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PRE-OPERATIVE & POST RECURRENCE BRAIN TUMOR MR IMAGES CLASSIFICATION AND PIXEL CHANGE DETECTION USING FRACTIONAL HUNTER PREY OPTIMIZATION (FHPO)-SQEEZENET METHODS

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Abstract
Brain tumor (BT) is recognized as a deadly tumor disease across worldwide and is generally found in every age group. Brain tumor is a group of tissues that spreads abnormally as well and it gradually leads to death. Moreover, earlier detection and classification of brain tumor help doctors to forecast the severity grades of tumor and increases the survivability of brain tumor-affected patients. The precise BT classification and the detection of pixel change utilizing pre-operative (pre-op) and post-recurrence (post-op) magnetic resonance imaging (MRI) images are a complicated chore. Here Fractional Hunter Prey Optimizer (FHPO)-SqueezeNet is presented for brain tumor classification utilizing pre-operative and post-recurrence MRI images. The adaptive wiener filter is employed for pre-processing pre-operative MRI as well as post-recurrence MRI images. Additionally the extraction of the Region of Interest (ROI) is also executed in a pre-processing step. The segmentation is done utilizing Psi-Net which is trained by FHPO. Moreover, FHPO is a merging of Fractional Calculus (FC) and Hunter–Prey Optimizer (HPO). Then, features are extracted in segmented outputs for the classification process. The brain tumor classification is executed by employing SqueezeNet that is also tuned by FHPO. At last, pixel change detection is conducted in classified outputs of pre-operative MRI and post-recurrence MRI images utilizing Speeded-Up Robust Features (SURF).

Keywords: Hunter–Prey Optimizer (HPO), Fractional Calculus (FC), adaptive Weiner filter, SqueezeNet, Psi-Net.

1. Introduction
In the area of clinical imaging analysis, MRI plays a vital part in complete support of neuroradiology during patient diagnosis. As it offers an extensive range of physiological differences to identify different developing tissues as well as the development of diverse tissue architecture found within diffuse gliomas, the MRI is widely used throughout the world as it helps to construct various categorization processes for multi-grade brain tumor MRI images. These MRI images have a significant part in diagnosis by reducing the need for procedures. According to research, the most prominent imaging method employed in the majority of hospitals is high-resolution MRI [2]. One of the most lethal and serious cancers in both adults and children is the brain tumor. To properly treat a brain tumor, it is crucial to identify a brain tumor in the early stage and classify it according to grade. Brain tumor as well

as tumors of the central nervous system is further broken down into grade I to grade IV malignancy levels by the World Health Organization (WHO) [10]. Even with significant improvements in therapeutic care, glioblastomas are still thought to be the most fatal type of tumor [11]. Histopathology is the main technique used to distinguish grade IV tumors from other grades. Necrosis, microvascular proliferation, and vascular thrombosis characteristics of grade IV tumors can be used to make a first distinction [12]. In contrast, these characteristics are not always obvious and may be challenging to identify, and pathologists have been noted to have differing opinions on them [13] [4].

Segmenting a brain tumor entails dividing the various tumor tissues from healthy brain tissues. To identify tissues of brain tumor, image segmentation from MRI is a crucial and difficult undertaking. The segmentation of the brain using brain MRI is a fundamental process with numerous uses in neurology, including quantitative analysis, operational planning, and functional imaging [9]. The complex structure and wide range of images make it a difficult endeavor. The various segmentation methods, including Berkeley Wavelet transform [15], semi-supervised learning with graph cuts [14], and genetic algorithms based on FCM [15] [16] [9], wavelet transform image segmentation [20], region growth segmentation, K-means clustering [18], spectral clustering [19], and the graph cut algorithm with co-segmentation for determining the precise cut point between edema and tumor [17] [21]. For the segmentation of brain tumor, hidden markov random field models have been developed [8].

Using pre-operative and post-recurrence MR imaging, the classification of brain tumor [25] and percentage in change detection is a very difficult assignment. The MRI scan of a patient taken just prior to surgery constitutes the pre-operative image. The pre-processing step involves running the input image by means of filtering approach and a ROI extraction to exclude exogenous catastrophes and undesirable noises [3].Bright corners of brain near the skull may cause flat lumps to look as tumor regions; this is removed post-operatively using a connected components labeling method [4]. As a post-recurrence procedure, the tumor cluster is excised and subsequently contoured using thresholding and active contours [9].

