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An Efficient Multi-Texture Flow Classifier for Medical Image Analysis on Pet Images

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Abstract: Medical image analysis for tumor and cancer detection needs to exactly identify the location and intensity of the lesions in the patient's images. The clinical study of tumors was either detected manually or semi-automatically in Positron Emission Tomography (PET) images. However making more efficient detection of tumors needs segmentation and classifier models on PET images. Existing tumor and lesion detection in PET images were constructed by generally classifying the lesions and shaping the medical images compromising quantitative classification and tumor detection rate. In this work to determine quantitative classification and improve the tumor detection rate in the medical PET images, a technique called, Multi-Textured Flow Classifier (MTFC) is introduced. MTFC classifies the contour points toward the object (i.e.,) of interest in PET image boundary with potential flow rate computation. The contour is initialized to zero while computing the potential force on PET image flow aiming at improving the tumor classification accuracy. MTFC classifies color, texture and contour features in the trained and test data set of PET images. MTFC color features are classified based on the Color Topology (CT) method. CT computes the mean, variance and skewness on each PET image, therefore reducing the tumor classification time on PET images. MTFC evaluate texture flow classification using the Flow Directional Threshold (FDT) method on the PET images. The FDT process offers probability result on the two pixels which are located with an inter distance and a direction, improving the tumor detection rate. In MTFC, the Geometric Description based on nonlinear transform function is used to classify the lesion, tumor and normal regions of the PET images this helps for improving the quantitative classification on PET images. The proposed technique has been extensively evaluated on 35 training subjects using primary tumor domain dataset extracted from UCI repository. The MTFC technique achieved higher classification accuracy of x% by reducing the tumor classification time by y% on PET images when compared to state of the art works.

Keywords: Positron Emission Tomography, Tumor and Lesion Detection, Multi-Textured, Flow Classifier, Color Topology, Flow Directional Threshold, Geometric Description

1. INTRODUCTION

The acquisition of PET images makes a feasible study to identify functional and anatomical modalities during segmentation and classification. Most of the recent research concentrated on certain labeling techniques and only a few recent studies have been devoted to the automatic detection of tumor and lesion in the PET images based on multiple modalities. Lacunarity in Multifractal Analysis of Breast Tumor Lesions (LMA-BTL) [1] evaluated Receiver Operating Characteristics aiming at efficient distinction between benign and malignant findings. Segmentation of Prostatic Zones using Active Appearance Models (SPZ-AAM) [2] segmented multiple objects with the objective of improving the segmentation time. A B Spline Coefficient with B Spline function [3] was used to reduce the segmentation computation cost. A multi object segmentation method [4] for efficient segmentation of multiple objects was presented using object-specific and boundary-specific modes. A feature selection approach [5] incorporate filter and wrapper techniques into a sequential search process for improving the classification performance of the features selected.

In [6], adaptive filtering under multiple degraded acquisitions was presented aiming at improving the classification results using optimal adaptive filtering. In [7], embedded level set method was applied to

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improve the segmentation results using Markov Random Field (MRF). In [8], self cross detection was applied to videos aiming at minimizing the erroneous results using cross detection algorithm. In [9], Hessian-based Norm Regularization was applied to TV images aiming at reducing the computation time using Iterative Reweighted Least Squares (IRLS). In [10], efficient segmentation of skin lesions was performed using texture-based skin lesion segmentation algorithm resulting in the segmentation accuracy. Segmentation of structure-and-motion is considered to be the most important step towards the dynamic scene interpretation when captured using a moving camera. Branch and Bound Model Selection [11] was applied for robust segmentation using combinatorial optimization approach. A Multiphase Join Segmentation [12] model was introduced aiming at improving the objects being tracked in an efficient manner using optical flow calculations. Shape-based normalized cuts [13] for biomedical applications were introduced resulting in good segmentation using normalized cut based segmentation algorithms. Co-segmentation algorithm [14] efficiently performed shape based co-segmentation for biomedical images aiming at improving the segmentation rate.

