Classification of Brain Tumors based on Coherence-based Atoms Correction in Overcomplete Models Learning

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ABSTRACT:
Brain tumor detection using MRI imaging has the potential to be greatly improved through the integration of medical knowledge. Solving the problem of brain tumor classification is highly important in the field of medicine as it can greatly impact the effectiveness of treatment options. However, the classification of tumors into Benign or Malignant categories remains a challenging task due to the need for detailed texture analysis and the possibility of errors. Image processing techniques such as dictionary learning-based classifiers can play a critical role in this field. This paper proposes a method that combines textural-statistical features to categorize brain tumors based on employing sparse non-negative matrix factorization (SNMF) and a dictionary learning-based model using a sparse representation technique. In the next step, the extracted features from the sparse coefficient matrix were fed into a ResNet10 model for the classification of the input image. The experimental results emphasize that the proposed method, which trains the dictionary atom based on the combinational features vector, can accurately distinguish different types of brain tumors with high precision. This is a significant method as it can improve the effectiveness of brain tumor classification, leading to more accurate treatment decisions for patients.

KEYWORDS: Brain Tumor Classification, Dictionary Learning, Sparse Representation, ResNet Deep Model, Sparse Non-negative Matrix Factorization.

1. INTRODUCTION

The investigation of magnetic resonance images (MRI) by a doctor plays an essential role in determining the type of tumor. Brain tumor diagnosis involves distinguishing the brain texture from the tumor and classifying it as Benign and Malignant. The classification is performed based on the comparison of healthy and diseased hemispheres, taking into account that the tumor is not located in symmetrical hemispheres. Signal processing techniques play a key role in brain tumor classification, especially when applied in combination with machine learning algorithms [1]-[3]. In [4], an algorithm for the classification of Benign, Malignant, and normal tumors was developed using texture features and a probabilistic neural network (PNN). The coefficients of wavelet transform in different frequency bands are used in this algorithm. The classification of four types of tumors, Astrocytoma, Meningioma, Carcinoma, and Sarcoma using gray-level co-occurrence matrix-based (GLCM) features, a neural network, and a non-linear optimization algorithm Levenberg Marquart was investigated in [5]. In [6], the classification of brain and bone tumors was done using features extracted from the GLCM and a back-propagation neural network. The results were reported for four levels of tumors. In [7], the
classification of brain tumors was proposed using features extracted from the GLCM and fast discrete curvelet transform (FDCT) and PNN with radial basis functions (RBF). The classification was done for Benign, Malignant, and normal types of tumors. In [8], the coefficients extracted from GLCM and K-nearest neighbor (K-NN) classification

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were used to classify normal and abnormal tumor data. In [9], the coefficients extracted from the GLCM and spatial K-means clustering were used to detect abnormal brain tumors. The classification procedure with the mentioned feature vectors was performed using neural network in [10]. In [11], the GLCM feature matrix extracted from MRI and tomography images and RBF neural network categories and support vector machine (SVM) are used to detect normal and abnormal brain tumors. In [12], the combination of features extracted from histogram, GLCM, gray level repetition length matrix, and SVM are used to identify Benign and Malignant tumors. In [13], the authors presented a classification algorithm for brain tumors based on PNN trained with the help of GLCM feature matrix and morphological operators obtained from discrete wavelet transform (DCT) coefficients. In [14], the authors compared the different algorithms presented for classifying brain tumors based on different characteristics and categories and evaluated their effectiveness in the diagnosis. In [15], the authors presented a method for identifying Malignant and normal brain tumors based on features obtained from the GLCM matrix and shape-based features extracted from the connected areas of the image. In [16], a sparse representation-based approach was presented to classify brain MR images that consists of least square regularized minimization technique to solve the problem of multiclass classification of tumors in brain MRI by exploring the discriminating properties of sparse representation. A brain tumor MR image classification method using convolutional dictionary learning with local constraint was introduced in [17]. The method integrates the multi-layer dictionary learning process into a convolutional neural network (CNN) structure to explore the discriminatory information present in the data. In [18], the authors propose a novel approach for multi-class brain tumor classification based on sparse coding and dictionary learning that uses K-singular value decomposition (K-SVD) algorithm. The authors propose that this approach combines topological and texture features to learn a dictionary. Although in the researches of recent years, methods based on deep learning have been used with good accuracy, but methods based on model learning include many advantages for the reasons that are mentioned below. A dictionary-based learning algorithm can be beneficial for solving brain tumor classification than deep learning-based classifiers because of its efficiency, robustness, flexibility, and simplicity. These algorithms are typically faster than deep learning-based methods, which can be advantageous when working with large medical image datasets. Also, the performance of dictionary-based learning algorithms is less dependent on the quality and quantity of the training data and more adaptable to different datasets and application scenarios. than deep learning-based methods. The dictionary learning-based algorithms are generally simpler and less computationally expensive than deep learning-based methods. This can make them more accessible to researchers and practitioners without specialized knowledge in deep learning. Also, dictionary-based learning algorithms are often more interpretable than deep learning-based methods, which can make them easier to understand and diagnose [19]-[20].