Speeded-up robust features (SURF) are used to determine the percent of change in tumor pixels in post-recurrence and pre-operative images. An altered location and percentage of the tumor's pixels that have altered are identified using pixel mapping and post-surgery MRI imaging. A digital image is made up of multiple pixels. These pixels are also termed pictures or image elements. An act of applying an algorithm to a digital image through the use of a computer is known as digital image processing. This makes the interior of image structures visible, even if they are obscured by elements like skin and bones. This facilitates diagnosis and proper treatment by physicians [3]. There have been numerous deep learning architectures suggested thus far to automate the process of brain tumor contouring, which recently enabled to signify features that might be difficult to capture by humans. Numerous generative adversarial models, convolution neural networks, residual architectures, inception-based networks, context-aware models, and other techniques fall under this category, but recent editions have made it abundantly clear that U-Net-based architectures perform better than others in this task. The variations of this encoder-decoder model include lightweight U-Nets, U-Nets with various loss functions, U-Nets that also capture the characteristics of the boundary tumor, hardware-optimized models, hybrid algorithms that combine U-Nets with densely-connected and residual architectures, ensemble U-Nets, and so on [1]. These techniques successively detect entire-tumor regions and thereafter segment particular kinds of brain tumor tissue

2. Literature Survey

Nalepa, J., *et al*. [1] designed a deep learning pipeline for the classification of pre-op and post-op MRI images. It obtained precise segmentation of pre-op as well as post-op MRI in a fraction of the time, but Response Assessment in Neuro-Oncology (RANO) calibrations was not adequate for quantifying tumor load. Shiny, K.V. and Sugitha, N.,[2] developed a Deep Belief Network and Convolutional Neural Network (DBN+CNN) for efficient BT classification to attain maximal assessments, even though it had high computation costs. Sugitha, N., and Shiny, K., *et al*. [3] introduced the Bir-Cat algorithm (BCA) for automated segmentation as well as classification of pre-op and post-op MRI images. This method attained low computation time, though it separated solid tumors only based upon textures. Sajjad, M., *et al*. [4] developed CNN for multi-level classification of BT. It assisted the radiologists in making accurate decisions to classify multi-grade BT into four kinds of grades, but still, it did not examine this technique for finely-grained classification.

Agrawal, P., *et al*. [5] devised 3D-UNet and deep neural network (3D-UNet+DNN) for segmenting and classifying BT. It was proven that neural networks such as CNN had great potential for BT classification. This method failed to help the wide applications of artificial intelligence to the global population. Togacar, M., *et al*. [6] presented Brain MR Net for detection of BT utilizing MRI. In this approach, the evaluations that affected negatively were reduced utilizing residual blocks. Kaplan, K., *et al*. [7] designed modified LBP feature extraction techniques for BT classification. This technique was simple, easier, and less costly, even though it failed to implement a decision support method for the radiologists. Mishra, S., *et al*. [8] introduced an adaptive sine cosine optimization algorithm and particle swarm optimization based local linear radial basis function neural network (ASCA+ PSO based LLRBFNN). It was utilized for the medical diagnosing process by medical experts or radiologists. This method failed to implement diverse hybrid algorithms and harmony search for the weight optimizations of a classifier.

3. Research Methodology

The main intention of this research will be to develop and design brain tumor classification and pixel data detection based on Squeeze Net Fractional Hunter Prey optimization (FHPO) utilizing MRI images. In Figure(1) the pre-operative MRI image acquired from the dataset [22] will be fed up into the pre-processing unit in order to remove the presence of noise using Region of interest (ROI) and adaptive wiener filtering. After that, the pre-processed image will be fed up to the segmentation process for brain tumors employed by Psi-Net [23], which will be trained utilizing the proposed FHPO. Here, the proposed FHP is an integration of hunter-prey optimization (HPO) [26] and Fractional Calculus (FC) [27]. Moreover, the tumor classification will be conducted using SqueezeNet [24], which will be trained using the proposed FHPO. Here, the classified tumors include edema (label 1), advancing tumor (Label 2), non-advancing tumor (label 3), and necrotic tumor core (label 4)**.** On the other hand, the post-operative MRI image will be also fed up into the pre-processing unit to remove the noises using ROI and adaptive Weiner filtering. After that, the segmentation process will be carried out by PSP-Net [25], which will be trained using the same FHPO. Furthermore, the segmented image will be subjected to the brain tumor classification employed by Squeeze Net [24], which will be trained using the proposed FHPO. By combining the outcomes of both pre and post-operative MRI images, pixel change detection will be accomplished by Speeded-up robust features (SURF) features. Figure(2) shows simplified form of figure(1).