One of the most important challenges faced in the medical image processing and analysis is the quick and efficient processing of huge amount of data, due to the growing diagnostic medical imaging devices. In [15], efficient segmentation of 3D images was performed by applying supervised determination method. This method not only improved the segmentation accuracy but also reduced the significant loss in reasonable amount of time. An efficient image segmentation approach using K-means clustering technique integrated with Fuzzy C-means algorithm was introduced in [16] for the detection of exact brain tumor. Automatic lung tumor segmentation mode on PET/CT images using fuzzy Markov random field was developed in [17] for achieving more effective tumor segmentation. The Gaussian mixture model (GMM) was developed in [18] for effective PET image segmentation. An automated detection and classification procedure was introduced in [19] for detection of cancer from microscopic biopsy images using clinically important and biologically interpretable set of features. The automated computer quantization was performed through image segmentation and also it involves both anatomical and functional images presented for specific tumor boundary description [20]. In [21], a systematic review on PET and CT studies were performed to measure the false discovery rate. In [22], Amplitude Modulation Frequency Modulation (AM-FM) technique was applied for efficient differentiation between normal and cancer lungs. This technique resulted in the improvement of accuracy of disease classification that too at an early stage.

In this article, we investigate the use of Multi-Textured Flow Classifier conditioned by the potential flow rate computation, for determining quantitative classification of lesion and tumor in the medical PET images. We aim to evaluate new objects of interests by eliminating the unwanted object of interest using potential flow rate computation. Next, mean, variance and skewness on each PET image for color features are obtained in more detail using the Color Topology method which characterize in more detail the tumor classification time. Next, the aim of improving the tumor detection rate is accomplished by Flow Directional Threshold (FDT) method on the PET images. In order to improve the quantitative classification on PET images, efficient classification of lesion, tumor and normal regions of the PET images are made using Geometric Description. The results obtained with the proposed technique are compared with LMA-BTL and SPZ-AAM methods, which represent a clinical standard for analysis of tumor and lesion classification.

2. MATERIALS AND METHODS

In this section, the technique proposed to characterize quantitative classification of tumor and lesions in the medical PET images and to improve the tumor detection rate is described. Figure 1 shows the flow diagram of Multi-Textured Flow Classifier in PET images.

Details are presented in the following sub sections, i.e. construction of potential flow rate computation from the training PET images and Classifier model enforcing the color, texture and contour features in the

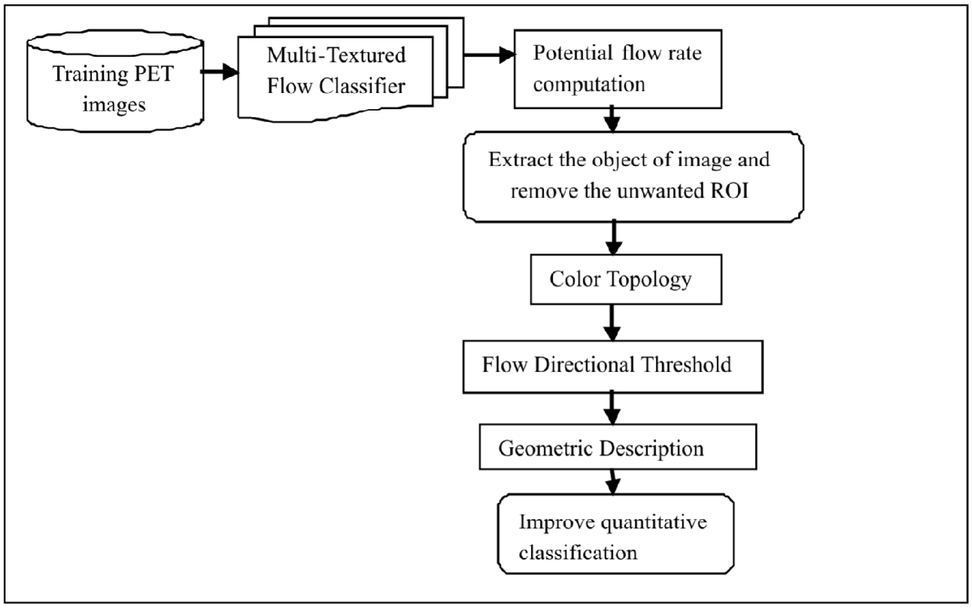

Figure 1: Flow diagram of Multi-Textured Flow Classifier in PET images

trained and test data of PET images and further integrating it to classify them as lesion, tumor or normal regions of the PET images.