The proposed approach integrates various statistical and texture features to train comprehensive models representing the attributes of each recognized brain tumor category using dictionary-learning technique, sparse representation concepts, and SNMF dictionary learning algorithm. Careful consideration of the consistency parameter ensures appropriate classification results. The features extracted from the sparse coefficient matrix in the previous step were subsequently fed into a deep learning model, namely, the ResNet10 model, to classify the input image. The purpose of this classification process is to analyze the features and determine the probability of the input image belonging to a certain category. The ResNet10 model is designed to handle images with high spatial dimensionality, which makes it an ideal candidate for this classification task. The extracted features are used as the input to the ResNet10 model, which applies multiple layers of convolutional neural networks to process the features and generate a final classification decision. The entire process is automated and the results can be obtained rapidly, making it a convenient solution for image classification tasks. The proposed method has several significant contributions to the field of medical, including:

- Introducing a new method for brain tumor classification that can mitigate the imbalances in the data.
- Addressing challenges in brain tumor classification, such as data representation, and model complexity.
- Developing and optimizing a dictionary learning-based model with the multi-attention mechanism to enhance the performance of classifiers.
- Employing the statistical-textural feature vector to capture low-level and high-level structures and learn complex relations between the captured features.
- Utilizing the benefits of employing coherence parameters to design a comprehensive overcomplete dictionary.
- Demonstrating the dictionary's ability to accurately classify brain tumor types under multiple scenarios, showing its efficiency and adaptability to varying situations.
- Offering an effective and scalable solution for enhancing the performance of this classification task based on ResNet deep model, with potential applications in the medical and treatment of patients.

Section 2 covers the dictionary learning and sparse representation algorithms. The texture and statistical features involved in categorization are thoroughly examined in Section 3. The proposed brain tumor categorization algorithm is provided in Section 4. In Section 5, the outcomes from applying the proposed method are evaluated and compared with others. A conclusion concerning the research findings is drawn in the final Section.

2.DICTIONARY LEARNING AND SPARSE REPRESENTATION TECHNIQUES

Brain tumors are a serious medical condition that can lead to severe health problems and even death if left untreated and their classification is a critical step in the diagnosis and treatment of this condition. Concepts of dictionary learning and sparse representation techniques can be helpful in this diagnostic step. In these techniques, the digital image I can be modeled as I_m=DX [21]. I_m is a data matrix consisting of different pieces of the input image I divided into blocks of 8×8 dimensions, where index m refers to the coordinates of the pieces. The sparse representation technique is used to code the data matrix I_m as a linear combination of atoms in an overcomplete dictionary D where $D \in R^{N \times L}$, L>N. An overcomplete dictionary is a matrix where the number of columns or atoms is multiple times the number of rows or the dimension of the feature space of the problem. The matrix D contains L columns or atoms with unit norm that each input data vector can be coded as a linear combination of K trained atoms, and usually, K is a small number [22]. Therefore, the sparse representation problem is expressed as follows based on the approximation or reconstruction error parts as

$$X^* = \arg\min_{X} \|I_m - DX\|_2^2 \text{ s.t. } \|X\|_0 \leq K \qquad (1)$$

The technique of learning an over-complete dictionary and sparse representation was proposed for the first time to remove noise from the image data [21]-[22]. This was followed by the development of the K-SVD algorithm, which led to the favorable results. The dictionary learning process includes two stages: sparse coding and updating atoms. The sparse coding procedure can be performed with any desired algorithm, and the sparse representation step used in the K-SVD algorithm is the orthogonal matching pursuit (OMP) method [23]. It is important to adjust the sparsity or cardinality rate carefully so that the approximation error does not increase beyond an optimal level.

