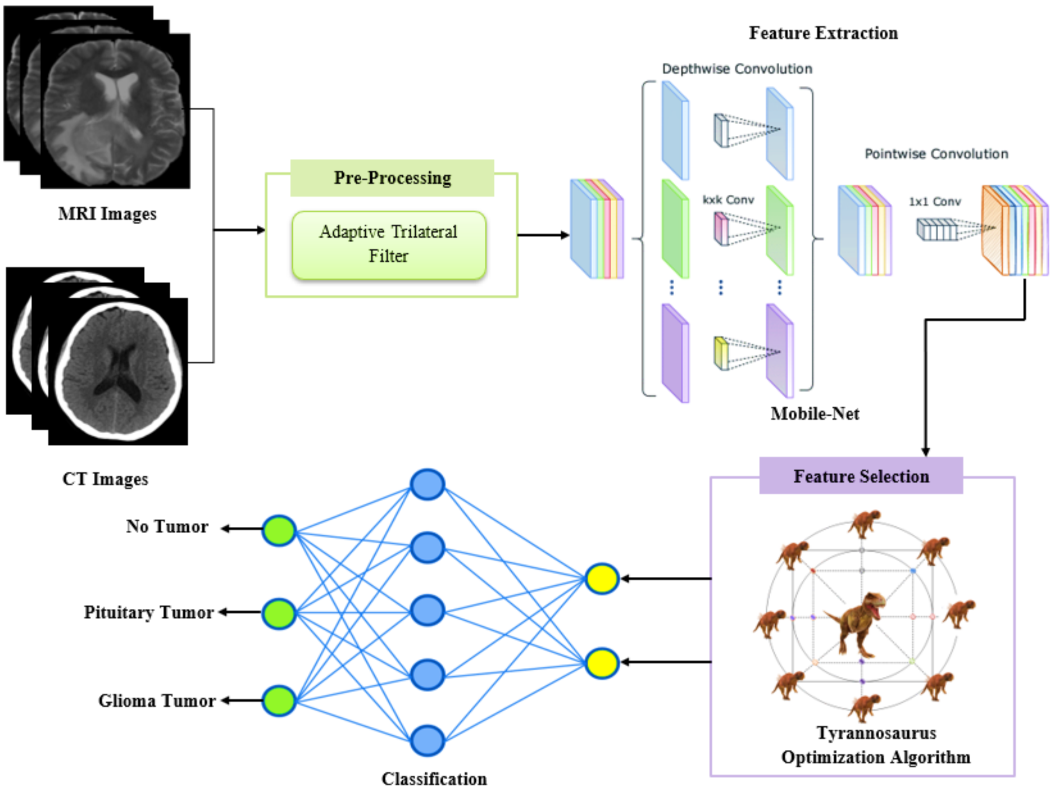

Figure 1. Architecture of Proposed Methodology

3.1. Image Pre-Processing

Image preprocessing is a perilous step in tumour detection, as it makes raw image data for more analysis and processing. The input images are under go pre-processing via the AT filter method to enhance the images.

3.1.1. Adaptive Trilateral Filter

AT filter is used in pre-processing to eliminate noise artefacts from the input medical images. It implements the guiding principles of the bilateral filter. The tilting angle $ti_{\emptyset}$ of a trilateral filter is produced when a bilateral filter is applied to the picture data. This is because, given $ti_{\emptyset}$ at the target pixel, a should average highly related surrounding pixels and exclude dissimilar pixels.

$$ti_{\emptyset}(x) = \frac{1}{k_{\emptyset}} \sum_x \sum_a f_a \, c(x,a) b(f_x, f_a) \quad (1)$$

When the kernel is tilted, the trilateral filter's $c\,(.)$ and $b\,(.)$ functions become non-orthogonal. Eqn (2) gives the value of each pixel at this plane.

$$g(x,a) = f(x) + ti_{\emptyset}.(||x-a||) \quad (2)$$

where x at a target pixel represents $f(x)$, the intensity, and $||x-a||$ is the dimensional separation between x and a. The tilting angle is denoted by $ti_{\emptyset}$. To find the output of a trilateral filter, the resulting image is first passed through a bilateral filter, and then the value g is removed from the surrounding area of the target pixel.

$$f_{op}(x) = f_{ip}(y) + L(y)\rho \quad (3)$$

where ρ is the spatial distance between pixels x and a, and $f_{op}(x)$ is the output function. Tilting improves the filter's capacity to smooth high gradient zones.

3.2. Feature Extraction

Feature extraction in brain tumor detection involves identifying and isolating specific characteristics from medical images, such as MRI scans and CT scans, The pre-processed image undergoes feature extraction using MobileNet.