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4. Features extraction:

Feature extraction is a critical phase in image processing applications, and efficient techniques can significantly enhance the performance of a model. Segmented outputs pre-operative and post-recurrence images are taken as an input to carry out feature extraction.
The features considered are

- Local Gradient Patterns (LGP),
- Line Operator of Orientation Pattern (LOOP),
- Local Binary Patterns (LBP) and various statistical features.

Statistical features are

- ❖ Mean
- ❖ Variance
- ❖ Standard deviation
- ❖ Entropy
- ❖ Skewness.

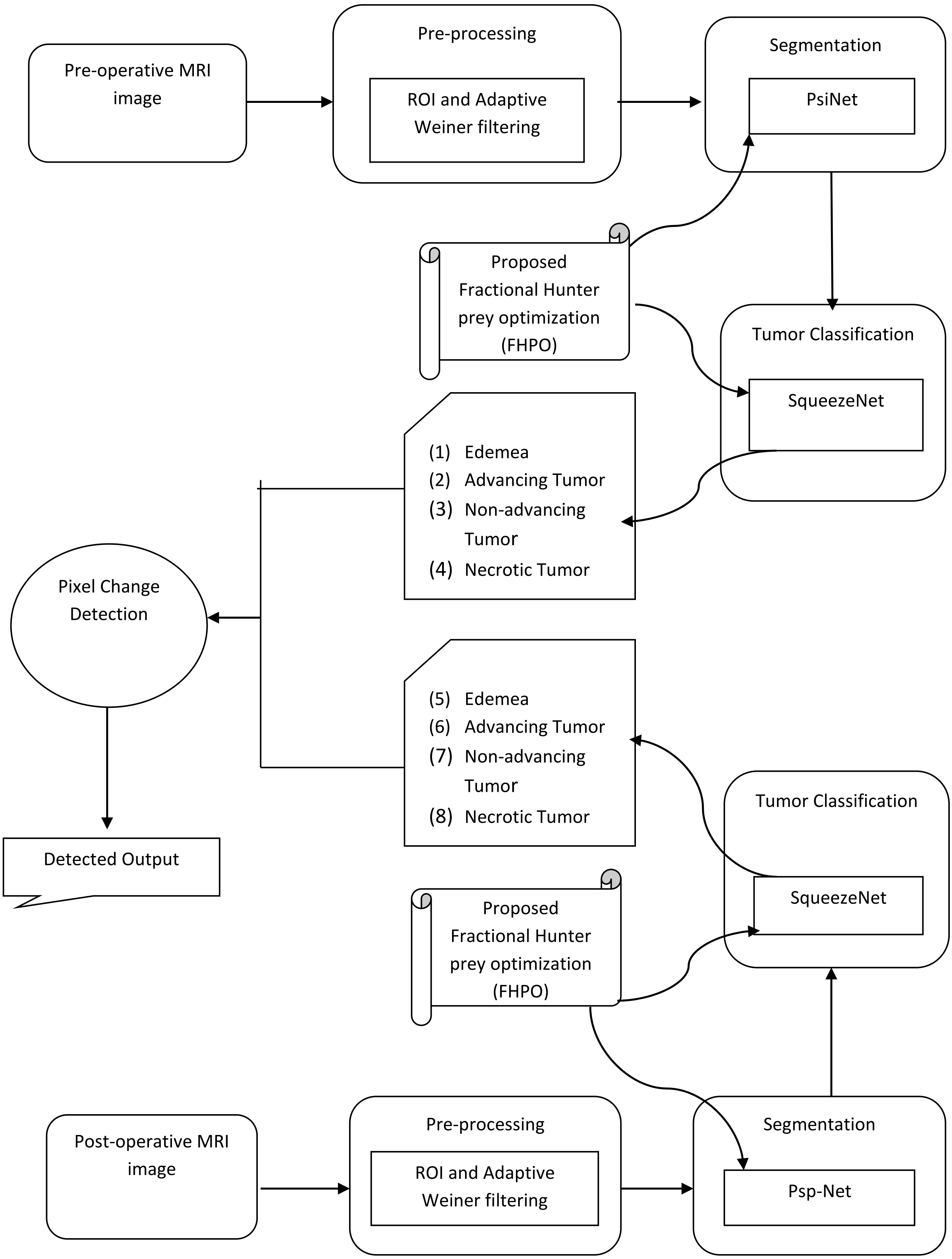

Figure 1. Block diagram for brain tumor classification and pixel change detection using proposed FHPO based MRI images