3.THE COMBINATIONAL STATISTICAL-TEXTURAL FEATURE VECTOR

The first step in the proposed algorithm is the preprocessing step. This includes converting the MRI images to gray levels and then reducing the dimensions of the images. This step is necessary to prepare the images for feature extraction. After that, feature extraction should be performed which is divided into two parts, texture-based and statistical-based feature vectors. local binary pattern (LBP) is a robust feature extraction method that is widely used in texture processing of image parts, particularly in analyzing gray spectrum images. This method is suitable for texture analysis in MRI images, as it can handle rotations of neighboring textures. Also, histogram of oriented gradients (HOG) is another popular feature extraction method that is efficient in target recognition. This method uses the gradient information of the local parts of the image to calculate the features. This technique is very sensitive to rotations and brightness variations. Also, the GLCM feature matrix is widely used in the field of image processing and can provide information about the texture of an image. The resulting statistical parameters are used to determine the content of the image texture. In the field of image processing, Moment parameters extracted from the image have gained importance due to their resistance to rotation. This feature set includes seven coefficients of the first to seventh Moments and has the beneficial feature that its values do not change when the image is rotated in the desired direction [5]- [7]- [15]- [22].

4.CLASSIFICATION OF BRAIN TUMORS IN THE PROPOSED METHOD

The proposed method classifies the MRI images into three categories: Meningioma, Glioma, and Pituitary brain tumors which are more common brain tumors types [17]- [22]. Feature extraction is performed for each data class, including a set of images related to a specific type of tumor. The extracted features are used as inputs to the classification model for recognition of tumor type. The recognition of brain tumors in this paper was performed in the different scenarios based on various feature vectors and two spars-based dictionary, KSVD/OMP, and SNMF dictionary learning method [24]-[25]. The first of these feature vectors is LBP widely used in the field of texture processing of image parts and is known to be robust. It is used to extract the features of adjacent textures in the analysis of gray scale images. This feature makes changing the position of the tumor in the image less unfavorable. Different patterns can be used to calculate the coefficients of LBP codes, including circular and diagonal neighborhoods. In the proposed method, a cell size of 8×8 and a block size of 2×2 is used. The second texture-based method is HOG that is efficient in target recognition and can handle rotations and brightness variations well. It uses the gradient information of the local parts of the image to calculate the features. The third method is GLCM used commonly to extract the texture of an image and is used in the analysis of gray level images. Other statistical characteristics that can be considered important in the field of image processing and are rotation-insensitive include the Moment parameters extracted from the image [22]- [26]. These parameters include the first to seventh Moments of the image and do not change when the image is rotated in the desired directions. Therefore, they can be valuable in the discussion of identifying targets in which rotation is one of the basic challenges, as well as in the analysis of texture information.

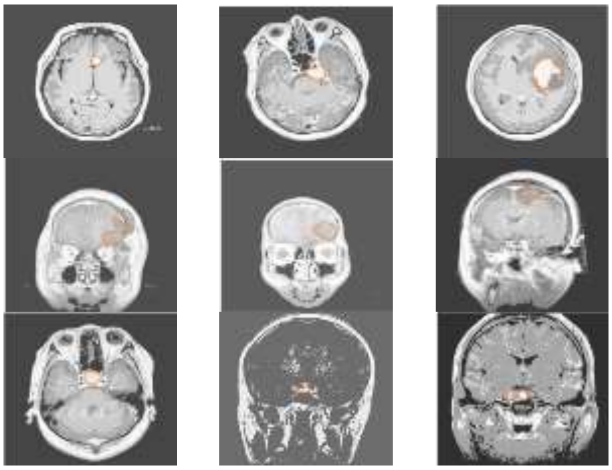

Fig. 1: Examples of MRI images related to tumors: first row: Meningioma. Second row: Glioma. Third row: Pituitary gland. The boundaries of tumors are marked with red color.