3.2.1. Mobile Net

MobileNet is a deep learning architecture well-suited for feature extraction in image recognition tasks. It utilizes a series of convolutional layers to progressively extract features from images. Standard convolutional layers in the initial stages capture basic features like edges and corners. The following depthwise separable convolutions are efficient at extracting spatial information from the image. Batch normalization and ReLU activation layers maintain stability and introduce non-linearity for improved learning. Emphasize the global average pooling layer as the key step for feature extraction.

The function of the dimension multiplier δ is to compress the connection equally at each tier. The dimension multiplier is applied to lower the width α of the source image. Equation (4) describes the total value of the C_s computations for the network's central layers.

$$C_s = E_c.E_c.\delta J_{p.}\alpha E_{n.}\alpha E_{n.} + \delta J_{p.}\delta J_{o.}\alpha E_{n.}\alpha E_n \quad (4)$$

Since the characteristic map is represented by $E_n \times E_n$ in equation (4) above, the kernel dimension is $E_c \times E_c$, the source data channel is J_p, and the output data is J_o. For the purpose of identifying illnesses in tea leaves, the width factor $\alpha = 1$ and the depth factor $\delta = 1$ were expressed. Equation (5) yields the typical convolution's computing cost O_o.

$$O_o = E_c.E_c.J_p J_{o.}E_{n.}E_n \quad (5)$$

Finally, the traditional resolution into depth-wise convolutional and point-wise convolution is used to estimate the reduction R_d for the feature extraction, that is stated in equation (6).

$$R_b = \frac{\alpha.\mu^2}{J_o} + \frac{\alpha^2.\mu^2}{E^2{}_c} \quad (6)$$

By utilizing the above equations Mobile Net model successfully extract the features of pre-processed MRI and CT scan images.

3.3. Feature Selection

Feature selection involves choosing the most relevant features from extracted images to improve model performance and reduce computational burden. It enhances accuracy by focusing on discriminative attributes, filtering out noise, and diminishing overfitting.

3.3.1. Tyrannosaurus optimization Algorithm (T-Rex)

The T-Rex optimization approach is proposed for selecting the features from extracted features of MRI scan and CT scan images. The T-Rex is introduced based on the social behavior of Tyrannosaurus. The prey-predictor hunting method is the source of inspiration for this tactic. In addition to this technique, the position of the prey and the T-Rex are generated at random. The hunting is done based on where the prey is nearest. The Tyrannosaurus Rex pursues its prey until it seizes them; in the interim, the victim makes an effort to escape the T-Rex.

3.3.1.1. Initialization

The number of preys in a search area is randomly generated by the population-based TROA algorithm. Tyrannosaurus here refers to the task, and prey is the server's processing power. As shown in equation (7), y_n refer to the prey region or processing, which is randomly created within higher and lower bounds in a search area.

$$y_n = r(j_c, i_c) * (v_f - u_g) + u_g \quad (7)$$

Where $n = 1, 2 \dots m$, m is the measurement, j_c is the number of populations, i_c is the measurement of the hunt space, v_f is the top restrict and u_g is the decrease restrict, and $y_n = [y_1, y_2, \dots y_m]$ is the prey area. When the estimate of reaching the dispersed prey is represented by the F_c.

$$Y_m = \begin{cases} X_m \; if \; r() < F_c \\ Random \;\; else \end{cases} \quad (8)$$

3.3.1.2. Selection

The Selection relies upon at the area of prey, i.e. area of the server prey and the hunting area. If the hunter fails to hunt then, the prey area will become 0. It is found out through evaluating the fitness function.

$$X_l^{m+1} = \begin{cases} update\ the\ target\ position & if \quad f(X) < f(X_m) \\ target\ is\ none & otherwise \end{cases}$$

Where, $f(X)$ is the fitness function for the prey position, and $f(X_m)$ is the fitness function for updated prey position.

3.4. Classification

DBN is a type of deep learning model consisting of multiple layers of Restricted Boltzmann Machines (RBMs), stacked hierarchically. The number of layers in DBNs correlates with the complexity of input data, while the number of output layers corresponds to the range of categories. DBNs use hidden variables to model data distributions. A two-step learning approach is employed: firstly, RBMs are trained greedily layer by layer to capture basic data patterns, then the entire system is fine-tuned to minimize the gap between original and reconstructed data. This process demands significant computational resources and persistence, but yields valuable results. The main characteristic of a DBN, h is determined by an RBM and learns $t\left(\frac{o}{p}, h\right)$. The previous average, p $\frac{k}{h}$, for concealed carriers. Equation (9) expresses the pace at which an apparent gradient is produced. Equation (10) represents the hidden layer of the DBN, with $sum(t_j)$ indicating the applied vector in the layer.

