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Computer Aided Diagnosis of Neurodegenerative Diseases Using RVM Classifier

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***Abstract*-- Neurodegenerative diseases comprise a wide variety of mental symptoms. Neurodegenerative diseases can find with image analysis method that describes discriminative brain patterns which is related to the presence of neurodegenerative diseases. In proposed method established by a fusion strategy that comprises of both bottom-up and top-down approaches. The identification of the defects in the images was based on the saliency obtained from the images. The saliency obtained describes the regions in the images that were having same intensity. The identified regions were then clustered and then features were extracted from the regions. Finally RVM classifier is fed with features such as intensity, textural and statistical information, binary tissue segmentations or cortical thickness estimations. Overall proposed algorithm used to decrease the computational time and the presence of irrelevant and noisy features. The Salient regions found with the proposed approach as systematically relevant for discrimination of AD patients this results completely coherent to what has been reported by clinical studies of AD.**

Index Terms— Alzheimer's disease (AD), automated pattern recognition, magnetic resonance imaging (MRI), relevant vector machines (RVMs).

I. INTRODUCTION

A. Introduction Document

The term neurodegeneration is a combination of two words - "neuro," referring to nerve cells and "degeneration," referring to progressive damage. The term "neurodegeneration" can be applied to several conditions that result in the loss of nerve structure and function. This deterioration gradually causes a loss of cognitive abilities such as memory and decision making. Neurodegeneration is a key aspect of a large number of diseases that come under the umbrella of "neurodegenerative diseases." Of these hundreds of different disorders, so far attention has been mainly focused on only a handful, with the most notable being Parkinson's disease, Huntington disease and Alzheimer's disease. A large proportion of the less publicized diseases have essentially been ignored. This causes problems with movement (called ataxias) or mental functioning (called dementias). Dementias are responsible for the greatest burden of disease with Alzheimer's representing approximately 60-70% of cases. Alzheimer's disease is the most common cause of dementia. The word dementia describes a set of symptoms that can include memory loss and difficulties with thinking, problem-solving or language. These symptoms occur when the brain is damaged by certain diseases, including Alzheimer's disease. This factsheet describes the symptoms of Alzheimer's disease, how it is diagnosed, and the factors that can put someone at risk of developing it. It also describes the treatments and support that are currently available. Alzheimer's disease, named after the doctor who first described it (Alois Alzheimer), is a physical disease that affects the brain. During the course of the disease, proteins build up in the brain to form structures called 'plaques' and 'tangles'. This leads to the loss of connections between nerve cells, and eventually to the death of nerve cells and loss of brain tissue. People with Alzheimer's also have a shortage of some important chemicals in their brain. These chemical messengers help to transmit signals around the brain. When there is a shortage of them, the signals are not transmitted as effectively. As discussed below, current treatments for Alzheimer's disease can help boost the levels of chemical messengers in the brain, which can help with some of the symptoms.

Alzheimer's is a progressive disease. This means that gradually, over time, more parts of the brain are damaged. As this happens, more symptoms develop. They also become more severe. Alzheimer's disease develops differently for every individual, there are many common symptoms. Early symptoms are often mistakenly thought to be 'age-related' concerns, or manifestations of stress. In the early stages, the most common symptom is difficulty in remembering recent events, known as short term memory loss. During the final stage of AD, the person is completely dependent upon caregivers. Language is reduced to simple phrases or even single words, eventually leading to complete loss of speech. Despite the loss of verbal language abilities, people can often understand and return emotional signals. Alzheimer is the common form of dementia a general term for memory loss and other intellectual abilities neurological disorder in which the death of brain cell causes memory loss and cognitive decline.

II. EXITING WORK

The Exiting work evaluating both its accuracy for discriminating different experimental groups and its capacity of determining the relevant anatomical regions together with their weights. This is accomplished using a fusion strategy that is GBVS implementation which mixes together bottom-up and top-down information flows. The bottom-up approach highlights relevant regions correlated with the AD diagnosis. The top-down scheme identifying patterns associated to pathological stages. In order to highlight the quality of the model is not only given by the quantitative performance measures, but by its aptness to automatically detect highly discriminative brain regions, consistent with those regions that have been described as important in the progression of the disease. The most popular technique has been proposed by support vector machine (SVM), which has been applied to classifying individuals with several neurological disorders.

The SVM classifier is usually fed with features such as intensity, textural and statistical information, binary tissue segmentations or cortical thickness estimations. Comparisons between the kernel group and the baseline have shown that the segregation of information into different feature-scale kernels, improves the classification performance in all subject groups. In prospective system they use the kernel function for feature extraction instead of existing method. This based on a two-phase visual saliency miniature that correlate bottom-up and top-down process to get definite analysis of brain MR images as ordinary controls or feasible AD subjects. Extension of the initial data into these various scale spaces attack to sparsify the raw intellect data, promoting the depth contraction.

