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Parametric Optimization Through Metaheuristics Approaches for Brain Tumor Detection Using Deep Learning Algorithm

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Abstract: The variation of appearance of brain tumors is a challenging detection task—the interpretation of cells due to abnormal growth in dimension decreases the accuracy of the detection algorithm. Recently, several algorithms have been applied based on transform-based and machine learning for detecting brain tumors. The major limitation of these algorithms is the mapping of extracted features of a brain tumor in the classification algorithms. This paper deployed a feature of a fusion-based approach for detecting brain tumors, the feature of a fusion approach using a transform-based function and a heuristic-based algorithm. The fused feature passes through the proposed machine learning algorithm for detection—the proposed detection using a multi-kernel support vector machine and ensemble classifier. The feature extraction process employed variants of transform functions such as discrete wavelet transforms, stationary wavelet transforms, and bio-orthogonal transform functions. The heuristic approach is employed as a hybrid swarm intelligence algorithm for feature selection in the classification approach. The proposed algorithm was tested in MATLAB environments with BRATS datasets in 2013. The proposed algorithm compares with existing algorithms for brain tumor detection, including CNN, SVM, and EL, among others. The experimental analysis of algorithms improves detection accuracy by 2–3 percent with the existing algorithm. The results suggest that the proposed algorithm is very efficient for brain tumor detection.

Keywords: - Brain Tumor, Transform Function, Feature Fusion, Optimization, Deep Learning Algorithm.

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I. INTRODUCTION

The abnormal growth of cells causes a nodule in the brain, which is known as a brain tumor because the cells divide and grow in an uncontrolled manner. The tumors in the brain can be cancerous and non-cancerous, which are known as malignant and benign. When such types of tumors grow, it causes pressure inside the skull of the brain, as the skull of the brain is rigid and it encloses the complete brain. Such types of pressure might cause damage to the brain and cause a threat to life. The classification of brain tumors is done as primary or secondary. The primary phase of brain tumors is originating in the brain, and after that, they spread to other parts of the human body, such as the lung and heart. Brain tumors are a critical leading disease in healthcare and now can lead to the death of a patient. The diagnosis of brain tumors is a very important phase for the primary stage of tumor detection.

Magnetic resonance imaging (MRI) is widely used in the diagnosis of patients with brain tumors; however, the full potential of these imaging modalities cannot be realized because there are insufficient efficient methods for handling the massive amounts of data generated by the image acquisition system. Using a strong magnetic field and radiofrequency signals to

excite the target tissues, magnetic resonance imaging is a non-invasive in vivo imaging method that creates internal images of the tissues' structure. By altering the excitation and repetition times during the image acquisition process, distinct MRI modalities can be created.

Different MRI modalities produce different types of tissue contrast images, which offer important structural information for precise tumor segmentation and diagnosis. Four standard modalities are obtained from the MRI: fluid-attenuated inversion recovery (FLAIR), T1-weighted MRI (T1), T2-weighted MRI (T2), and T1-weighted MRI with gadolinium contrast enhancement (T1-Gd). T1 images are used to identify healthy tissues, and T2 images are used to identify edema regions because they show a bright signal on the images. The size and noise variations of the tumor pixels present a current challenge in locating them in the brain image. A small number of scanning devices used in medical systems produce noise while scanning images. The pixel affected by noise bears a striking resemblance to the brain tumor pixels. This adds complexity to the suggested method of detecting brain tumors. Therefore, it is urgently necessary to identify and eliminate any noise from the brain images. The proposed methodology is based on a feature extraction approach for the detection of brain tumors. The process of feature extraction employed the wavelet transform function.

The wavelet transform function is texture-dominated feature extraction. The process of feature extraction collects extracted features as low content and high content. The lower content of features has some local noise, which compromises the detection process. Now, employees are using an intelligence-based optimization approach. For the detection of brain tumors, apply deep learning and machine learning algorithms. When a machine receives a labeled set of input data and is expected to extract appropriately labeled data from previously undiscovered datasets, this is known as supervised learning. In other words, supervised learning occurs when a machine learns from an input set and applies that knowledge to other datasets, while unsupervised learning occurs when a machine operates independently. After identifying patterns in one dataset of untrained input, the machine applies the same learning process to the other dataset, continuing to learn from each one.

This paper proposes efficient brain tumor detection methods based on deep learning algorithms. The proposed algorithm is very efficient compared to existing algorithms for brain tumors. The rest of the paper is organized as follows: in Section II, related work, and in Section V.