2.1. Design of potential flow rate computation

MTFC classifies the contour points toward the object (i.e.,) of interest in PET image boundary with potential flow rate computation. The contour is initialized to zero while computing the potential force on PET image flow aiming at improving the classification accuracy. Let us consider a training PET image '$Image_i = Image_i, \ldots, Image_n$' for which the contour points have to be classified towards the object of interest using potential flow rate computation. The potential flow rate for obtaining object of interest is evaluated as given below.

$$PFR(001) = \sum_{i=1}^{n} \frac{BP = C_i}{BP} \qquad (1)$$

From (1), the potential flow rate '*PFR*' for object of interest '001' is evaluated based on the base potential value '*BP*' and the contour value 'C_i' respectively. With the object of interest extracted from the original PET images, the unwanted regions of interest (ROI) are eliminated aiming at improving the classification accuracy.

2.2. Design of Multi-Textured Classifier model

The Multi-textured Classifier model classifies color, texture and contour features in the trained and test data set of PET images. MTFC color features are classified based on the Color Topology (CT) method that measures the mean, variance and skewness on each PET image. Followed by this, the Multi-textured Classifier model evaluates texture flow classifications using the Flow Directional Threshold (FDT) method on the PET images. Finally, the contour features are classified using Multi-textured Classifier model with the aid of Geometric Description with the objective of efficient classification of PET images as lesion, tumor or normal regions. Figure 2 shows the block diagram of Multi-textured Classifier model.

2.3. Color Topology (CT) method

The Multi-textured Classifier model classifies color features based on the Color Topology (CT) method. The CT method computes the mean, variance and skewness on each PET image, therefore reducing the

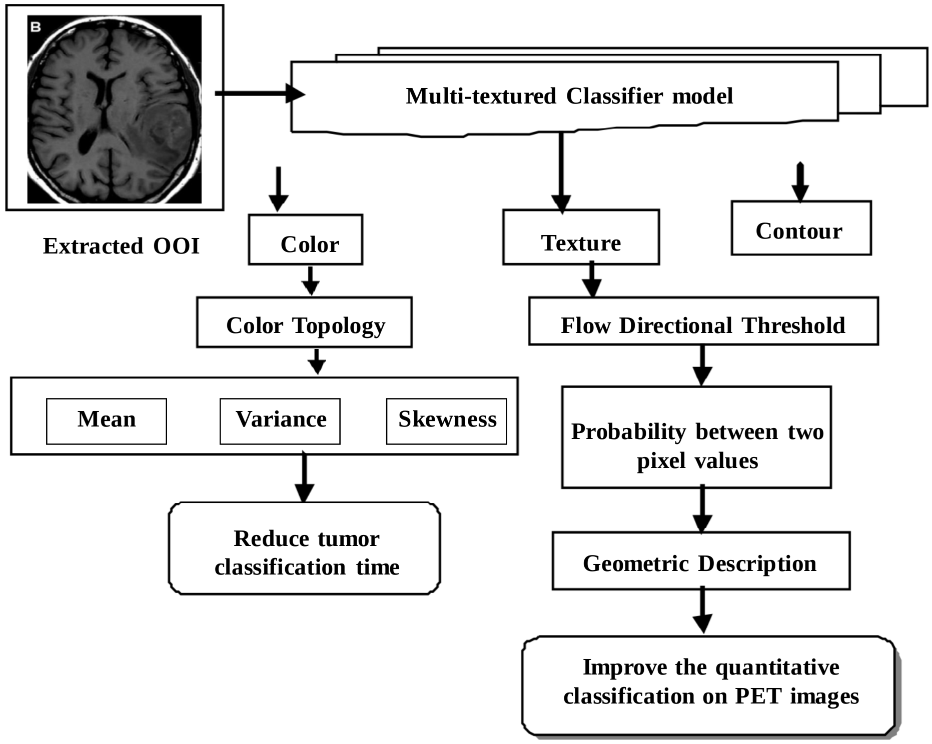

Figure 2: Block diagram of Multi-textured Classifier model with Geometric Description

tumor classification time on PET images. Let us consider an image '$Image_i$' with the object of interest with color features represented as samples '$x_1, x_2, \ldots x_n$', then the mean value of the object of interest '$Mean_{001}$', variance 'σ_{001}' and skewness '$Skew_{001}$' on each PET image is formulated as given below.

$$\mu_{001} = \frac{x_1 + x_2 + \ldots + x_n}{n} \tag{2}$$

$$\sigma_{001} = \sqrt{\left(\frac{x_1 + x_2 + \ldots + x_n}{n}\right)} - \mu_{001} \tag{3}$$

$$Skew_{001} = 2\sqrt{\left(\frac{x_1 + x_2 + \ldots + x_n}{n}\right)} - \sigma_{001} \tag{4}$$

With the mean, variance and skewness values obtained through (2), (3) and (4), the tumor classification time on PET images are reduced in a significant manner.