In the proposed method, feature extraction is performed for each data set, including a set of images related to a type of tumor, and examples of these images are shown in Figure 1. In the following section, we will explain and examine in detail the different parts of the proposed method for detecting tumors from MRI images. The first step in dictionary training is to represent each piece of input image data using a small number of atoms, known as the dictionary. This is achieved by applying a sparse representation to the data, where each piece is represented as a linear combination of a smaller number of atoms than the total number of pixels in the image. The number of atoms used to represent the data is determined by a parameter called the cardinality rate, which is set by the user or learned from the data. The next step in dictionary training is to update the dictionary atoms based on the input data pieces. This is done by iteratively adjusting the coefficients of each atom to minimize a cost function, which measures the similarity between the image data and the linearly combined atoms. This process is called dictionary optimization, and there are many different algorithms that can be used to perform this optimization. One of the algorithms used in the proposed brain tumor classification algorithm is the least angle regression with coherence criterion (LARC) sparse representation method, which is a generalization of the least-angle regression (LARS) algorithm [27]. In this method, the sparseness of the representation is achieved by calculating the coefficients that represent the linear combination of atoms. The stopping condition for calculating the sparseness coefficients is based on the fact that the atoms must be consistent with the data pieces to represent the content of the training set more appropriately. This consistency is measured by a parameter called residual coherence. If this parameter is less than a predetermined threshold, then the atoms are considered to be consistent with the data and can be used to represent the input images. By reducing the dimensionality of the data using a small number of atoms, and then adjusting the atom coefficients to optimize the similarity between the data and the representation, the dictionary training process transforms the input images into a set of coefficients that can be used to represent the content of the training set more compactly. The LARC algorithm is known for its use of a variable sparsening rate rather than a fixed rate used by most representation methods. This means that the upper limit for the sparseness parameter K is determined and each piece of data can be represented by a maximum of K atoms. This representation method was initially presented to represent the sparseness of speech signals. The sparse representation based on this technique can be expressed as:

$$X^{*} = \mathrm{LRAC}\left(D, X,\ K, \mathrm{Coh}\right) \tag{2}$$

where K represents the sparsening rate or the variable cardinality, and the Coh parameter expresses the degree of remaining coherence. When setting the cardinality rate, it is important to note that an incorrect setting does not lead to source disturbance or source distortion. The Coh parameter represents the coherence between the atom and the data. It is important to note that setting the value of this parameter too high can cause only the atoms that have coherence higher than this value to be included in the dictionary, and their number is small and may cause a problem in designing a complete dictionary with the desired redundancy rate. Conversely, if the value of this parameter is chosen low, then the data consistency parameter and the atom selection method will not have much effect in designing dictionary atoms compatible with the data.

In this study, a novel brain tumor classification method was presented using a combination of coherence-based learning and dictionary learning techniques. The goal of the proposed method is to extract the key features from the MRI images of brain tumors that can be used to construct the classification model. The dictionary learning algorithm based on K-SVD is a suitable procedure for training atoms based on a set of training data. Regarding the consistency between the dictionary atoms, it is crucial to note that there is minimal consistency between the dictionary atoms so that the spatial bases are as independent as possible from each other and the representation is done to show the content of the data pieces in the best way. The significance of addressing these parameters increases when the training data belonging to different classes are structurally very similar. In this case, the higher consistency between the dictionary atoms belonging to each class and the lower mutual consistency between the atoms of different dictionaries will result in a lower approximation error, and the data classification model of every class will be done with higher accuracy. The mutual coherence parameter between the atoms of a dictionary is defined as the maximal value obtained by multiplying different atoms by two:

$$\mu(\mathrm{D}) = \max_{1\le i,j\le L, i\ne j} \left|d_i . d_j\right| \tag{3}$$