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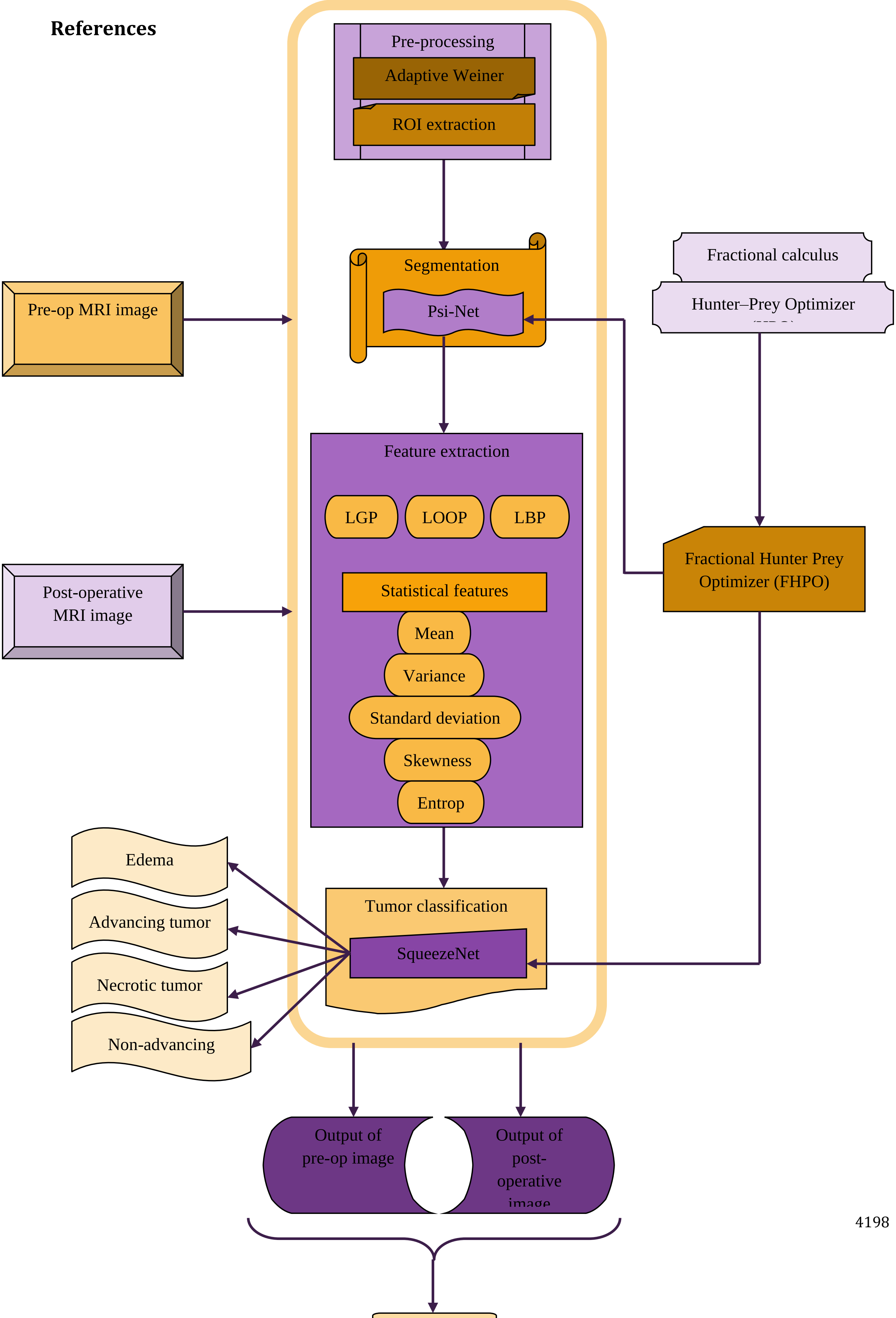

Figure(2) Simplified block diagram for brain tumor classification and pixel change detection using proposed FHPO based MRI images

Tumor classification using SqueezeNet is done by following steps:

1. **Data Preparation:**

- Collect a labeled dataset of medical images containing both tumor and non-tumor samples.
- Split the dataset into training, validation, and test sets.

