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Automatic Segmentation of Brain MR Images of Neonates and Premature Infants using KNN Classifier

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Abstract —***This paper focuses on the development of an accurate neonatal brain MRI segmentation algorithm and its clinical application to characterize normal brain development and investigate the neuro-anatomical correlates of cognitive impairments. Neonatal brain segmentation is challenging due to the large anatomical variability as a result of the rapid brain development in the neonatal period. The segmentation of MR images of the neonatal brain is a fundamental step in the study and assessment of infant brain development. The highest level of development techniques for adult brain MRI segmentation are not suitable for neonatal brain, because of substantial contrasts in structure and tissue properties between newborn and adult brains. Existing newborn brain MRI segmentation approaches either depend on manual interaction or require the utilization of atlases or templates, which unavoidably presents a bias of the results towards the population that was utilized to derive the atlases. In this paper, we proposed an atlas-free approach for the segmentation of neonatal brain MRI, based on the KNN classifier. The segmentation of the brain in Magnetic Resonance Imaging (MRI) is a prerequisite to obtain quantitative measurements of regional brain structures. These measurements allow characterization of the regional brain development and the investigation of correlations with clinical factors.***

Keywords-KNN; Newborn; Premature; Segmentation, MRI.

I. INTRODUCTION

The use of MRI in neuro- imaging has revolutionized health care with its potential to obtain non-invasive section images of the brain without using ionizing radiations. Brain MRI is used to investigate seizures, strokes, infections and injuries of the brain, hemorrhages, brain tumors, multiple sclerosis, neuro degenerative diseases such as Alzheimer's, and others [1]. A fast emerging subspecialty is pediatric neuro imaging with special emphasis on imaging the neonatal brain. MRI of the new born brain helps identify anomalies such as hypoxic ischemic encephalopathy, hydrocephalus, congenital malformations, infarction and infections [2]. Thus brain MRI forms a vital part in diagnostic neuro radiology, particularly in the neonatal stage. The brain development of preterm infants can be evaluated using MR brain images. These images can provide quantitative descriptors such as volume, surface area, and morphology of the cortex, which may help in identifying which children are at risk of complications due to preterm birth [3,4], especially when evaluated longitudinally

Feature extraction and selection are important steps in breast cancer detection and classification. An optimum feature set should have effective and discriminating features, while mostly reduce the redundancy of features pace to avoid "curse of dimensionality" problem [5] .Feature selection strategies often are applied to explore the effect of irrelevant features on the performance of classifier systems [6-8]. In this phase, an optimal subset of features which are necessary and sufficient for solving a problem is selected. Feature selection improves the accuracy of algorithms by reducing the dimensionality and removing irrelevant features [9] [10]. The Orientation of histogram feature provides the histogram of orientation of edges in the image [11]. Moreover Feature extraction of image is important step in MRI brain image classification. These features are extracted using image processing techniques. Several types of feature extraction from digital mammograms including position feature, shape feature and texture feature etc. Textures are one of the important features used for many applications. Texture features have been widely used in MRI brain image classification. The texture features are ability to distinguish between abnormal and normal cases. [12, 13]. Texture measures are two types, first order and second order. In the first order, texture measure is statistics calculated from an individual pixel. In the second order, measures consider the relationship between neighbour [15, 14]. Texture features has been extracted and used as parameter to enhance the classification result.

Different Classification methods from statistical and machine learning area have been applied to Neonates and Premature Infants Brain Classification. Classification is a basic task in data analysis and pattern recognition that requires the construction of a Classifier. Many machine learning techniques have been applied to classify the tumor, including Fisher linear Discriminat analysis [16], k-nearest neighbour [17] decision tree, multilayer perceptron [18], and support vector machine [19]. The research on neonatal brain MRI segmentation is highly diversified in intent, design, implementation and outcome. While a few algorithms merely skull strip the brain images [20, 21], most of the mare capable of identifying the prominent brain portions such as GM, WM and cerebrospinal fluid (CSF) [22]; some are adept at further segmenting the brain into eight issue classes [23, 24] while a recent research has been successful in parcellating the brain into as many as 50 regions [25]. Moreover, the developed algorithms are often tested on locally acquired brain MR datasets and validated against manually delineated brain tissue portions due to the lack of a single standard publicly available neonatal brain database. Such vastness in scope, method, performance and direction in the literature necessitates the comparison of these techniques on common grounds.