In they suggested model, the input space is the space of saliency maps, so a kernel function measures the affinity between saliency maps. Sparsify is derived by the goal of discover a diminished set of saliency maps that better summarize optical designs to discriminate feasible AD cases from normal restraint. In the prospective access the pre-defined kernels follower the input image into specific feature saliency maps, whose voxels correspond to dimensions of the saliency map space. Finally using this Feature Extraction values classify the values by using the SVM Classifier. This event clarify that the learning technique here in used is able to individually analyze the framework space and to optimally combine or merge each part.

III. PROPOSED WORK

The proposed method is based on a two-phase visual saliency model that combines bottom-up and top-down approaches to achieve accurate classification of brain MR images as normal controls or probable AD subjects.The input MRI is obtained. Saliency map is identified from the input MRI images. The saliency map combines information from each of the feature maps into a global measure where points corresponding to one location in a feature map project to single units in the saliency map. Saliency at a given location is determined by the degree of difference between that location and its surround. Saliency typically arises from contrasts between items and their neighborhood, such as a red dot surrounded by white dots, a flickering message indicator of an answering machine, or a loud noise in an otherwise quiet environment.

Humans and other animals have difficulty paying attention to more than one item simultaneously, so they are faced with the challenge of continuously integrating and prioritizing different bottom-up and top-down influences. The obtaine saliency is then normalized. To changing the Intensity, Coordinates values, etc. the normalization process is needed. In image processing, normalization is a process that changes the range of pixel intensity values. Applications include photographs with poor contrast due to glare.

Normalization is sometimes called contrast stretching or histogram stretching. Auto-normalization in image processing software typically normalizes to the full dynamic range of the number system specified in the image file format. The features were extracted using the kernel functions. Kernel methods have received major attention, particularly due to the increased popularity of the Support Vector Machines. Kernel functions can be used in many applications as they provide a simple bridge from linearity to non-linearity for algorithms which can be expressed in terms of dot products.

Most often, the space is divided into an appropriate number of ranges, often arranged as a regular grid, each containing many similar color values. The color histogram may also be represented and displayed as a smooth function defined over the color space that approximates the pixel counts. The obtained features were then classified using Relevence vector Machine classifier. Relevence vector machines (RVMs, also support vector networks) are supervised learning models with associated learning algorithms. That analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an RVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier.

An RVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. Based on the classified results the regions of the images were identified. RVM is a kernel method, linear in the parameters and similar to the “support vector machine” (SVM). However, it offers several advantages over SVM, mainly probabilistic predictions and automatic estimation of hyper-parameters. They are based on a Bayesian formulation of a linear model with an appropriate prior that results in a sparse representation. As a consequence, they can generalize well and provide inferences at low computational cost.

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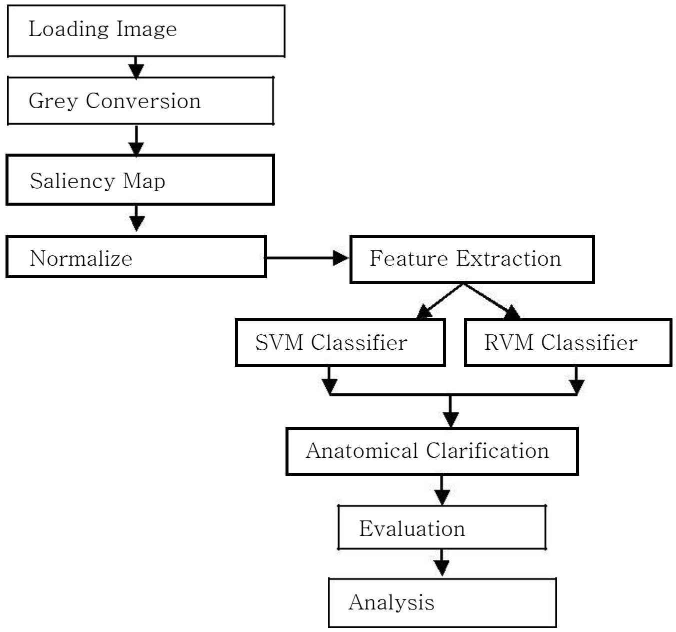

Figure 1. System architecture

In our project, dataset are collecting. The user is mainly collected the dataset in data. That data should be kernel feature extraction and classification purpose used for RVM classifier. The find the disease in the brain. Finally, to produce the proposed system result compare between existing systems. To produce the less execution time for accuracy and performance in the classification process.