where d stands for the dictionary atoms. To minimize the approximation error in the sparse representation, it is crucial to optimize the consistency parameters and ensure minimal consistency between the dictionary atoms. The proposed brain tumor classification method involves training a neural network model to recognize the type of brain tumor present in MRI images [27]. The model is trained using a dictionary learning algorithm based on K-SVD, which is a suitable procedure for training atoms based on a set of training data. Each input image is represented with a sparse linear combination of K atom coefficients that are learned by considering the two data consistency factors. The first factor measures the degree of consistency between the input data and the dictionary atoms, while the second factor measures the consistency between the dictionary atoms. The goal is to reduce the approximation error in the sparse representation of the input data as much as possible, which can be done by optimizing the consistency parameters and ensuring minimal consistency between dictionary atoms. In [28], a novel method called Iterative Rotation and Representation (IPR) is introduced to obtain the Gram matrix as unitary as possible for each dictionary. The first step of IPR involves thresholding the non-diagonal coefficients of the Gram matrix based on a set of rules. These rules, referred to as structural constraints, limit the number of nonzero eigenvalues. The thresholding process sets the off-diagonal coefficients that should be zero in the ideal state of the Gram matrix to a very small determined coherence value to reduce the Frobenius norm of the error between the Gram matrix and the unit matrix. Next, the eigenvalues of the Gram matrix are limited by keeping only the N largest eigenvalues. The second step of IPR involves rotating the dictionary atoms using an orthogonal matrix W so that the approximation error does not increase due to the thresholding done in the first step. This technique was initially presented to improve music signal reconstruction [28] that applied to improve the training procedure of the dictionaries used in brain tumor classification. In this problem, the learned dictionaries for each data class should not be similar as much as possible and the distinction between different categories should be well established. Therefore, it will be important that the atoms of the dictionaries associated with each of the classes have the least degree of coherence with the atoms of the dictionaries of other classes. So what matters is whether there are atoms with the same structure in the dictionary associated with each data class. If there is similarity between the trained atoms, then a procedure should be adopted to reduce this dependence. In the proposed method, in order to correct this problem and reduce the coherence between the dictionary atoms of a class, first a compound dictionary D= [D_M D_G D_P] consisting of dictionaries related to the tumor data of Meningioma D_M, Glioma D_G, and Pituitary D_P is made. Then, the coding of the data volume related to each type of tumor is done on this compound dictionary as

$$\begin{aligned} &\boldsymbol{X}_M^*, \boldsymbol{X}_G^*, \boldsymbol{X}_P^* = \mathrm{LARC}\left(\boldsymbol{I},\ \left[\mathrm{D_M\, D_G\, D_p}\right], \mathrm{coh}\right) \\ &\rightarrow \arg\min_{\boldsymbol{X}_M, \boldsymbol{X}_G, \boldsymbol{X}_P} \| \boldsymbol{I} - \left[\mathrm{D_M\, D_G\, D_p}\right] \begin{bmatrix} \boldsymbol{X}_M \\ \boldsymbol{X}_G \\ \boldsymbol{X}_P \end{bmatrix} \|_F^2 \end{aligned} \tag{4}$$

In order to evaluate the effectiveness of the proposed, the extracted features from the sparse coefficient matrix were then introduced into the ResNet10 model, which is a deep learning model designed to classify images. The purpose of this process is to analyze the features and determine the probability of the input image belonging to a particular category. The ResNet10 model is designed to handle images with high spatial dimensionality, which makes it an ideal candidate for this task. The extracted features serve as the input to the ResNet10 model, which applies multiple layers of convolutional neural networks to process the features and generate a final classification decision. The entire process is automated, and the results can be obtained quickly, making it a convenient solution for image classification tasks. Overall, the goal is to minimize the degree of coherence between the dictionary atoms of different dictionaries to enhance the distinction between different classes. By performing this process, the proposed solution addresses the issue of similarity among dictionary atoms belonging to different classes, ensuring appropriate representation of the data for classification purposes. The proposed category classification method, which leverages dictionary-based sparse representation, is shown in Figure 2. The input data is first processed using the combined dictionary D to obtain its sparse representation. Then, the ResNet10 deep model was employed to classify the input image based on the sparse representation feature vectors. The sparse representation-based classification technique has been used in many applications so far [18]-[19]-[31]-[32]. By using a sparse representation-based method, the proposed solution does not require additional categories and can classify inputs solely by analyzing their sparse representation on each dictionary. This paper addresses the problem of representing brain tumor data using a set of incoherent dictionaries to improve the classification accuracy. The resulting classification method is efficient and reliable, avoiding the need to rely on other classifiers such as neural networks or SVM.