II. RELATED WORK

In medical diagnosis, various researchers have proposed numerous approaches for Neonates and Premature Infants Brain classification: A handful of important researches are offered in this segment among them. Chelli N. Devi et al. [26] have explained the review of Neonatal brain MRI segmentation. These methods provided an Overview of clinical magnetic resonance imaging (MRI) of the newborn brain and the challenges in automated tissue classification of neonatal brain MRI. It presents a complete survey of the existing segmentation methods and their salient features. The different approaches were categorized into Intracranial and brain tissue segmentation algorithms based on their level of tissue classification. Further, the brain tissue segmentation techniques were grouped based on their atlas usage in to atlas-based, augmented atlas-based and atlas-free methods. In addition, there search gaps and lacunae in literature was also identified.

Moreover, Pim Moeskops et al. [27] have explained the Automatic segmentation of MR brain images of preterm infants using supervised classification. Here, they explained an algorithm for the automatic segmentation of unmyelinated white matter (WM), cortical grey matter (GM), and cerebrospinal fluid in the extra cerebral space (CSF). The algorithm uses supervised voxel classification in three subsequent stages. In the first stage, voxels that was easily be assigned to one of the three tissue types were labeled. In the second stage, dedicated analysis of the remaining voxels was performed. The first and the second stages both use two-class classification for each tissue type separately. Possible inconsistencies that could result from these tissue-specific segmentation stages were resolved in the third stage, which performs multi-class classification. A set of T1- and T2-weighted images was analyzed, but the optimized system performs automatic segmentation using a T2-weighted image only. They investigated the performance of the algorithm when using training data randomly selected from completely annotated images as well as when using training data from only partially annotated images. The method was evaluated on images of preterm infants acquired at 30 and 40 weeks postmenstrual age (PMA).

Additionally, Makropoulos et al. [28] have explained the Automatic Whole Brain MRI Segmentation of the Developing Neonatal Brain. Here, they developed a framework for accurate intensity-based segmentation of the developing neonatal brain, from the early preterm period to term-equivalent age, into 50 brain regions. They present a segmentation algorithm that models the intensities across the whole brain by introducing a structural hierarchy and anatomical constraints. The method was compared to standard atlas-based techniques and improves label overlaps with respect to manual reference segmentations. They demonstrated that the technique achieved highly accurate results and was very robust across a wide range of gestational ages, from 24 weeks gestational age to term-equivalent age.

III. PROBLEM DEFINITION

The primary intention of my research is to design and develop an approach for automatic segmentation of MR images of the neonatal brain. In general, the aim of brain segmentation is to delineate both large-scale brain areas, such as the cerebellum, the brainstem and the two hemispheres, and small-scale structures (tissues), such as the gray matter (GM), the white matter (WM), and the cerebrospinal fluid (CSF). In addition to these tissues, in the case of newborns we are also interested in distinguishing between cortical and sub cortical gray matter, and between myelinated and unmyelinated white matter, which is crucial in the evaluation of the white matter myelination process. Therefore, segmenting the brain tissue from premature infants Magnetic Resonance Imaging (MRI) data is a challenging task.

IV. MATERIAL AND METHOD

The algorithm is structured as pipeline which consists of following steps; preprocessing, brain extraction, tissue detection at global level and micro level and classification.

4.1 Preprocessing

T-1 weighted and T-2 weighted brain MR images are the input, we have to enhance the images in preprocessing stage. In preprocessing we apply following techniques on input images to enhance the quality of image they are as follows: intensity inhomogeneity correction, alignment to radiological orientation, affine registration and Gaussian Filtering to remove the noise.

$$\hat{g}(x,y)=\frac{1}{2\Pi\sigma^2}e^{\frac{-x^2+y^2}{2\sigma^2}}$$

Where, σ is the standard deviation of the Gaussian distribution.

