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AUTOMATIC SEGMENTATION OF INFANT BRAIN MRI USING SOFT COMPUTING TECHNIQUES

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Abstract

This article is concerned with exploration and diagnostic implementation of an effective neo-anatomical brain MRI classification method to classify primal cognitive development and investigate neuro-anatomical intellectual disability correlations. A crucial stage in the research as well as appraisal of the newborn brain growth is neonatal brain tissue classification. Owing to the major variations in anatomy and tissues among neonate and mature brains, the largest proportion of developing technology for the classification and segmentation of the adult brain really aren't sufficient for newborns brain. The existing brain tissue classification strategies for MRIs rely either on manual interactions or involve the use of atlases or models, which ultimately skew the findings from the population used to extract atlas. This article, focuses on atlas free soft computing approach to classify the neonatal brain tissue. Classification of brain tissue is the main process in which regional brain tissue examination is conducted. This helps the regional brain development to be characterized and the correspondence with therapeutic conditions to be studied. The modified BM3D approach is utilized for image enhancement along with 32 Gabor filter bank-based feature extraction. The innovative aspect of this research is the multistage classification methodology, which produces higher dice coefficients and lower MHD values when compared to existing approaches.

Keywords:

Classification, Infant, Soft Computing, BM3D, Atlas-Free, Brain Tissue

1. INTRODUCTION

In neuroimaging, usage of magnetic resonance imaging revolutionized healthcare and its capacity to generate non-invasive brain segment images. Brain MRI is being used to analyze brain, brain and neurodegenerative infections and accidents [1]. Infant brain screening with particular focus on imaging the newborns brains is a rapidly growing subcategory. It helps distinguish multiple brain tissue and disorders [2]. In diagnosing neuro-radiology, brain MRI is therefore an important component, especially in the perinatal stage. Using MR brain pictures, the brain function of premature babies may be measured. These images can be used for predictive analysis using multiple criteria, such as cortical length, surface area and anatomy, to better classify brain tissues [3] [4].

Abstraction of feature as well as sorting is essential measures for the classification and segmentation of brain tissue [5]. Feature selection methods are also used to study the efficiency of classification schemes based on non-relevant features [6]-[8]. It increases the performance of techniques by lowering dimensions as well as deleting unimportant characteristics [9]-[11]. Additionally, image retrieval is a crucial task in the classification of the MRI brain images. These characteristics can be derived by means of imaging technologies. A variety of features such as location, form and texture characteristics are derived from brain MRI. For several apps textures are one of main features. Texture characteristics of MRI brain image segmentation are commonly utilized [12]-[15]. Texture characteristics is stripped so that segmentation precision is increased.

Different assessment techniques have been used in Newborns and Preterm delivery Infant Brain Classification through mathematical and machine learning strategies [16]-[19]. Investigation of infant brain MR images is a very diverse area. Few algorithms only strip the representations of the brain [20, 21]. Current techniques can be used to segment the representations of the Brain MRI in GM, WM and CSF [22]-[25]. Many investigators utilized MR images obtained localized as well as correlated these findings with manual segmentation because of the lack of the gold standard in this area. It therefore offers a broad forum and spectrum for comprehensive and reliable segments for neonatal MR images in the Brain.

2. LITERATURE SURVEY

Number of researchers already suggested different solutions for the classification of newborns and immature infant brain tissue in diagnostic imaging. Several segmentation techniques have been proposed throughout the past several decades for the automated classification of the newborn brain MRI. All of these techniques are designed to detect things of different importance: the brain, tissues or more specialized characteristic. These methods conduct brain tissue classification and are categorized as atlas-based methods [26]-[31], augmented atlas [32]-[35] method and atlas free approach [36]-[37].

