

Computer Aided Diagnosis of Neurodegenerative Disorders: A Short Review

Salil Batra

Department of Computer Science
Lovely Professional University
salil.16836@lpu.co.in

Makul Mahajan

Department of Computer Science
Lovely Professional University
makul.14575@lpu.co.in

Simarjit Singh Malhi

Department of Computer Science
Lovely Professional University
simarjit.15976@lpu.co.in

Gursharan Singh

Department of Computer Science
Lovely Professional University
gursharan.16967@lpu.co.in

ABSTRACT

Emergence of neurodegenerative disorders with population aging is a major concern nowadays. Correct and timely diagnosis of these kinds of disorders is a major challenge faced by doctors and neurologists. This paper determines how different computer aided techniques and their applications have been utilized to develop expert systems for the diagnosis of neurodegenerative disorders (ND). It presents the consolidated outlook of research progress in the field of ND disorders through a literature survey from 2005 to 2019. This paper extends its discussion with the feature extraction methods along with the classification techniques primarily used for the construction of intelligent systems. It also identifies the research progress using the expertise of intelligent techniques for world's top two neurodegenerative disorders: Alzheimer's and Parkinson's. The study identifies that principal component analysis (PCA) as a most widely used feature extraction method for representing the features in lower dimension. Support Vector Machines (SVM) with and without kernel functions are also showing their utility as a major classifier for most of the (Computer aided diagnosis) CAD systems. The survey is also identifying the usage of various kinds of datasets over the years for obtaining best results.

Keywords— *Principle component analysis, Support vector machines, Random forests, Dementia, Machine learning*

1 INTRODUCTION

Early diagnosis of neurodegenerative disorders is a vital challenge for most of the physicians and doctors nowadays. Neurodegenerative disorders represent the loss of neurons which can hamper the functioning of central nervous system. The most common subset which covers these types of disorders is related with dementia. Dementia denotes the decline of mental ability with age [1]. The decline of mental ability leads to memory loss, problems in focusing and understanding things etc. Various other symptoms like problems in reasoning, visual perception, communication also denotes the presence of dementia. Dementia is a generalized terminology, its various types and their symptoms cover its range and scope [1]. Dementia is characterized by its various types such as: Alzheimer disease, Vascular dementia, Dementia with Lewy

bodies, Parkinson's disease, Frontotemporal disease, Huntington's disease, Mixed Dementia etc [2]. The varied types of dementia and their underlying features are hard to recognize. The major challenge lies not in the diagnosis of dementia, rather the type of dementia. The main reason for the existence of this challenge is that the symptoms of various dementia types can overlap and hence the ambiguity remains. Although, various advanced imaging techniques exist but still the challenge of accurate classification of dementia type remains [5].

The most common type of dementia is Alzheimer's disease, and according to the latest survey around 20 million people worldwide are affected by this disorder. It is expected to get tripled over the next 50 years [9]. The major cause for this disease is the formation of protein based structures called 'plaques' and 'tangles' in the core and central brain region known as hippocampus. There are various symptoms which highlight the introduction of this disorder, such as difficulty in remembering newly learned information, problems in communication, reasoning, planning, feeling of anxiety and restlessness etc.

The second type of dementia which is also affecting millions of people worldwide is Parkinson's disease. It is also a progressive disorder which is difficult to diagnose. This disorder generally affects body movement [1]. The common symptoms are like: No swing of arms while walking, expressionless face, variations in speech like softening of voice. The major cause for this disorder is the decreased level of dopamine inside brain [2]. Dopamine is like a chemical messenger which helps the nerve cells to communicate with each other. The other reason could be the development of Lewy body structures inside brain. Lewy bodies are unwanted deposits of brain protein also termed as alpha-synuclein.

The similarities in the symptoms and their distinct causes make it difficult to classify the superset of dementia into its several types. Over the past two decades a lot of work has been done in the accurate classification/diagnosis of dementia types. New techniques in the form of medical imaging, neuropsychological scores, statistical tests, clinical biomarkers, gene prediction have emerged to assist the physicians and neurologists. Machine learning, which is one of the core subfield of artificial intelligence, is integrated with these techniques to provide better diagnostic results. The next section of introduction gives description about various techniques and procedures.

Machine learning is the branch of computer science that provides ability to learn and recognize without being manually programming computers. It denotes the set of algorithms that are designed in such a way that they can learn the patterns from the given data so that accurate predictions can be made. The basic evolution of machine learning is from pattern recognition and computational learning theory in artificial intelligence. Depending upon the nature of learning we can classify machine learning into four categories such as: Supervised, Unsupervised, Semi-Supervised and Reinforcement learning. In supervised learning, computer is presented with set of inputs and desired outputs. Computer will learn according to the general rules which are assisting in providing desired output. Unsupervised learning is performed without providing the desired outputs. Learning mechanism is dependent on the input set and computer will identify the hidden patterns without any expected output. Semi-Supervised learning is same as supervised learning with incomplete desired output sets. Reinforcement learning is related with input and output sets but the degree of closeness to the goal is not known.