5.THE PROPOSED BRAIN TUMOR CLASSIFICATION METHOD

To simulate the results of the proposed method, two-dimensional MRI images were used [29]. These images were the result of T1-weighted CE-MRI imaging collected from 233 patients between 2005 and 2010. This collection included 3064 images of three types of brain tumors, including 708 images of Meningioma, 1426 images of Glioma, and 930 images of the Pituitary gland. The dimensions of these images were 512×512, and the size of the pixels was 0.49×0.49 mm square.

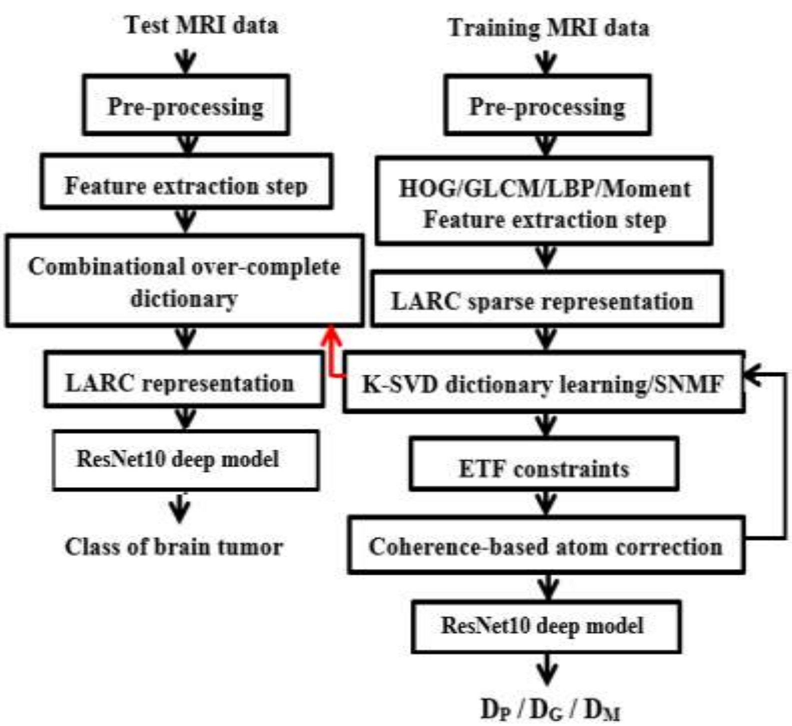

Fig. 2: Block diagram of the dictionary learning-based method for brain tumor classification.

5.1. Simulation Details

In the proposed method, dictionary training is used to classify brain tumor types. In the simulations, various features introduced in Section 3 were used as training data extracted from images. The sparsity rate required in sparse coding using the LARC algorithm depends on the dimension of the training data and is different for each feature extraction procedure. The *Coh* coherence parameter used in Equation 4 was set to 0.15 in all simulations. Also, according to the results of the simulations, the lower limit value of atom-data coherence used in the LARC algorithm was considered to 0.45. The redundancy rate for overcomplete dictionaries of all brain tumor classes was adjusted depending on the type of features, which states with what redundancy rate each dictionary will be super complete. To learn the dictionary in the training step, 70% of the data from each class was used, and the rest was used in the test step and for evaluation. The performance of the algorithm was evaluated based on its classification accuracy rate, which was calculated as the percentage of correctly classified data to the total test data. Feature extraction in the experiments of this section was done with the help of the HOG directional gradient histogram descriptor with a cell size of 8×8 with 50% overlap and a block size of 2×2. The adaptive moment estimation (Adam) optimizer that computes adaptive learning rates for each parameter is selected for the designed ResNet10 model. This optimizer is employed in stochastic gradient descent (SGD) to train deep-learning model layers. Using this optimizer an initial learning rate of 0.001 is used which is multiplied by 0.1 at epochs 10 and 20. Also, the learning rate is decreased every 10 epochs by 50% and the batch size is set to 32. For more efficiency, the number of iterations is set to 15 and the ResNet10 is learned for 50 epochs at each iteration.