2.1 ATLAS BASED METHODS

For classification of white matter into myelinated and un-myelinated white matter, Prastawa et al. [28] used a probabilistic atlas, graph clustering, sample pruning, and non-parametric kernel density estimations. For the reconstruction of newborn brain, Xue et al. [29] employed a GA-based atlas and tissue priors.In addition, the EM–MRF method was used for partial volume correction. For neonatal brain MRI tissue classification and anomalous brain development, Song et al. [30] exploited tissue probability maps and supervised learning. Weisenfeld et al. [31] deployed spatial priors and a supervised learning strategy for neonate brain MRI tissue classification.

2.2 AUGMENTED ATLAS BASED METHODS

Shi et al. [32] employed atlases, multi-region atlases [33] and hybrid atlases [34] for brain tissue segmentation of infant babies. Wang et al. [35] utilizes longitudinally oriented Level Sets for the classification of White, Gray and CSF based on local intensity, prior atlas and cortical thickness, as well as Combines patches-based subjects with Level Set Framework.

2.3 ATLAS FREE APPROACH

Leroy et al. [36] deployed Neonatal segmentation of less than 2 months of age on a minimal contrast and curvature-based field and deformation of linked surfaces. Gui et al. [37] used brain morphology, including tissue location and structure, to classify brain tissues at the global and tissue levels.

Devi et al. [38] summarizes segmentation approaches and reflects on research discrepancies in this field. Furthermore, Moeskops et al. [39] proposed supervised brain MR image description for premature babies was described. In their supervised voxel classification algorithm, they used three subsequent steps. In the first step, voxels were classified conveniently attributable to one of the three forms of tissue. In the second step the remaining voxels were studied in depth. In the first two levels, two classifications have been used separately for each type of tissue. Discrepancies after the first two processes of the last process is overcome. The inputs for this rating are T1 and T2 weighted photos and their accuracy has been evaluated. The procedure has been tested on MR images of premature children aged 30 to 40 weeks.

3. MULTISTAGE CLASSIFICATION APPROACH

The automated Brain MR Image segmentation of premature babies has therefore been accomplished using a supervised classification [39]. The algorithm has been performed in three steps. In the first step, one of the three tissue types was allocated to voxel by weighted kNN. In next phase, the remaining voxels were examined with dedication using multi kernel SVM. In last step, ANN classifier excluded potential differences arising from this tissue specific segmentation phase. Fig.1 depicts the overall flow of proposed multi stage classification approach

3.1 PREPROCESSING

Various types of noise can impair a digital image. Depending on the type of noise, there are different algorithms for denoising the image. In terms of performance, BM3D is recognized as the best denoising filter available. While comparing to certain conventional procedures, it produces outstanding outcomes.

BM3D follows a two-step process.

- It creates a basic estimate of the noisy image using harsh thresholding in the first stage.
- The Wiener filter is then used in the second stage to denoise the noisy image.

In order to achieve so, BM3D employs the first step's basic estimate as an oracle in the Wiener filter, though BM3D succeeds decent denoising performance [40].

BM3D is an advanced technique. Owing to very precise block-matching in the stronger edges areas their denoted findings can always be higher compared in the smoother or weaker edge areas. This makes improved image denoising with the use of adjustable block sizes in various image areas. BM3D filtering and grouping process is known as the collaborative filter method [41].

We modified classical BM3D by adjusting variables such as optimum d-distance, largest number of combined blocks, and the Wiener filter variable, the UQI and the VIFP get much better than the classical BM3D. The Table.1 illustrates the various performance parameters obtained for modified BM3D preprocessing method.