2.4. Flow Directional Threshold (FDT) method

MTFC evaluate texture flow classification using the Flow Directional Threshold (FDT) method on the PET images. FDT method provide the probability result on the two pixels which are located with an inter distance and a direction, improving the tumor detection rate. The FDT method evaluates the similarity between the training and testing PET images '$Image_i$' for the pixel values '(a, b)' using the mathematical formulation as given below.

$$FD = \sum_{i=1}^{n} ((Training\ Image_i(a, b)) - (Testing\ Image_i(a, b))^2) \tag{5}$$

From (5), the images that obtain least flow directional value 'FD' are sorted in such a manner that they obtain the first location and in this manner, the top 'n' matches are obtained. This in turn improves the tumor detection rate.

2.5. Geometric Description

Contour features are classified in MTFC using the Geometric Description which in turn first maps the input vectors into a decision value using a nonlinear transform function [5]. With this nonlinear transform function, efficient classification of lesion, tumor or normal regions of the PET images are made using an appropriate threshold value, improving the quantitative classification on PET images.

$$MAP\ fun\ (x) = W^T a(x) + a \tag{6}$$

From (6), mapping function '*MAP*' is evaluated using a weight vector '*W*', a bias '*a*' and '$fun\ (x): R^n \rightarrow R$' is a decision function which yields a final classification by means of a linear classification for each 'x_i'.

$$Classification\ y(i) = +1,\ fun(x) > \delta,\ considered\ to\ be\ tumor \tag{7}$$

$$Classification\ y(i) = -1,\ fun(x) < \delta,\ considered\ to\ be\ lesion \tag{8}$$

$$Classification\ y(i) = 0,\ fun(x) = \delta,\ considered\ to\ be\ normal\ regions \tag{9}$$

From (7), (8) and (9), the samples acquired from the user is classified to be as either tumor, lesion or normal regions based on the user defined threshold value 'δ'. Figure 3 shows the Geometric Description algorithm.

Input: Image '$Image_i = Image_1, Image_2, \ldots, Image_n$', Pixel '$(x, y)$', Samples '$x_i = x_1, x_2, \ldots, x_n$', Pixel values '$(a, b)$'
Output: Optimized quantitative classification on PET images
Step 1: Begin
Step 2: For each PET Images $Image_i$
Step 3: Extract Object Of Interest using (1)
Step 4: End for
Step 5: For each samples x_i
Step 6: Measure mean value of the object of interest using (2)
Step 7: Measure variance value of the object of interest using (3)
Step 8: Measure skewness value of the object of interest using (4)
Step 9: End for
Step 10: For each pixel values (a, b)
Step 11: Measure flow direction using (5)
Step 12: End for
Step 13: For each samples x_i
Step 14: if $fun(x) > \delta$
Step 15: Samples are considered to be tumor
Step 16: End if
Step 17: If $fun(x) < \delta$
Step 18: Samples are considered to be lesion
Step 19: End if
Step 20: If $fun(x) > \delta$
Step 21: Samples are considered to be normal regions
Step 22: End if
Step 23: End for
Step 13: End

Figure 3: Geometric Description algorithms

As shown in the figure, the Geometric Description algorithm includes four steps. In first step, for each PET image extracts the object of interest using potential flow rate. With the object of interest extracted from the original PET images, the unwanted regions of interest (ROI) are removed aiming at improving the classification accuracy. Followed by this, for each samples, the CT computes the mean, variance and skewness on the object of interest for reducing the tumor classification time. The third step measures the flow direction based on the similarity distance between the training and testing PET images, aiming to improve the tumor detection rate. Finally, an efficient classification of tumor, lesion or normal regions is performed for each samples based on the user defined threshold value with geometric description. If the mapping function is greater than the threshold value (δ), then the samples are considered to be tumor. If the mapping function is less than the threshold value (δ), then the samples are represented as lesion. Then the mapping function is equal to the threshold value, the samples are considered to be normal regions.