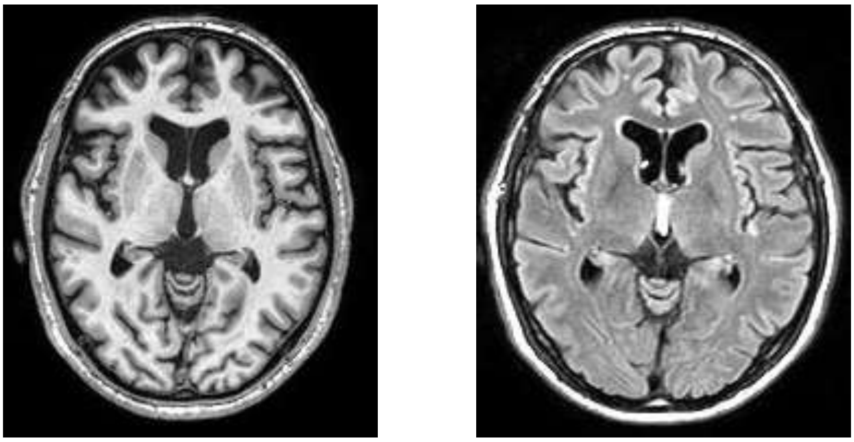

Figure 1 (a) Input MR Image ***(b) Pre-processed Image***

4.2 Skull stripping & Brain extraction

To process the image first of all we have to remove the skull area, and then we have to extract the brain potion. So for this purpose first of all we have to make contouring of brain portion. Following figure shows the steps to extract the brain portion.

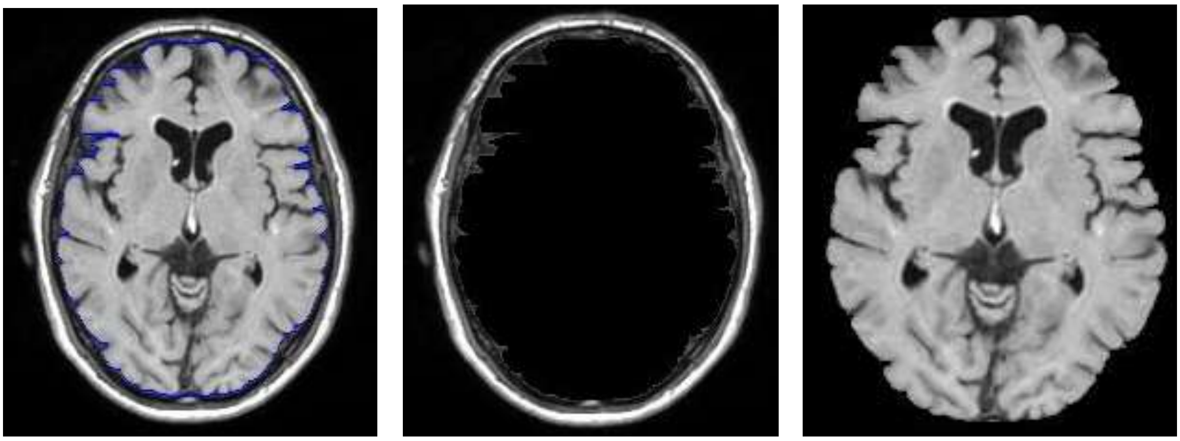

Figure 2 (a) Contouring of brain portion ***(b) Skull stripping*** ***(c) Brain extraction***

4.3 Tissue detection

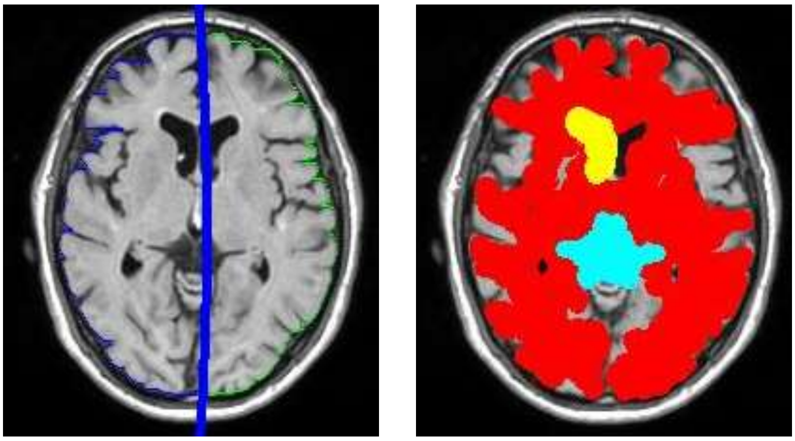

Figure 3 (a) Hemisphere Separation ***(b) Detection of cortical gray matter, unmyelinated white matter & CSF***