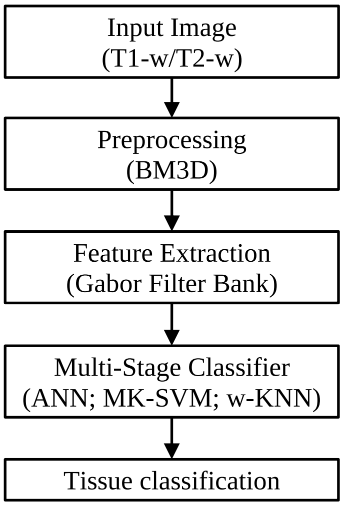

Fig.1. Flow of Proposed Multi Stage Classification Approach

Table.1. Preprocessing Parameters achieved using modified BM3D

Image	MSE scikit	PSNR scikit	RMSE scikit	EG	RMSE	UQI	VIFP
1	0.23	28.21	0.50	0.30	0.32	0.96	0.95
2	0.33	29.76	0.65	0.28	0.23	0.97	0.96
3	0.26	22.83	0.58	0.35	0.36	0.97	0.96
4	0.28	29.41	0.69	0.51	0.31	0.96	0.97
5	0.21	21.39	0.57	0.39	0.33	0.97	0.96
Mean	0.25	26.32	0.60	0.37	0.31	0.96	0.96
Ideal	0	inf	0	0	0	1	1

3.2 FEATURE EXTRACTION

The feature plays an extremely important function in medical image analysis. Before obtaining features, several image pre-processing processes are done on the input brain MR image [42]-[43]. Here 32 Gabor filter bank along with various edge filter (with changeable values of σ ranging from 3 to 9), the expression used for Gabor filtering bank is given as follows.

$$g\left(x,y;\lambda,\theta,\psi,\sigma,\gamma\right)=\exp\left(\frac{x^2+\gamma^2\cdot y^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x}{\lambda}+\psi\right)\right) \quad (1)$$

As the edges of medical research are of paramount significance. Hybrid combination of all above methods is the novelty of this research work. Optimum features are selected for this purpose to improve classification accuracy with dice coefficient.

3.3 CLASSIFICATION

Proposed three stage framework is used for the classification of brain tissues present in T1w and T2w MRI images of newborn infant. Misclassification of brain tissues pixels can be avoided with the help of proposed three stage classification framework. Multistage classification approach improves the brain tissue classification accuracy for better diagnosis and treatment planning.

3.3.1 Stage I: Weighted K-Nearest Neighbor Classifier:

Weighted K-Nearest Neighbor (w-KNN) is used to designate one of the tissue groups labelled for voxels. The kNN is a non-parametric type supervised classification technique. In this classification technique the output is function of class membership. Majority of votes from its neighbors is prime function of kNN which is used to classify the object [44]. In kNN the value of k is definable and it can be any positive integer value. The value of k defines how many nearest neighbors must be used for voting. If value of *k* is 1, then the class of only available neighbors will be assigned to object under classification. As the value of *k* increases the boundary of the different classes becomes smoother and reduces the noise effect. In traditional kNN algorithm, the weights assigned to all the *k* nearest neighbors are equal. The traditional kNN algorithm can be modified by assigning variable weights to different k nearest neighbors. The value of weights is depending on the distance between the target object and neighbor under consideration. Normally the closer neighbor has higher weight as compare to remote neighbor i.e. weight is inversely proportional to distance to the neighbors. The modified kNN technique is referred as weighted kNN algorithm [45].

3.3.2 Stage II: Multi-kernel SVM Classifier:

Multi-kernel SVM is employed for interpretation of voxel which are leftover. Multi-kernel vector support machine (MKSVM) is used in this phase rather than SVM. The integration of MKSVM might increase the accuracy of the SVM classification of both linear and non-linear data. In this case, RBF, quadratic function and polynomial function as kernels is utilized to further improve SVM performance.

This technique needs be adjusted using kernel learning in classify non-linear separable data. It is challenging to choose the right kernel during learning, although several experts are striving to build highly efficient kernel learning termed multiple kernel learning (MKL). This implementation provides design of SVM method classification model that was updated and used for tissue classification utilizing multiple kernels.

3.3.3 Stage III: ANN Classifier:

Ultimately, the segmented area is defined by means of an artificial neural classification. ANNs have a tremendous benefit of higher computation in massively parallel execution, which has enhanced the need for study in this field. ANN is a set of linked input output networks in which each connection has a weight. One input layer, one or more intermediary layers, and one output layer make up this system. Modifying the weight of connections in a neural network allows it to learn. The network's performance is increased by adjusting the weight repeatedly.