II. RELATED WORK

The progressive development of deep learning algorithms cracks accurate brain tumor detection. The accurate and improved brain tumor detection has saved millions of human lives. Several authors proposed a deep learning-based algorithm that improves the accuracy of tumor detection. Recently developed algorithms describe merits and demerits. The author [1] used MRI scans to classify three different types of brain tumors using a novel hybrid CNN-based architecture.

This research proposes a hybrid deep-learning classification approach based on CNN, combining two different methodologies. The author proposed a CNN model for the analysis of brain cancer MRI images, along with parametric optimization methodologies. In nine simulation iterations of the proposed model, following Taguchi's L9 design of experiments, the accuracy achieved was precisely 100%.

The author [3] employed a CNN model called DenseNet-169 for classification tasks in conjunction with a novel optimization technique known as the Process for Lightning Attachment (PLA) algorithm. The author [4] discussed the process through which several study phases were carried out in the research methodology section. A systematic literature review was conducted on brain tumor detection using MRI images.

The author [5] presented a solution to the segmentation problem of brain tumors. To achieve this, a technique was proposed for generating artificial CT images to augment existing MRI datasets and improve segmentation accuracy. The author [6] investigated the effectiveness of deep learning methods such as 2D and 3D CNN models and vision transformers, using one of the largest datasets, BraTS 2021.

The author [7] described the 3D brain tumor semantic segmentation task as a sequence-to-sequence prediction problem and proposed SwinBTS, a novel 3D medical image segmentation method combining transformers, CNNs, and an encoder–decoder

architecture. The author [8] suggested that this discovery could provide clinicians and patients with a shared platform for brain tumor diagnosis in the future. However, a limitation of the study is its reliance on a publicly available dataset, as real-time data collection was not feasible due to the pandemic.

The author [9] demonstrated through ablation studies that the proposed model is highly adaptable and generalizable and can be easily incorporated into a variety of neural networks to further enhance their performance, outperforming several state-of-the-art techniques. The author proposed an enhanced U-Net3+ segmentation network with stage residual connections [10].

Experimental results showed improvements in sensitivity for WT, TC, and ET by 1.34%, 4.6%, and 8.44%, respectively. The author [11] incorporated attention modules to eliminate irrelevant features passing through skip connections, thereby reducing computational cost and improving accuracy. The author [12] proposed an integrated hybrid approach for accurate segmentation and classification of brain MRI tumors using deep convolutional neural networks combined with machine learning classifiers. The author [13] reported that the proposed approach achieved strong tumor segmentation results, with dice scores of 83.88% and 88.47% on the MICCAI BraTS'17 and US datasets, respectively.

The author [14] presented an ensemble approach for fully automated brain tumor segmentation using four distinct 3D multimodal MRI scans, based entirely on deep learning. The author [15] applied the Sobel algorithm with an 8-directional template to enhance edge detection in MRI images of brain tumors. The proposed method was compared with other conventional edge-detection algorithms. The author [16] highlighted that hospitals can benefit from this technology for computer-assisted brain tumor classification. In this work, the HPWF filtering technique was first employed to denoise and preprocess the original images.

The author [17] investigated ML-based, CNN-based, CapsuleNet-based, and Vision Transformer-based methods for brain tumor classification and segmentation and provided a comprehensive review of these approaches. The author [18] reported that the segmentation performance of the proposed method was superior to previous methods, with dice coefficients for the tumor enhancement region and tumor core increasing by 1.3% and 2.4%, respectively.

The author [19] designed a network architecture where the encoder and decoder are connected through multi-resolution feature fusion modules, which combine semantic features from deeper layers with spatial detail features from earlier layers. This improves the network's ability to recognize and segment local details, thereby enhancing segmentation accuracy. The author proposed a lightweight and computationally efficient 3D CNN for brain tumor MRI segmentation, replacing traditional CNN layers with improved depth-wise CNNs to reduce computational cost [20].

The author [21] demonstrated that their approach outperforms several other methods across various metrics. The kernel low-rank model's integration of a sparsely constrained coefficient matrix in the kernel space helps preserve local structures and tumor details. The author [22] introduced a method that delays floating-point encoding and decoding operations until the end of the network layers, enabling most dot-product operations to be performed using integer arithmetic for improved efficiency.