$$T(o) = \sum_k (\mathrm{p}\ \frac{k}{h} t\left(\frac{o}{p}, h\right)) \tag{9}$$

$$sum(t_j) = \sum_{g_u=1}^{j} M(pjg_u) \tag{10}$$

The output of the hidden or invisible layer based on the weight and bias of the images be depicted in equation (21).

$$E^j = \left[\sum_{i=1}^{k} \mathfrak{x}_{iL}^{F^r} * \mathfrak{Z}_{\mathrm{i}}\right] E_j\ \forall \mathfrak{f}_i = w_i^2 \tag{11}$$

E^j represents the hidden layer bias of data and E_j be the output of the RBM layer for the multilayered classification process. The most representative features for modeling the data are those obtained in the layer of the DBN is expressed in equation (12).

$$Q_h = q_{t1}, q_{t2}, \ldots, q_{t\mathrm{i}} \tag{12}$$

Where t stands for the network's top layer, ℹ for the number of features in multilayer networks, and Q_h for the DBN input vector. Finally, the brain tumors are classified as no tumor, pituitary tumor, and glioma tumor.

4. RESULTS AND DISCUSSION

This subsection uses the BRATS2020 dataset to evaluate the effectiveness of the suggested model. The source of the input MRI images is the BRATS2020 dataset.

The visualization outcomes of the proposed approach utilizing the BRATS2020 dataset are shown in Figure 2(a & b). Denoising the input CT and MRI images of brain tumors (column:1) improves picture quality and eliminates distortions (column:2). These previously processed photos are fed into Mobile Net concurrently in order to extract the features (column:3). Subsequently, patients' various brain tumor cases are distinguished using the categorization strategy (column:4).

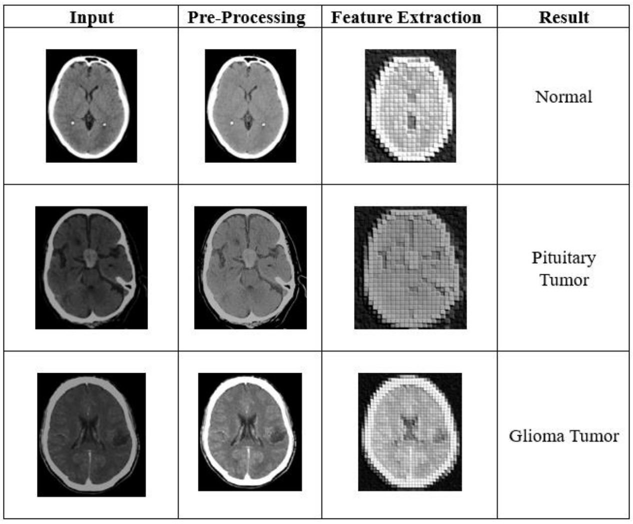

Figure 2 (a). Experimental Results of the Brain CT images of Proposed Model

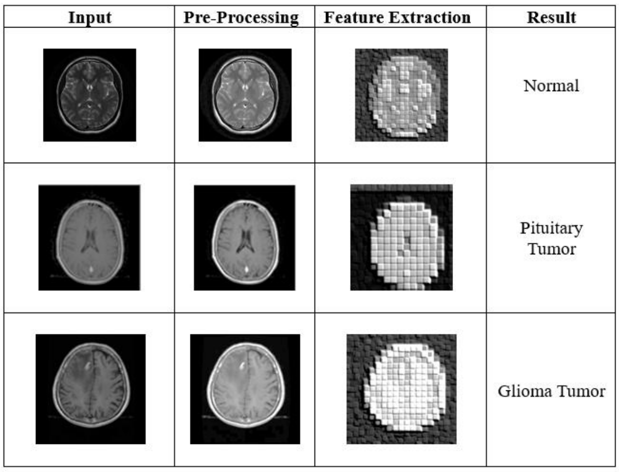

Figure 2 (b). Experimental Results of the Brain MRI images of Proposed Model

4.1. Performance Analysis

The evaluation metrics previously described can be generated with simple parameters such as True Positive ($\mathrm{t}\,p_{\mathrm{os}}$), True Negative ($\mathrm{t\,N}_{eg}$), False Positive ($\mathrm{F\,p}_{os}$), and False Negative ($FN_{eg}$).

$$Acc = \frac{\mathrm{t}\,p_{\mathrm{os}} + \mathrm{t\,N}_{eg}}{\mathrm{t}\,p_{\mathrm{os}} + \mathrm{t\,N}_{eg} + \mathrm{F\,p}_{os} + F\,N_{eg}} \times 100 \tag{13}$$

$$Pre = \frac{\mathrm{t}\,p_{\mathrm{os}}}{\mathrm{t}\,p_{\mathrm{os}} + \mathrm{F\,p}_{os}} \tag{14}$$

$$Recall = \frac{\mathrm{t}\,p_{\mathrm{os}}}{\mathrm{t}\,p_{\mathrm{os}} + FN_{eg}} \tag{15}$$

$$F1.S = \frac{2}{\frac{1}{(Recall)} + \frac{1}{(Pre)}} \tag{16}$$

The efficiency of the planned model by classifying Brain Tumor, is shown in the Table.1. The proposed model has a 99.3% accuracy rate. Additionally, the proposed Attention Link Net achieves an F1 score of 98.09%, respectively.