- **2. Preprocessing:**
- Preprocess the images, including resizing them to the input size expected by SqueezeNet (e.g., 224x224 pixels).
- Normalize pixel values to a suitable range (often between 0 and 1).
- Augment the training set with techniques like rotation, flipping, and zooming to increase robustness.

3. Model Selection and Transfer Learning:

- Download the pre-trained weights of SqueezeNet. SqueezeNet is often available in popular deep learning frameworks like PyTorch or Tensor Flow.
- Remove the final classification layer(s) of SqueezeNet, as it was originally trained on a different task (e.g., ImageNet classification).
- Add a new set of fully connected layers at the end of the network for your specific tumor classification task.

4. Model Training:

- Train the modified SqueezeNet on your tumor dataset. Use the training set for training and the validation set for tuning hyper parameters and preventing over fitting.
- Monitor training metrics such as accuracy, loss, and validation accuracy.

5. Fine-Tuning (Optional):

- If necessary, fine-tune the model on your dataset. This involves training the model for additional epochs with a lower learning rate.

6. Evaluation:

- Evaluate the trained model on the test set to assess its performance on unseen data.

Use evaluation metrics such as accuracy, precision, recall, F1 score, and area under the Receiver Operating Characteristic curve (AUC-ROC) depending on your specific requirements. Feature extraction and brain tumor classification is shown in figure(3) and its Algorithm is shown in table(1). SqeezeNet Architecture dimentions are shown in Figure(4).

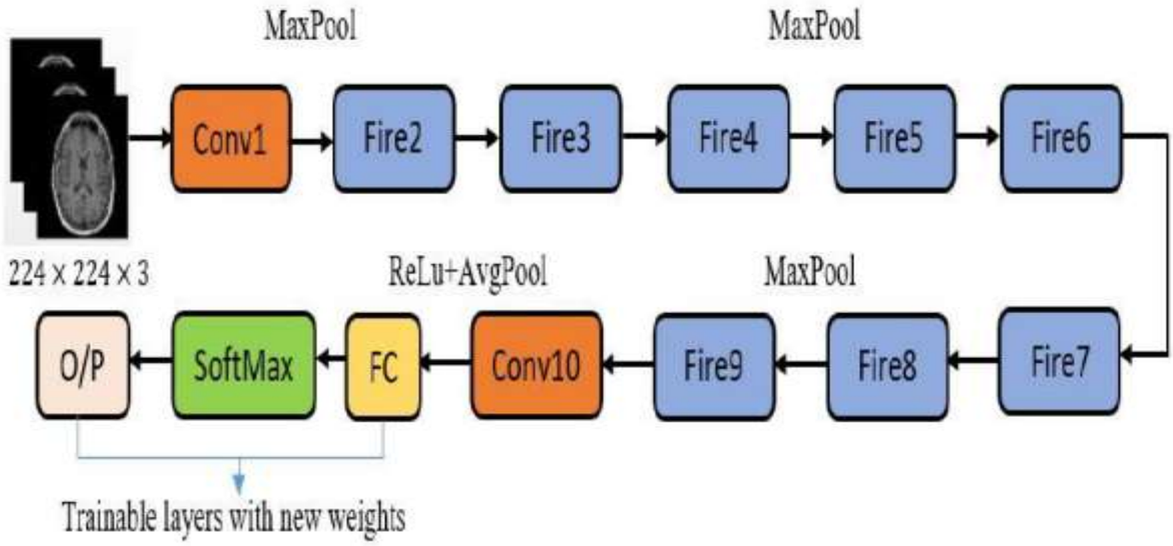

Figure (3) Squeezenet Architecture

Table (1) Algorithm:Brain Tumor Method detection

Algorithm:Brain Tumor Detection Method

1.Input :Image Dataset

2.Output:Trained brain tumor classifier

3.Data Preparation:

Resize the image dataset

Spli the dataset learning data Dtot (Training data Dtt, Validation data Dtv, Testing data Dts)

4. CNN parameters setting

Initialize hyper parameters

5.The Proposed CNN network setup: the layers are generated as follows

#Convolution layer (CONV 1)

#Eight fire modules

#Convolutional layer (10)