The author [23] pre-processed the brain input using a median filter, extracted features using the GLCM method, and separated tumor regions from the background using thresholding and K-means clustering. The author [24] aimed to develop an end-to-end multimodal brain tumor segmentation system capable of distinguishing the background, healthy tissue, and the entire tumor core. The author [25] showed through simulation results that the proposed method achieves lower error rates and higher accuracy compared to alternative methods. Experimental evaluation was conducted to validate the model's effectiveness.

III. PROPOSED METHODOLOGY

This section describes the proposed methodology for brain tumor detection. The process of brain tumor detection is represented in figure 1. The process of model encapsulation occurs in three phases: first phase feature extraction, second phase feature optimization, and finally detection of the tumor.

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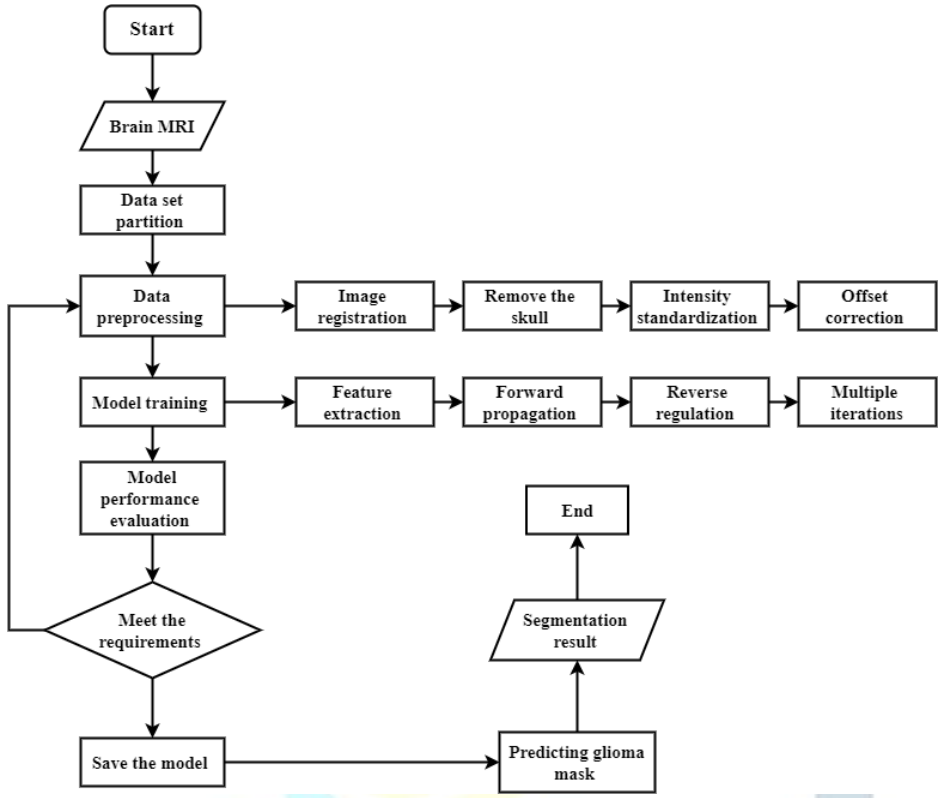

Figure 1: Proposed model of number plate detection

The employees transform SWT (2) into a dedicated dataset of MRI. The employed SWT (2) process decomposed the feature content of brain tumors, and data mapped as a function

$$Fx_{(N)} = \sum_{j-1}^{n} S_j^{diag}(N) Frj,k+wv(M)\ j=1,2,\ldots\ldots\ldots,Nt \ldots\ldots\ldots\ldots\ldots\ldots (4.6.1)$$

Here $r_{j,k}$ denotes the texture feature coefficient of T1 and T2.

Here $X = [x_1, x_2, \ldots\ldots, x_N] \subset F^t$, each x_i represents a feature coefficient, where l is the total number of coefficients, N is the number of layers of transform.

$$N^t \to F, x_i \to \emptyset(x_i) \ldots\ldots\ldots\ldots\ldots\ldots (4.6.2)$$

The features X is expressed in the high feature space for convocational neural network F as follows:

$$\emptyset(X) = \emptyset(x_1), \emptyset(x_2), \ldots\ldots\ldots\ldots \emptyset(x_N),] \ldots\ldots\ldots\ldots\ldots\ldots (4.6.3)$$

The processing of CNN estimation procedures and finds the optimal features for effective detection of characters. The process of CNN proceeds as a convolution layer, a pooling layer, and a fully connected layer. Each layer of the CNN network performs a distinctive function for constructing features maps. The pooling layers deal with the sampling of features, and the fully connected layer estimates the embedding position.