Table 1. Evaluation of results of the proposed Model

Classes	Accuracy	Precision	Recall	Specificity	F1 score
Glioma tumor	99.42	98.02	98.27	98.04	98.46
Pituitary tumor	99.35	98.66	96.75	95.97	98.39
No tumor	99.13	95.45	97.15	96.64	97.44

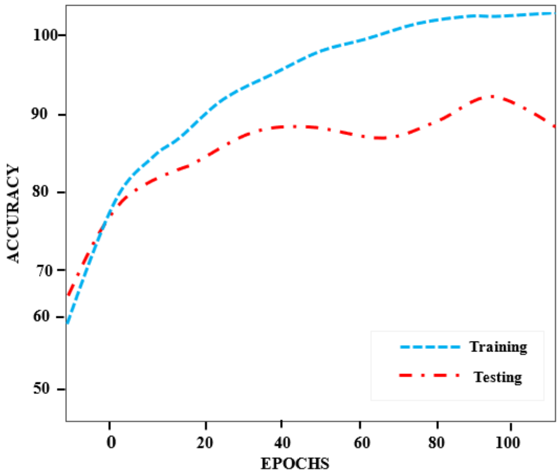

Figure 3. Accuracy of proposed model

The accuracy graph in Figure 3 was produced with a reliability range and 100 epochs. As the number of epochs increases, the proposed DBN's success rate also improves.

Figure 4 illustrates the relationship between epochs and loss, indicating a decrease in loss as the number of epochs increases. Utilizing MRI images and CT images, the proposed model exhibits a high level of reliability in identifying different stages of Brain Tumor. The detection accuracy of the DBN model with 100 training epochs was 99.3, and it had a low rate of errors.

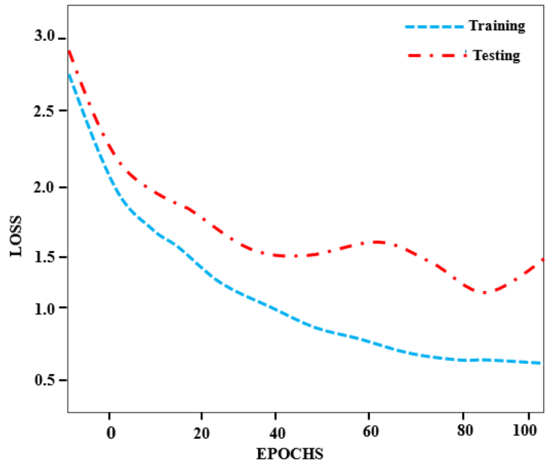

Figure 4. Loss of proposed Model

4.2. Comparative analysis

The efficiency of each neural network was assessed to confirm that the suggested model produces results with an outstanding level of reliability. The proposed model is compared with three deep learning classifiers Link Net, Reg Net, Res Net.

Table 2. Comparison of different approaches

NETWORKS	Accuracy	Precision	Recall	Specificity	F1 score
Link Net	98.05	96.31	96.42	95.24	96.04
Reg Net	97.09	96.76	97.30	96.13	96.39
Res Net	99.07	97.22	97.30	96.11	95.72
Proposed Model	99.3	97.37	97.39	96.88	98.03

The accuracy attained by the proposed model is 99.3%, which is higher than the traditional DL networks. The proposed model has high accuracy than Link Net, Reg Net, and Res Net which obtains 1.25%, 2.21%, and 0.23% while having a significantly lower computational cost than other networks.

Table 3. Compare the performance of existing models and the proposed model

AUTHOR	METHODS	ACCURACY
Haq, et al [16]	SVM-RBF	98.30%
Mostafa, et al., [17]	DCNN	98%
Sharif, *et al.*, [19]	MC-SVM	99.06%
Proposed model	DBN	99.3%

According to the comparison Table above, the suggested model outperforms the SVM-RBF, DCNN, and MC-SVM in terms of overall accuracy by 1%, 1.3%, and 0.24%, respectively. The suggested network, however, outperformed the earlier networks in terms of performance. Because of this, the results of the suggested model for classifying cases of brain tumors are quite trustworthy.

CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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