2.6. Experimental settings

The presented technique has been evaluated by experiments using Primary Tumor Data Set extracted from UCI repository. The metrics used to evaluate the MTFC technique are tumor classification accuracy and tumor classification time. The MTFC technique is implemented using MATLAB to enhance the quantitative classification of lesion and tumor at a faster rate with minimal tumor classification time and therefore improve the tumor classification accuracy.

The MTFC technique uses the dataset Primary Tumor Data Set provided by the University Medical Center, Oncology Institute that has appeared repeatedly in the machine learning literature for efficient tumor and lesion detection in PET. The number of instances provided in the Primary Tumor Data Set was 339, out of which it includes 18, including the class attributes. The class attributes refers to the location of tumor namely, lung, stomach, kidney, liver, bladder and so on between age category 30 and 60 years of age.

The tumors were collected from both male and female. By using Primary Tumor Data Set from UCI repository and the defined testing method results are compared with existing method. The MTFC technique is compared with the existing Lacunarity in Multifractal Analysis of Breast Tumor Lesions (LMA-BTL) [1] and Segmentation of Prostatic Zones using Active Appearance Models (SPZ-AAM) [2]. Experiments are performed and evaluated on the basis of the metrics including, classification time and classification accuracy.

Classification accuracy is the number of PET images properly classified divided by the total number of images provided during experimentation, multiplied by 100 to turn it into a percentage.

$$A = \sum_{i=1}^{n} \frac{images\ properly\ classified}{image_i} * 100 \tag{10}$$

From (10), the classification accuracy 'A' is measured with respect to the number of PET images given as input '$Image_i$'. It is measured in terms of percentage (%). Higher the classification accuracy, more efficient the method is said to be. The tumor classification time is the time taken to classify the object of interest '*001*' based on the samples provided by the user. The mathematical formulation for tumor classification time is as given below

$$CT = \sum_{i=1}^{n} x_i * 001(Time) \tag{11}$$

From (11), the tumor classification time 'CT', is measured on the basis of the sample, 'x_i', provided during the experimentation. Lower the classification time, more efficient the method is said to be.

3. RESULTS AND DISCUSSION

The result analysis of Multi-Textured Flow Classifier (MTFC) technique is compared with existing Lacunarity in Multifractal Analysis of Breast Tumor Lesions (LMA-BTL) [1] and Segmentation of Prostatic Zones using Active Appearance Models (SPZ-AAM) [2] respectively.

Classification accuracy is defined as the number of images that are correctly classified to the total number of image. The mathematical formulation for classification accuracy is shown in (1).

Figure 4 illustrates that the classification accuracy rate of three methods namely MTFC technique, LMA-BTL, SPZ-AAM. From the figure the proposed MTFC technique provides higher classification accuracy when compared to the two other existing works. This is because with the application of the potential flow rate computation where extraction of object of interest is made and unwanted object of interest are eliminated resulting in the improvement of classification accuracy rate by 26.99% compared to LMA-BTL [1]. Furthermore, the proposed MTFC using the Geometric Description for classifying the contour features. The lesion, tumor and normal regions of the PET images are classified using an appropriate threshold value. This helps to increases the classification accuracy rate by 38.72% compared to SPZ-AAM [2].

In figure 5, we depict the tumor classification time with 70 samples in the range of 35 MB to 185 MB for experimental purposes. From the figure, the value of tumor classification time using the proposed MTFC techniuqe is lower when compared to two other existing works Lacunarity in Multifractal Analysis of Breast Tumor Lesions (LMA-BTL) [1] and Segmentation of Prostatic Zones using Active Appearance Models (SPZ-AAM) [2] respectively.