Medical imaging is integrated with machine learning techniques to build various computer aided diagnostic systems. There are various neuroimaging techniques available such as: MRI, SPECT, PET, DWI, fMRI etc. Depending upon the need any neuroimaging technique can be utilized. Various types of clinical biomarkers are also developed such as: CSF (Cerebrospinal fluid). Various datasets are available which signifies the patterns contributing towards neurodegeneration. The next section of this paper describes various computing techniques applied over existing datasets for the diagnosis of neurodegenerative disorders. The section also describes why a particular technique is preferred over each other. It also demonstrates various merits and demerits. The third section of this paper enlists various types of imaging techniques along with the popular datasets available for assisting the researchers.

2 REVIEW OF LITERATURE

The literature review presented in this paper starts from the year 2005 and extends up to 2019. Various online databases such as: ScienceDirect, IEEE Xplore, Pubmed, Google Scholar and Springer were searched for the relevant research articles. Around 430 research articles were found and filtering reduced this number up to 110. Most suitable papers were selected and the phrases used for searching were “Computer aided techniques”, “Intelligent techniques”, “Machine learning techniques” for the diagnosis of neurodegenerative disorders. Disorder specific searching was also performed. A systematic review has been done and various technique-wise categories are also developed.

The major observation drawn from the state of the art is that most of the datasets used for the computer aided diagnosis are image based. For image based datasets dimensionality reduction has been performed for obtaining better results. Dimensionality reduction can be performed in two ways: Feature Extraction and Feature Selection. Feature extraction is the transformation of existing features into space with lower dimension whereas Feature selection is the selection of subset of features without any transformation. Feature extraction and reduction is performed in order to reduce the complexity imposed with the increased number of features. So the best way is to select an appropriate feature space. Feature selection and extraction is followed by the classifier which again covers up various machine learning algorithms. The main purpose is to identify the major contribution of various categories of machine learning algorithms in correct diagnosis of neurodegenerative disorders. Following are the list of feature selection/extraction techniques identified from the study of intelligent systems for neurodegenerative disorders. Later part demonstrates the consolidated classifiers used for the correct diagnosis of dementia and its types.

2.1.1 Techniques for Feature Extraction

Various feature extraction techniques identified from review are: Lattice Independent Component Analysis (LICA), Principle Component Analysis (PCA), Partial Least Squares (PLS), Empirical Mode Decomposition (EMD), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Combination of PCA and LDA, Non Negative matrix factorization and Genetic Algorithm. Following is the visual representation of various techniques for feature extraction used for aiding the diagnosis of neurodegenerative disorders

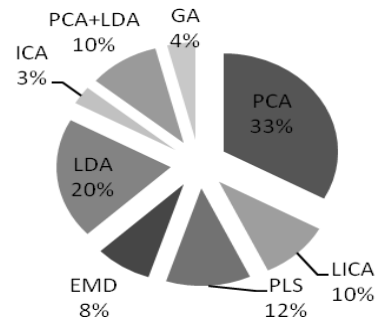


Figure 1: Techniques used for Feature Extraction

2.1.1.1 Lattice Independent Component Analysis

LICA feature extraction method is implemented by [16] and [23] for the aiding the classification of normal, MCI, Alzheimer's subjects. The main advantage of using approach is that there is no need to impose any statistical assumptions to find the valid sources. The other benefit lies in its unsupervised and incremental nature [16]. LICA is a non linear alternative for Independent Component analysis

2.1.1.2 Principle Component Analysis

PCA for feature extraction is most widely used method for feature extraction in the study of neurodegenerative disorders [18]. PCA provides the non-parametric way of obtaining relevant information from ambiguous datasets. Its functionality is totally dependent on Eigen values and Eigen vector analysis of covariance matrix. It converts the given feature space into lower dimension using orthogonal transformation [21]. It creates linearly uncorrelated variables which are commonly known as principal components. The key advantage of using PCA over others is there will be reduction of noise as maximum variance is already taken. Moreover there is less redundant data as orthogonal components are used for data representation [9]. The major drawback lies in the difficulty in the proper evaluation of covariance matrix and incapability of detecting small invariance.