Input values are initially propagated through the network then errors calculated, and the errors are then reverted back to the network to set linkage weights to reduce error. The method initially computes the gradient of the loss function with respect to the weights of the nodes in the hidden and output layers. Then the weight of the input layer and hidden layer nodes is determined by the loss function gradient. It subtracts the gradients from the appropriate weight vectors to acquire the new weights for the connections after computing them. This procedure is continued until the network generates the required results.

ANN layers are rows of neuronal housed data points, each using the same neural network. Weights are used by ANN to learn. Weights in ANN are adjusted after each round across the neuron. ANN then goes back and adjusts the weights based on the accuracy measured by a cost function. Lastly, for testing purpose database [48] is used and assessment of the results in terms of segmentation performance is obtained using suggested technique.

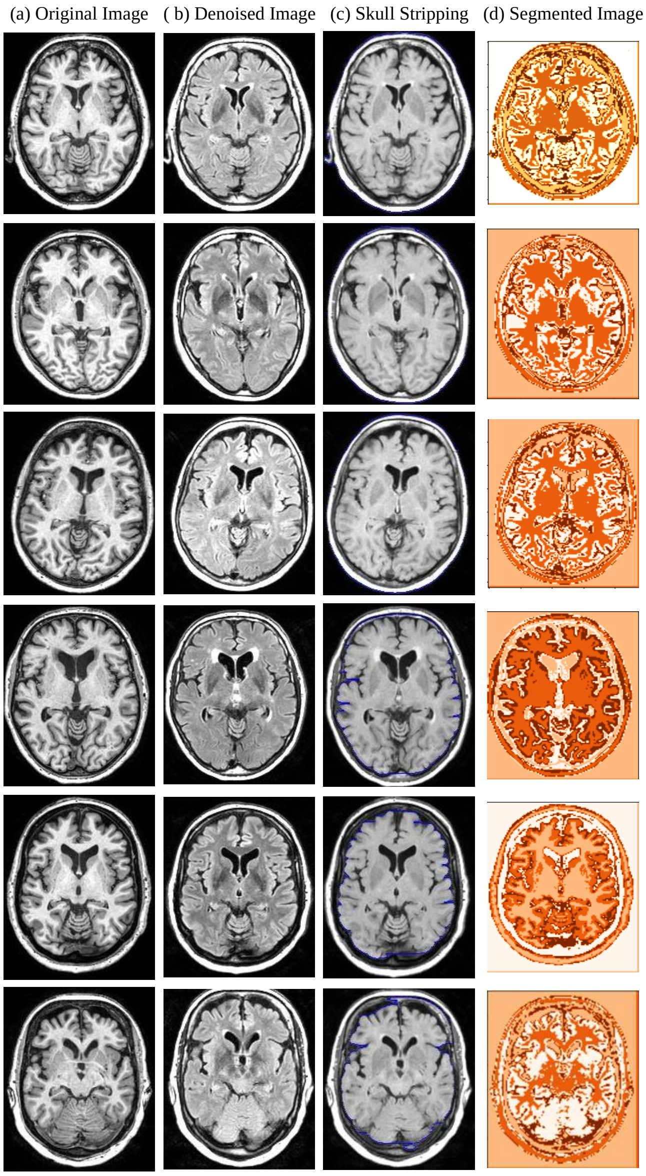

Fig.2. Simulation Results for Proposed Multi Stage Classification Approach

4. RESULTS

The proposed approach has been implemented using Python 3.7. The results of the proposed method are obtained in terms of statistical parameters and simulation results. We used 30 images for this study. Statistical parameters like accuracy and dice similarity index are computed and illustrated in Table 2.