IV.METHODOLOGY

A. Saliency map

Automatic estimation of salient object regions across image without any prior assumption or knowledge of the contents of the corresponding scene. Introduce a regional contrast based salient object extraction algorithm which simultaneously evaluated global contrast different and spatial weighted coherence scores. Proposed algorithm is simple, efficient, and naturally multistage and produces full resolution high-quality saliency maps. Further used to initialize a novel iterative version of grab cut for high quality salient object segmentation. We evaluated our algorithm using traditional salient object deletion dataset as well as more challenging internet image dataset. Algorithm consistently outperforms existing salient object detection and segmentation methods. Yielding higher precision and better recall rates. Saliency map has its root in feature integration theory and appears first in the class of algorithmic models above it includes the following elements.

i. An early representation composed of a set of feature maps computed in parallel permitting separate representations of several stimulus characteristics.
ii. A topographic saliency map where each location encodes the combination of properties across all feature maps as a conspicuity measure.
iii. A selective mapping into a central non-topographic representation through the topographic saliency map of the properties of a single visual location.
iv. A winner takes all networks implementing the selection process based on one major rule conspicuity of location.
v. Inhibition of this selected location that causes an automatic shift to the next most conspicuous locations. Feature maps code conspicuity with in a particular feature dimension.

The saliency map combines information from each of the feature maps into a global measure where points corresponding to one location in a feature map project to single units in the saliency map. Saliency at a given location is determined by the degree of difference between that location and its surround. Saliency typically arises from contrasts between items and their neighborhood, such as a red dot surrounded by white dots, a flickering message indicator of an answering machine, or a loud noise in an otherwise quiet environment. Humans and other animals have difficulty paying attention to more than one item simultaneously, so they are faced with the challenge of continuously integrating and prioritizing different bottom-up and top-down influences.

B. Normalization

In image processing normalization is a process that changes the range of pixel intensity values. Applications include photographs with poor contrast due to glare. Normalization is sometimes called contrast stretching or histogram stretching. In more general fields of data processing such as digital signal processing it is referred to as dynamic range expansion. To changing the Intensity, Coordinates values, etc….In image processing, normalization is a process that changes the range of pixel intensity values. Applications include photographs with poor contrast due to glare. Normalization is sometimes called contrast stretching or histogram stretching. Auto-normalization in image processing software typically normalizes to the full dynamic range of the number system specified in the image file format.

C. Kernel Feature Extraction

Kernel methods have received major attention, particularly due to the increased popularity of the Support Vector Machines. Kernel functions can be used in many applications as they provide a simple bridge from linearity to non-linearity for algorithms which can be expressed in terms of dot products.Each measurement has its own wavelength range of the light spectrum, some of which may be outside the visible spectrum. If the set of possible color values is sufficiently small, each of those colors may be placed on a range by itself; then the histogram is merely the count of pixels that have each possible color.

Most often, the space is divided into an appropriate number of ranges, often arranged as a regular grid, each containing many similar color values. The color histogram may also be represented and displayed as a smooth function defined over the color space that approximates the pixel counts. Kernel methods have received major attention, particularly due to the increased popularity of the Support Vector Machines. Kernel functions can be used in many applications as they provide a simple bridge from linearity to non-linearity for algorithms which can be expressed in terms of dot products. Most often, the space is divided into an appropriate number of ranges, often arranged as a regular grid, each containing many similar color values. The color histogram may also be represented and displayed as a smooth function defined over the color space that approximates the pixel counts.

D. SVM Classifier

Support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

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E. RVM classifier

Now a day, so many techniques are developed for satellite image classification. The earlier day maximum likelihood classifier is used for classification. In recent times, artificial intelligence techniques are developed for remotely-sensed image classification application. Relevance vector machine (RVM) is a kernel based classification which is alternative for SVM classifier. RVM is a identical form of SVM classifier, but RVM is a probabilistic classifier. The advantages of RVM classifier over SVM are listed below.

1. RVM classifier requires smaller amount of relevance vector than the SVM.
2. The testing time is less than SVM classifier.
3. The design complexity and cost is low for RVM when compared to SVM.

Generally RVM classifier is designed for binary classification. It fits functions in high-dimensional feature spaces, through the use of kernels; Despite a possibly large space of functions available in feature space, good generalization performance is nevertheless achieved by margin maximization It is sparse: Only a subset of training examples is retained at runtime, improving computational efficiency. However, there are also some disadvantages although relatively sparse, SVM make unnecessary literal use of basic functions since the number of support vectors (SV) required typically grows linearly with the size of the training set. Some form of post-processing is often required to reduce computational complexity; Predictions are not probabilistic. In regression the SVM Outputs a point estimate and in classification a 'hard' binary decision. Ideally we desire to estimate the conditional distribution in order to capture the uncertainty in out prediction. It is necessary to estimate the error/margin trade-off parameter C.