Convolution layer: - the potential of convolution to derive the patterns of features using the filter.

The output of filter is estimated as f_y.

$$fy = \left(S_q^P\right) + \sum_{g=1}^{K} \sum_{\delta=k}^{k1} \sum_{h=k1}^{k2} \left(F_q^p\right) * \left(f_g^{q-1}\right) g + \delta + k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.6.7)$$

Here * is convolution and k is features of filters and variable g, K is range of maps of features.

Pool layer: the processing of pooling layer deals with fixed operator operation.

Fully connected layers: the output of the pooling layer process as input of the FC layer. After the processing of layers, estimate the final region for the embedding.

Training pilot symbol of signal $(X_i \in N, O_i \in M)$, $i = 1, \ldots\ldots n$, subcarrier k, message length l, kernel of network $\emptyset(.)$, bias $b = 10^{-1}$,threshold $Thres = 1$

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$Vector\ of\ symbol$ if $*= vec$ or if $*= dia$

$[x^1, \ldots . x^k] \leftarrow [rand(1,k) \times (vector - l)] + 1$

$KF \leftarrow N$ number plate features in the feature space of CNN

For $i \leftarrow 1\ \ toN\ do$

$N_*^i \in K^l \leftarrow amplitude\ of\ S$

$IS_*^i \in N^l \leftarrow vector\ from\ of\ T1\ \&\ T2$

End for

Matching of estimation $e_*^1, \ldots \ldots . e_*^m$ to a SE variance

$N_{FF} \in O^{l \times m} \leftarrow \emptyset([e_*^1, \ldots \ldots . e_*^m])\quad update\ baise$

$W \in N^{l \times m} \leftarrow F\quad Maligaint$

Polling of CNN network $W \in N^{m \times m}$

$FF_c \in N^{l \times m} \leftarrow (V(K) + Wc)^{-1}$

End for

IV. EXPERIMENTAL ANALYSIS

To evaluate the efficiency of the proposed algorithm, implement MATLAB tools with version R2014a. The setup of system hardware and software is an i7 processor, 8 GB RAM, and the Windows 11 operating system. The detection of brain tumors is determined by the confusion matrix. The factors of the confusion matrix are TP (true positive), TN (true negative), FP (false positive), and FN (false negative). The classification of tumors is categorized into two classes, class-1 and class-2. The representation of class-1 is abnormal, and class-2 is abnormal. The description of parameters is [24, 25, 26]. To validate the proposed algorithm, use the BRATS dataset 2013. The 2013 dataset consists of 65 gliomas; in the 65-glioma dataset, 51 are high-grade gliomas and 14 are lower-grade gliomas.

$$Accuracy\ = \frac{TP + TN}{TP\ +\ TN + FP + FN} \times 100$$

$$Sensitivity = \frac{TP}{TP\ +\ FN} \times 100$$

$$Specificity\ = \frac{TN}{TN\ +\ FP} \times 100$$

TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

To validate the proposed algorithm, use the BRATS dataset 2013. The 2013 dataset consists of 65 gliomas; in 65 glioma datasets, 51 are high-grade gliomas and 14 are lower-grade gliomas.

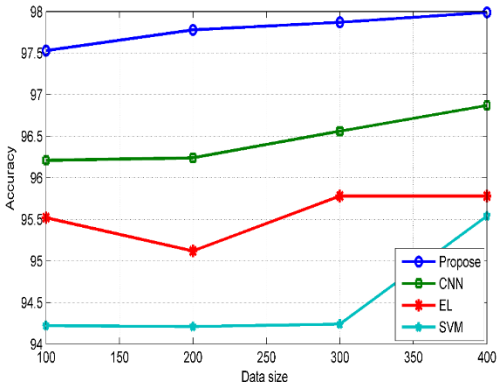

Figure: 1 Performance analysis of accuracy on tested BRATS 2013 dataset

Figure 1 depicts the detection accuracy of the 2013 brain tumor dataset. The grouping of sample data sizes in ratios of 100, 200, 300, and 400 The accuracy of the proposed algorithm is higher than that of other existing algorithms such as CNN, extreme learning, and support vector machines. The hybrid feature extraction process is employed in all classification algorithms. The increased accuracy of the detection algorithm is only due to the optimization of the lower-content features of the MRI images dataset. The employed optimization algorithm reduces lower-level content noise and improves the detection of tumor and non-tumor regions of images. In comparison to existing algorithms, the proposed algorithm has an accuracy of up to 98%. The detection accuracy of CNN, EL, and support vector machines ranges from 96 to 97%.