Table.2. Statistical Results

Image	Accuracy	Dice Coefficient	MHD	AVD
1	0.8181	0.884	2.3	6.7
3	0.8028	0.892	2.5	8.5
7	0.8478	0.897	2.4	3.8
10	0.8945	0.944	2.2	2.1
15	0.8478	0.937	2.4	4.6
Mean	0.8422	0.9108	2.3	5.9

The Table.3 gives comparison of proposed and existing segmentation approaches. The proposed segmentation and classification approach out performs as compared to state of art approaches as indicated in Table.3 with reference to Dice Coefficient.

Table.3. Performance Comparison

Tissue Classification	MHD	Dice Coefficient
Proposed	2.3	0.92
Vedran et al [49]	3.1	0.90
Wang et al [50]	3.5	0.91

The Fig.2 illustrates the major procedures conducted on the MR brain input images. The Fig.2 (a) represents original input images of infant brain as T1w and T2w. (b) represents the filtered image obtained using BM3D approach. (c) Depicts the skull stripping operation. (d) Illustrates various brain tissues classification.

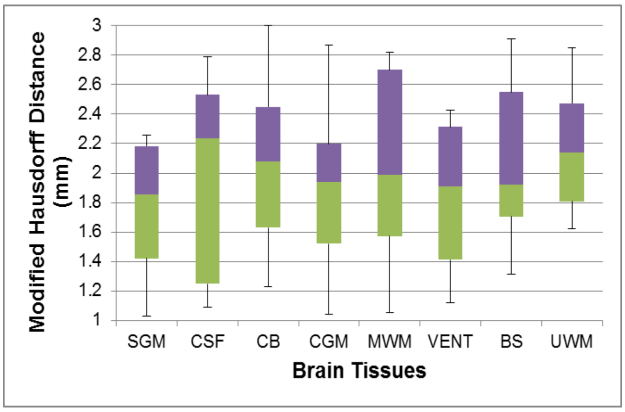

Fig.3. Box plot analysis for MHD of proposed dataset

The Fig.3 shows box plot analysis of Modified Hausdorff Distance. Plot shows that brainstem (BS) has highest MHD values among classified brain tissues.

Absolute value is being utilized to represent segmentation outcomes that are higher or less as compared to gold standard. The Fig.4 shows box plot analysis of Absolute Volume Difference. Plot shows that cortical gray matter and myelinated white matter has highest AVD values as compared to other segmented brain tissues.

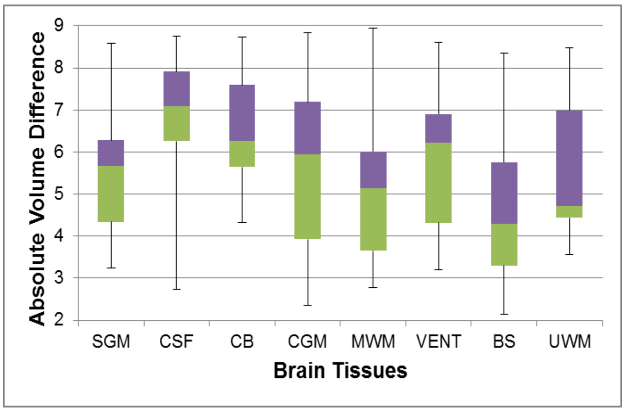

Fig.4. Boxplot analysis for AVD of proposed dataset

5. CONCLUSION

Three stages for the automated neonatal brain tissue classification approach have been suggested in this work. Infant MR imaging data are automated to segment and classify brain tissues which is substantially more complicated than adults. The growth of neonatal brain accompanies major shifts of structures' form and appearance. PV effect and a small SNR both generate automated approaches with challenges.

The modified BM3D approach is utilized for image enhancement along with 32 Gabor filter bank-based feature extraction. The innovative aspect of this research is the multistage classification methodology, which produces higher dice coefficients and lower MHD values when compared to existing approaches.

For the early diagnosis of neural disturbances this research plays a significant role. Thus, the study suggested would provide neuro-physicians with additional knowledge in order to help handle new born infants.

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