This generally entails a cross-validation procedure, which is wasteful both of data and computation. The kernel function must satisfy Mercer condition. That is, it must be the continuous symmetric kernel of a positive integer operator. RVM's advantages rise due to its ability to yield a decision function that is much sparser than SVM, while maintaining its classification accuracy. This can lead to significant reduction in the computational complexity of the decision function, thereby making it more suitable for real-time applications. The RVM was proposed by Tipping, as a Bayesian treatment of the sparse learning problem. The RVM preserves the generalization and sparsity of the SVM, yet it also yields a probabilistic output, as well as circumventing other limitations of SVM, such as the need for Mercer kernels and the definition of the error/margin trade-off parameter C.

F. Anatomical Interpretation

Red regions are pathology and blue regions are normality identifying the diseases in brain.The discipline of anatomy is divided into macroscopic and microscopic anatomy. Macroscopic anatomy, or gross anatomy, is the examination of an animal's body parts using unaided eyesight. Gross anatomy also includes the branch of superficial anatomy. Microscopic anatomy involves the use of optical instruments in the study of the tissues of various structures, known as histology and also in the study of cells.

The history of anatomy is characterized by a progressive understanding of the functions of the organs and structures of the human body. Methods have also improved dramatically, advancing from the examination of animals by dissection of carcases and cadavers (corpses) to 20th century medical imaging techniques including X-ray, ultrasound, and magnetic resonance imaging. Anatomy is the study of the structure of animals and their parts, and is also referred to as zootomy to separate it from human anatomy.

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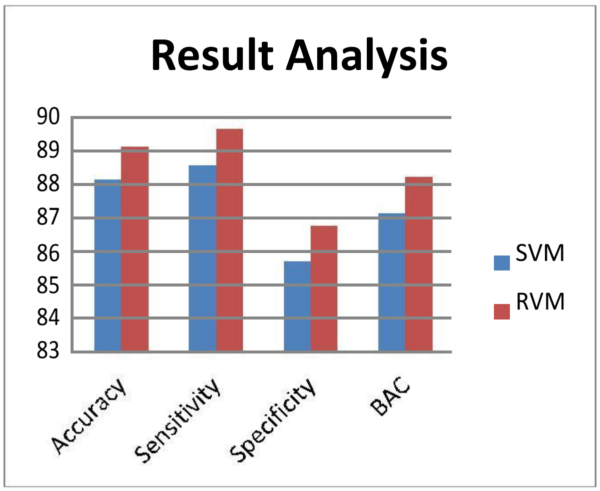
G. Performance Analysis

Result analysis of our process accuracy,sensitivity,specificity. To avoid the possible inflated performance estimation on the unbalanced datasets, the balanced classification accuracy was also computed, a simple arithmetic mean of the sensitivity and specificity. The balanced accuracy (BAC) removes the bias that may arise by imbalanced datasets. In a binary classification problem, if the classifier performs equally well on either class, BAC reduces to the ordinary accuracy. If, however, the classifier has taken advantage of an imbalanced dataset, then the ordinary accuracy will be inflated, whereas the BAC will drop to chance (50%), as desired. The time is set aside during the training phase and then classified using the SVM model trained with the remaining subjects. To avoid the possible inflated performance estimation on the unbalanced datasets. The balanced accuracy (BAC) removes the bias that may arise by imbalanced datasets. The balanced classification accuracy was also computed, a simple arithmetic mean of the sensitivity and specificity. Result analysis of our process accuracy, sensitivity, specificity.



V. Conclusion

The thesis has introduced and adapted biologically inspired methods for identification of diagnostic-relevant image regions in a very complex and challenging problem, the Alzheimer's disease (AD). The automatic strategies herein developed have included prior anatomical and medical knowledge within the morpho-metrical analysis. The set of proposed tools constitute an innovative framework in the context of anatomical studies: sparse-based representations and visual attention methods, together with machine learning techniques, provide efficient representations of the image content in terms of visual features, leading to the discovery of visual patterns directly related with a specific pathology. The present investigation has included an extensive validation and parameter study, evaluating both its accuracy for discriminating different experimental groups and its capacity of determining the relevant anatomical regions together with their weights. Regarding discriminative power, different parameters involved in the top-down and bottom-up information flows, were assessed in terms of classification accuracy, allowing identifying the influence of the different visual features and image scales in the final discrimination between AD and NC classes.

The simpler version of our proposal (combining a single saliency-based kernel with SVM learning) has reached an equivalent performance to a state-of-the-art approach (FBM proposed by. Finally, we want to highlight that the quality of the model is not only given by the quantitative performance measures, but by its aptness to automatically detect highly discriminative brain regions, consistent with those regions that have been described as important in the progression of the disease.

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