From figure 5 it is illustrative that the tumor classification time using MTFC technique is reduced because the technique uses a Color Topology (CT) method. By using CT method, mean, variance and skewness on each PET image based on the object of interest are extracted using potential flow rate computation. This in turn reduces the tumor classification time of MTFC technique by 15.90% compared to LMA-BTL [1]. Also, with the PET images provided as input, the object of interest for color images are

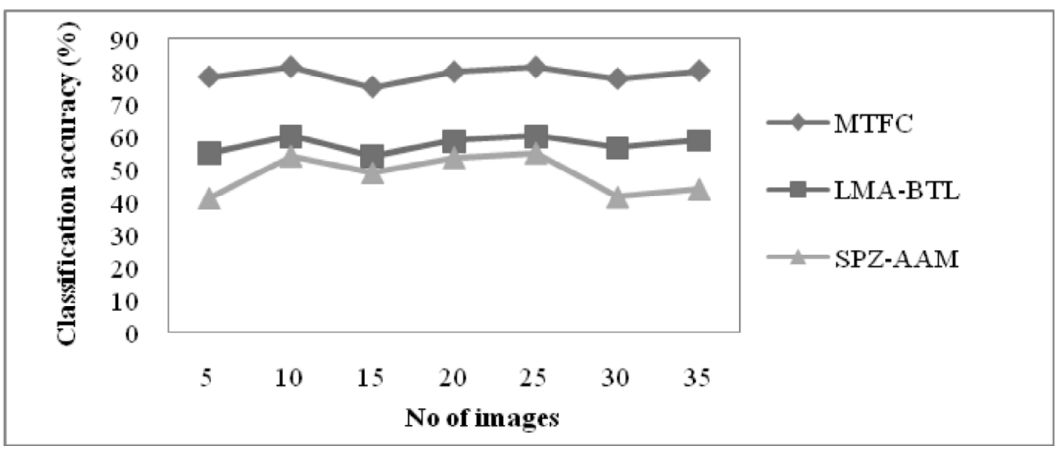

Figure 4: Measure of classification accuracy

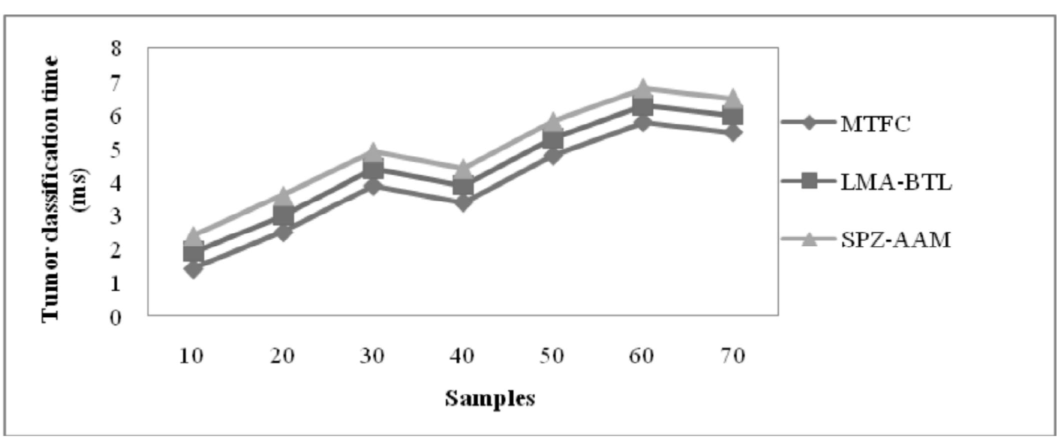

Figure 5: Measure of tumor classification time

obtained with color features represented as sample. These samples are then used for classification based on appropriate threshold value which in turn reduces the tumor classification time in a significant manner using MTFC technique by 32.39% compared to SPZ-AAM [2].

4. CONCLUSION

In this paper, we considered the design of a Multi-Textured Flow Classifier (MTFC) technique to improve the tumor classification accuracy and tumor classification time on PET images. An integrated framework is considered and determining quantitative classification of tumor and lesion in the medical PET images. We can improve the classification accuracy, the solution of which results in eliminating unwanted object of interest and extracting the required object of interest using Potential Flow Rate Computation method. The MTFC technique offers less tumor classification time using Color Topology method. Next, Flow Direction Threshold and Geometric Description method is applied to MTFC technique aiming at improving the quantitative classification on PET images. We compared the performance with many different system parameters, and evaluated the performance in terms of different metrics, such as classification accuracy, tumor classification time and quantitative classification on PET images. The results show that the MTFC technique offers better performance with significantly reducing the tumor classification time by 24.15% and improving the quantitative classification on PET images by 15.70% compared to state-of-art methods.

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