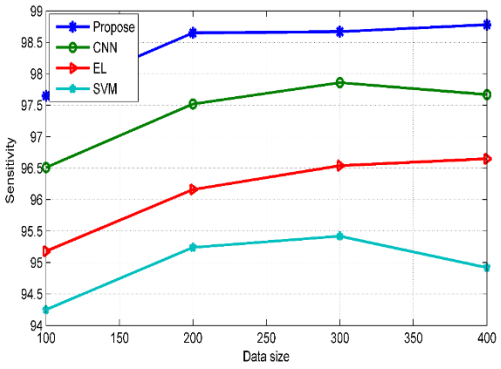

Figure 2: Performance analysis of sensitivity on tested BRATS 2013 dataset

Figure 2 represents the sensitivity of detection in the BRATS 2013 dataset. The sensitivity of the proposed algorithm reaches up to 98.9% instead of other existing algorithms such as CNN, extreme learning, and support vector machines. The hybrid feature optimization increases the sample selection ratio of MRI image data for the process of detection. The process of optimization overcomes the limitation of feature automapping in classification. The sensitivity of the other employed classification algorithms is between 98% and 98%. The enhanced results of sensitivity prove the effectiveness of the proposed algorithm. The sample data is segmented into 100, 200, 300, and 400.

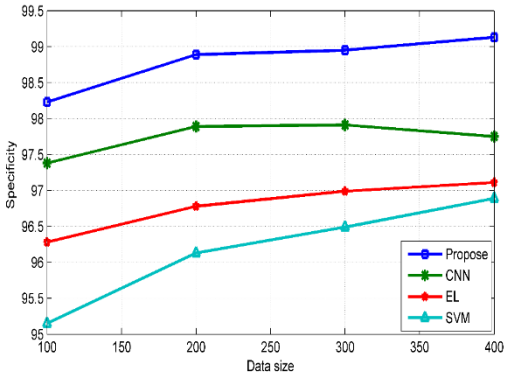

Figure 3: Performance analysis of specificity on the tested BRATS 2013 dataset

Figure 3 depicts the results of the specificity of the BRATS 2013 dataset. The results of specificity explore the enhancement of training of the feature component of the MRI images dataset. The maximization of training increases the specificity ratio of proposed algorithms. Instead of the proposed algorithm, other algorithms also perform well, but the existing algorithm suffers from the feature optimization and feature selection processes. The proposed algorithm applies an optimization algorithm to minimize the limitations of parameters and enhance the results of specificity up to 98.8%. The BRATS dataset is divided into four segments: 100, 200, 300, and 400.

V. CONCLUSION & FUTURE WORK

The objective of the proposed "stacking ensemble" algorithm is accurate detection of brain tumors. The proposed stacking algorithm is an ensemble of MKSVM. The major contribution of this paper is the proposed hybrid feature optimization based on fireflies and glowworm optimization algorithms. The process of optimization reduces the lower content of noise extracted by three feature extractors, such as DWT, BWT, and LWT. As a result, the proposed algorithm optimized the mapping process, gave better results in all ways, and is appropriate for mapping the features in the brain tumor images. In comparison to CNN, SVM, and EL, the proposed algorithm is evaluated. The proposed model achieved 99.7% accuracy, which is 1.17% to 3.13% higher than other techniques, with a sensitivity of 97.32%, which is 2.06% to 5.1% better than other approaches, and a specificity of 98.24%, which is 0.5% to 3.6% improved compared to other techniques. The future use of a hybrid deep learning approach using a deep transfer learning model for classifying brain tumors using pertinent image datasets may improve performance. Our results were determined to be 2% better than the previously best-known deep learning result of 92.30%, demonstrating that our suggested approach is extremely capable of boosting brain tumor detection. We strongly advocate that the proposed system serves as a second opinion to radiologists and clinical professionals for this extremely successful decision-support system for the early detection of brain tumors in the susceptible population.

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