6.Results and Discussions

As mentioned, feature extraction was performed using the invariant LBP coefficients with rotation and non-overlapping 2×2 cells, resulting in 10 features per image. The important parameters obtained from the GLCM matrix were also investigated, including nine characteristics of average, variance, energy, range of changes in relative abundance values, contrast, homogeneity, maximum relative abundance value, correlation, and entropy. The co-occurrence matrix coefficients of the gray level were calculated in four directions 0°, 45°, 90°, and 135°, resulting in a feature vector with 36 coefficients for each input image. In this paper, three scenarios are considered to compare the effect of each statistical or textural feature and the classifier. The feature vector in the first scenario (Scenario I) is based on a combinational vector that includes HOG and GLCM. After conducting several simulations for each feature vector independently, the results were found to be inadequate and omitted from the report. In the second Scenario (Scenario II), the feature vector in Scenario I is concatenated with the LBP features. Also, in the third scenario (Scenario III), all mentioned statistical-textural feature vectors consisting of HOG, GLCM, LBP, and Moments are employed to learn dictionary atoms using sparsity and coherence constraints. The results of the proposed brain tumor classifier are compared to a multi-layer perceptron (MLP) neural network with 5 hidden layers [30], a SVM classifier [31], and SNMF [32]. The results of the sparsity and redundancy rates for these features are set to 100 and 2, respectively. The results for Scenario I, Scenario II, and Scenario III are demonstrated in Tables 1-3.

The obtained results show that the use of statistical features such as parameters extracted from GLCM coefficients and Moments, along with other texture-based features such as LBP and HOG, leads to favorable results in the field of brain tumor data classification based on dictionary model learning, and also SNMF. In order to check the performance of the atom correction step proposed in the previous section, the results of the proposed category based on learning the model without the atom correction step are reported in Table 4.

Table 1. Accuracy of classification of brain tumors based on MLP neural network, SVM, NMF and the proposed dictionary-based method in the Scenario I.

	MLP [30]	SVM [31]	SNMF [32]	Proposed
Meningioma	80.36	84.38	89.08	**92.22**
glioma	81.71	83.56	88.33	**93.67**
Pituitary	85.49	82.52	88.14	**92.61**

Table 2. Accuracy of classification of brain tumors based on MLP neural network, SVM, NMF and the proposed dictionary-based method in the Scenario II.

	MLP [30]	SVM [31]	SNMF [32]	Proposed
Meningioma	86.25	86.26	91.24	**94.22**
glioma	87.41	87.33	91.48	**94.61**
Pituitary	88.52	87.47	90.51	**95.27**

Table 3. Accuracy of classification of brain tumors based on MLP neural network, SVM, NMF and the proposed dictionary-based method in the Scenario III.

	MLP [30]	SVM [31]	SNMF [32]	Proposed
Meningioma	88.63	87.59	93.56	**96.22**
glioma	89.93	88.48	92.96	**96.67**
Pituitary	90.05	89.61	93.22	**97.31**

These results clearly demonstrate the positive impact of the atom correction step by removing atoms with similar performance in representing input data, which ultimately increased the classification accuracy. In the third scenario, which produced the best results according to Table 3, it was shown that the effectiveness of the atom correction step in dictionary training has a significant impact on the accuracy of the proposed method. If this step is not performed, the results of the simulation are nearly identical to those obtained using the non-negative method. Therefore, it is evident that the proposed method, with the atom correction step applied, is the more effective approach. Table 5 assesses the impact of three key blocks, including LARC sparse representation steps, ETF dictionary correction, and atom correction of different dictionaries, on the mutual coherence of atom-data, within coherence between atoms of the same dictionary, and the coherence between atoms of a dictionary with the dictionaries of other classes. The results of the coherence value based on the trained dictionary with the help of the LARC sparse representation method, which has no coherence constraint, are consistently lower than other scenarios. When applying the LARC algorithm with an increased atom-data coherence constraint, which selects only atoms with high atom-data coherence and ignores those with low coherence, the coherence values increase. This improvement has a positive impact on signal reconstruction, as it increases the extracted feature of the correct sparse representation and helps to classify the test data more accurately using ResNet10 deep model.