4.4 Classification

In this stage, K-Nearest Neighbor (KNN) is used to assign, voxels to one of the tissue classes, which are labeled WM, GM, CSF. In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

Finally, various brain MR images will be collected from benchmark database [29] and subjected to the proposed technique to evaluate the performance in segmentation performance. The implementation is done in MATLAB.

V. RESULTS

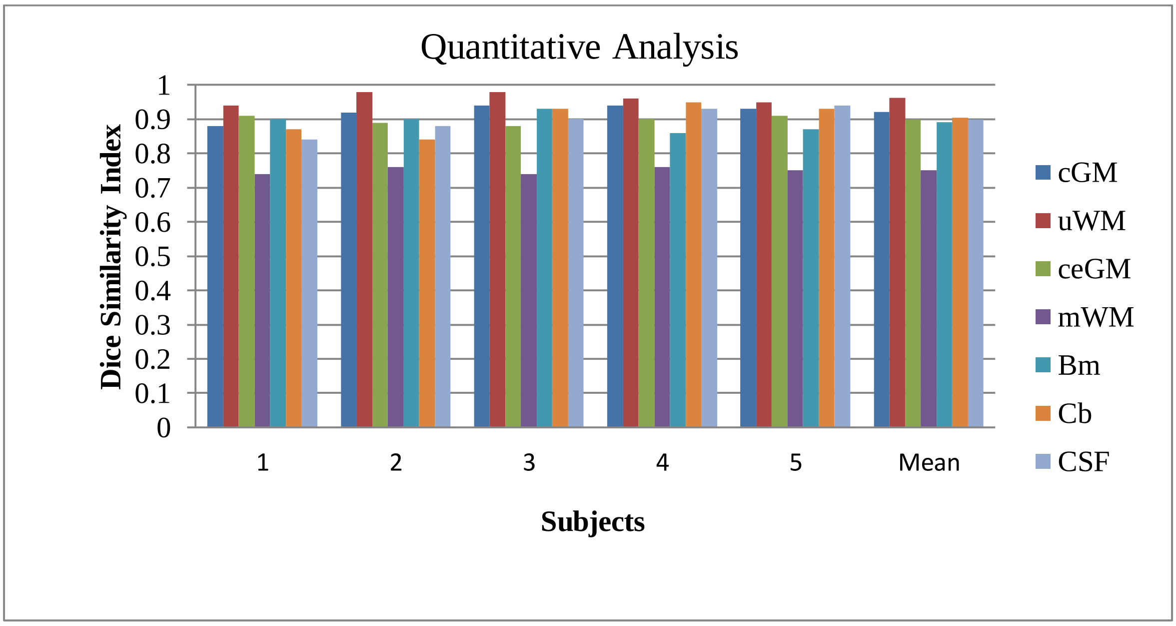

Figure 4 Quantitative analysis of various infants

Above figure shows the dice similarity index representation graph of the proposed dataset, from that the dice similarity index, value of Gray Matter, White Matter, Sub cortical Gray Matter, Myelinated White Matter, Brain stem , Cerebellum and CSF are comparative more than the existing techniques mentioned in the related work section.

CONCLUSION

The presented method accurately segmented WM, GM, and CSF in T2-weighted images and is robust to differences in age and acquisition protocol. Furthermore, the method accurately segmented the images when trained with a limited number of training samples from the given population, without any additional parameter tuning. This reduces the time and effort required to create reference annotations and may therefore extend the applicability of the method. The resulting segmentations can be used for volumetric measurements and quantification of cortical characteristics. This analysis play important role for neurologist for early detection of neural disorders. Hence proposed research work will provide more information to neurophysicians for better treatment of newborn babies.

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