#softmax layer

6. Training:For all Epochs do

Train the defined CNN architecture

Fine tuned hyper parameters to choose the best model and avoid over fitting

Save weights

End for

7.Validation and Testing:For Dtv,Dts, do

Re-define CNN architecture and load weights

Test the proposed model

Classify the the classes and generate confusion matrix

Calculate Accuracy,Sensitivity,Specificity, Precision

End for

Table(2) Comparative discussion of FHPO-SqueezeNet

layer name/type	output size	filter size / stride (if not a fire layer)	depth	s_{1x1} (#1x1 squeeze)	e_{1x1} (#1x1 expand)	e_{3x3} (#3x3 expand)	s_{1x1} sparsity	e_{1x1} sparsity	e_{3x3} sparsity	# bits	#parameter before pruning	#parameter after pruning
input image	224x224x3										-	-
conv1	111x111x96	7x7/2 (x96)	1				100% (7x7)			6bit	14,208	14,208
maxpool1	55x55x96	3x3/2	0									
fire2	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	11,920	5,746
fire3	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	12,432	6,258
fire4	55x55x256		2	32	128	128	100%	100%	**33%**	6bit	45,344	20,646
maxpool4	27x27x256	3x3/2	0									
fire5	27x27x256		2	32	128	128	100%	100%	**33%**	6bit	49,440	24,742
fire6	27x27x384		2	48	192	192	100%	**50%**	**33%**	6bit	104,880	44,700
fire7	27x27x384		2	48	192	192	**50%**	100%	**33%**	6bit	111,024	46,236
fire8	27x27x512		2	64	256	256	100%	**50%**	**33%**	6bit	188,992	77,581
maxpool8	13x12x512	3x3/2	0									
fire9	13x13x512		2	64	256	256	**50%**	100%	**30%**	6bit	197,184	77,581
conv10	13x13x1000	1x1/1 (x1000)	1				**20%** (3x3)			6bit	513,000	103,400
avgpool10	1x1x1000	13x13/1	0									
	activations	parameters					compression info				1,248,424 (total)	**421,098** (total)

5. Results and Discussion

Fractional Hunter prey Optimization (FHPO) Squeeze Net acquired finest results while comparing with deep learning pipeline, DBN+CNN, 3D-UNet+DNN and BrainMRNet and the achieved outcomes are interpreted in table 2. The table clearly demonstrates FHPO-SqueezeNet obtained maximum accuracy, sensitivity and specificity of 90.4%, 92% and 92.2% for pre-op image while considering training data=90%.

Images	Analysis based on	Metrics/ Methods	Deep learning pipeline	DBN+CNN	3D-UNet+DNN	Brain MRNet	Proposed FHPO-SqueezeNet
Pre-operative	*Training data=90%*	*Accuracy*	78%	79%	83%	88%	**90.4%**
		Sensitivity	79.6%	80%	85.7%	87.7%	**92%**
		Specificity	76.4%	79.4%	86.5%	85.5%	**92.2%**
	K group=9	*Accuracy*	75.7%	80%	82.7%	85.9%	93%
		Sensitivity	75.7%	80%	87.7%	88.9%	91.9%
		Specificity	79.6%	81%	85.7%	87.7%	90.5%
Post-operative	*Training data=90%*	*Accuracy*	75.7%	79.6%	85.7%	87.7%	92.7%
		Sensitivity	79%	76.5%	79.7%	89.6%	92%
		Specificity	79.6%	80%	85.7%	87.7%	90.7%
	K group=9	*Accuracy*	74.9%	78.8%	84.8%	86.8%	91.8%
		Sensitivity	78.2%	75.7%	78.9%	88.7%	91.1%
		Specificity	78.8%	79.2%	84.8%	86.8%	89.7%

Figure(4) Sqeezenet Architecture Dimentions

6. Conclusion

Earlier detection and classification of brain tumor enhances clinical options as well as affected patients' recovery chances. MRI is considered a common imaging modality utilized for detecting and diagnosing brain tumor. Moreover, manual classification and identification of BT from the huge count of MRI images in the medical field exclusively depends upon the time and skill of clinical experts. In this work, FHPO-SqueezeNet is introduced for BT classification utilizing post-op and pre-operative MRI images. Obtaining pre-operative and post-recurrence MRI images from specific databases are pre-processed initially. In pre-processing, unwanted noises are eliminated utilizing an adaptive Weiner filter, and extraction of Region of Interest (ROI) is also performed. Psi-Net is employed to carry out segmentation, wherein Fractional Hunter prey Optimization (FHPO) is used to train Psi-Net. However, FHPO is a combination of Fractional calculus (FC) and Hunter Prey Optimization (HPO). Afterward, features namely statistical features, LBP, LOOP, and LGP are extracted. Afterward, BT classification is done by SqueezeNet, which is also tuned by FHPO. Lastly, pixel change is accomplished using two classified images based on SURF.

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