Table 4. Accuracy of brain tumors classification based on the combined feature vectors in Scenario III of the proposed method with and without atom correction step.

	SNMF	Proposed without atom correction step	Proposed
Meningioma	93.56	93.68	**95.22**
glioma	92.96	93.05	**94.67**
Pituitary	93.22	93.14	**95.31**

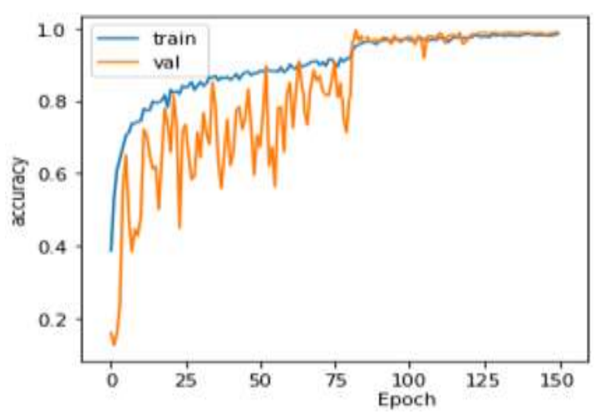

Fig. 3. The traing progress plot of the accuracy the proposed ResNet10-based brain tumor classifier based on model learning procedure in the training step.

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Table 5. Coherence value between atoms and data, coherence value within dictionary atoms of each class, and coherence value between dictionary atoms of different classes in the proposed method.

	Atom-data Coherence			Whitin class coherence			Between class coherence		
	Meningioma	Glioma	Pituitary	Meningioma	Glioma	Pituitary	Meningioma/ Glioma	Glioma/ Pituitary	Pituitary/ Meningioma
OMP sparse representation	0.42	0.49	0.45	0.77	0.72	0.74	0.62	0.46	073
LARC sparse representation	**0.75**	0.80	0.74	0.73	0.68	0.66	0.70	0.75	0.79
LARC sparse representation /ETF post processing	0.76	0.82	0.76	0.41	**0.45**	0.44	0.69	0.73	0.71
LARC sparse representation /ETF post-processing /Atom correction (Proposed)	**0.75**	**0.85**	**0.79**	**0.36**	**0.45**	**0.43**	**0.56**	**0.48**	**0.54**

Additionally, after applying a dictionary editing step to achieve an ETF dictionary, which ensures that the dictionary's Gram matrix is as close to a unitary matrix as possible, the coherence parameter of dictionary atoms decreases as much as possible. Last but not least, in the proposed method, a step has been applied to correct the coherence of atoms related to other classes by removing the atoms of a dictionary that have a large representation energy in coding the data of the adjacent class. Overall, the proposed method, which includes all three steps, has been able to achieve the desired coherence values. The results indicate that the proposed approach results in improved coherence values, which ultimately enhances the accuracy of the classification process. Also, the training progress plot of the accuracy and loss function in the train and test steps for the employed ResNet10 model can be seen in Figure 3 which emphasizes the proper convergence in this classification task.

7.CONCLUSION

The development of effective tools for medical image processing is a critical field due to the vital role they play in improving treatment outcomes. To address this, a solution has been proposed in this paper to classify brain tumors using sparse representation and dictionary learning techniques. Features obtained from these concepts are employed to design an over-complete model. The proposed approach, which integrates the sparse representation and dictionary learning steps, yields over-complete models that exhibit maximum consistency between atoms and data and minimum consistency between atoms within their dictionary and atoms across different dictionaries. Then, a ResNet10 deep model was employed to classify the input image based on the sparse representation coefficients in model learning of the combinational feature vector. Furthermore, this paper compares different feature extraction methods, including texture-based and statistical techniques. It reveals that the combined feature category of GLCM/MOM/LBP/HOG leads to more favorable results for tumor classification in MRI images in comparison to other approaches such as neural networks, SNMF, and SVM classifiers. Therefore, using this combined feature category as the optimal feature set for brain tumor classification in medical image processing is recommended.

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