2.1.1.3 Partial Least Squares

Partial least squares (PLS) identify the linear regression by projecting two types of variables such as: predicted and observable into new area [14]. It helps to generate latent vectors by maximizing covariance factor among different set of variables. It has been observed that provides better discriminative view among two classes as compared to PCA. PLS is mainly used for creating such predictive models in which the supporting factors in the dataset are highly collinear [13,22,23]. The major drawback lies in the fact that if there are outliers they can alter the resulting scores and relationship with the response.

2.1.1.4 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is closely related to Analysis of Variance which tries to find out linear combination of variables which are further aiding in differentiating set of classes[14]. The main role of LDA in medical datasets is to maximize the component axes for class separation. It works by computing eigen vectors and corresponding eigen values of scatter matrices. LDA is used for dimensionality reduction and the created eigen vector matrix transforms the existing samples into new space.

2.1.1.5 Independent Component Analysis

This technique is used to represent n-dimensional random vector as a combination of independent components. It finds the best linear basis; hence the statistical dependence among the projected components is decreased to a major extent [15]. The extended usage of Independent Component Analysis is to project the dataset such as images into non-gaussian filter space. We can obtain the final projection after converting the finding the inverse of the initial random vector. It is evident from the graph PCA has given its major contribution towards feature extraction which is the key role of any machine learning based computer aided system.

2.1.2 Techniques for Classification

The most vital step for the diagnosis comprises of training with the most suitable classifier. The selection of correct classification algorithm is the crucial part. From the study of computational methods for neurodegenerative disorders following methods are identified and their usage in percentage.

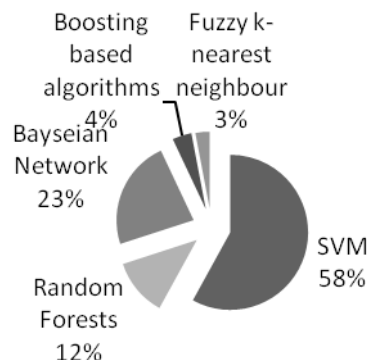


Figure 2: Techniques for classification

It is clear from the given graph that SVM (Support Vector Machines) has been utilized extensively for the purpose of classification [21]. It is one of the supervised learning algorithm which works on data with high dimensionality. It utilizes the concept of hyperplanes in order to separate binary test data into relevant classes. It tries to deploy maximum distance for binary test data from the hyperplane in order to remove the chances of misclassification. There can be chances that data separation is not possible linearly then kernel functions can be used in order generate a non-linear decision boundary. Different types of kernel functions identified from the study are Quadratic, Polynomial and radial functions. The other most popular classifier is based upon bayesian network. BN(Bayesian network) is a collection of variables which are random in

nature. The network representation is done with the help of DAG (Directed Acyclic Graphs), where the nodes are the variables and the edges connecting the nodes shows the dependency among the variables.

3 OBSERVATIONS

Over the last two decades a lot of research has been done for the computer aided diagnosis of neurodegenerative disorders. From the literature survey, year range wise progress has been derived.

3.1 Consolidated graph for research progress

It is quite evident from the given figure that a lot of computing techniques and systems are developed over past five years for neurodegenerative disorders. Research for finding the excellent diagnostic power has reached to greater extent. It has been a progression over the years. Early years have shown a slow rate, but with the passage of time the emergence of machine learning techniques have shown its impact.

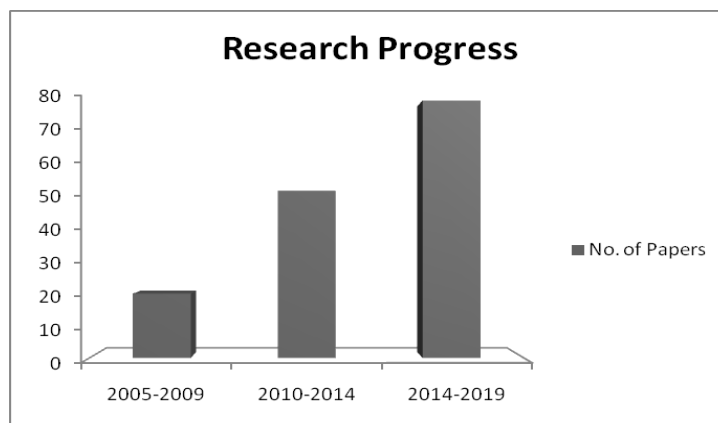


Figure 3: Research progress for Neurodegenerative disorders

Next figure demonstrates the evolution of computer aided diagnosis for world's top two neurodegenerative disorders. Alzheimer and Parkinson's disorders are affecting most number of people worldwide. So, a lot of work is going on the early diagnosis of their emergence. Early diagnosis can help to minimize their impact and after effects.

3.2 Consolidated graph for diagnosis of Alzheimer and Parkinson's disorders

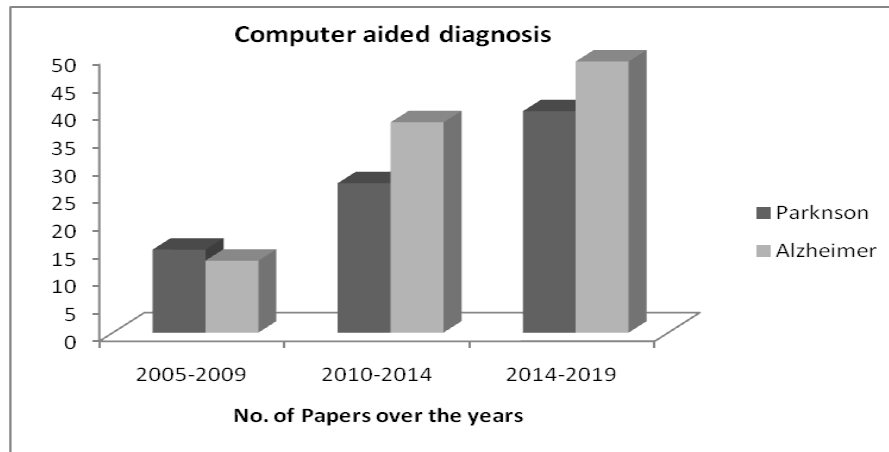


Figure 4: Year range wise paper distribution

From the given graph it is clear that machine learning techniques are implemented with a great rate over the years. Over the years development of intelligent methods for Alzheimer and Parkinson have gone side by side. From the last five years building up of diagnostic systems for Alzheimer disorder have pushed to greater levels. The amount of research for a particular disorder depends upon the severity and impact of that particular disorder on society.

Implementation of machine learning techniques for a particular disorder depends upon the availability of appropriate datasets. During review a conclusive interpretation has been also drawn for the type of datasets extensively used for the implementation of intelligent methods developed by researchers over the years. Different types of datasets available for the diagnosis of neurodegenerative disorders are: i) Image ii) Neuropsychological scores iii) EEG signals iv) Integrated datasets v) Gene expressions vi) Audio recordings vii) Video/Gait recordings viii) Electromyography. Depending upon the availability and expertise relevant dataset can be used to draw inference and hidden patterns can be digged out. The chart following this discussion highlights the percentage of datasets used by the intelligent methods over the years for correct assessment of Alzheimer

3.3 Consolidated piechart for dataset usage of Alzheimer disorder

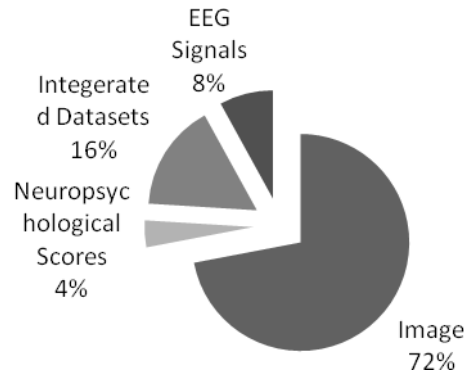


Figure 5: Dataset usage of alzheimer's disorder

The given chart explains the trends of dataset usage over the last two decades for implementation of machine learning techniques. From the given visual representation it is very much clear image datasets are widely used over the years. The reasons identified from the state of the art are: availability of image dataset is very high; correlation among the features given in the image datasets are highly conclusive; less noisy data; less variance among the data values; Image attributes are very helpful in determining the degeneration of nerve cells as compared to physical symptoms. All these advantages are conclusive enough for proving the fact of 72% usage of image datasets.

Overlapping of various symptoms sometimes give same brain structure for various types of neurodegenerative disorders, so sometimes image based diagnosis can be misleading. So, instead of using image attributes various other attributes can be summed up so that better classification can be performed. For this purpose integrated datasets can also be used. Integrated datasets may consist of image attributes, neuropsychological scores, CDR (Common Dementia rating) ratings, physical symptoms and various other attributes in terms of medical history. After image datasets most frequent used datasets are integrated one. These types of datasets are used nowadays as they provide more authentic and appropriate results.

4 CONCLUSION

The research progress identified in the paper clearly visualizing the severe nature of ND disorders and need of developing more computing methods for identifying the disorder. Conclusion drawn out of the review is signifying the development of various computing methods using machine learning techniques over the years which are getting better and better. Now the focus area should be on classifying the type of dementia. Although the symptoms may overlap but the researchers should develop such techniques which can minimize the effects of overlapping. Research can be extended to identify the correct stage if a particular type of ND has been correctly diagnosed. Integrated datasets should be used extensively in order to enhance the diagnostic power.

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