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An Experimental Study on Classification of Brain Images

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ABSTRACT

Introduction: The brain is the major and vital organ of the central nervous system. After the age of 60 or in old age, the human brain may suffer from various disorders. Brain diseases may also occur due to some inevitable causes in the normal human body. As the brain stops functioning, the human body goes into a paralyzed state. To treat various brain diseases, neurologists use different brain imaging techniques.

Aims: Magnetic Resonance Imaging (MRI) technique is one of the promising imaging techniques used in recent days for analyzing brain diseases. Manual analysis and classification of brain images into normal or deceased is a tedious task. So different supervised learning techniques are used for this purpose.

Methodology: This paper focuses on the experimental study on feature selection using PCA and LDA and classification of two of the brain image datasets i.e. Glioma and Alzheimer.

Result: The experimental study suggested that the PCA+MLP classifier obtained accuracy values of 92.68% for the Glioma dataset and 90.023% for the Alzheimer dataset. PLC is used for feature reduction and MLP is used as a classification task.

Conclusion: The results suggested that PCA with MLP outperformed the other models.

Key Words: Magnetic Resonance Imaging, Classifier, Perceptron, Decision Tree, Principal Components, Dimension Reduction, Noninvasive

INTRODUCTION

The nervous system is the major constituent of the biological structure of the human body. The vital component of the nervous system is the brain that controls all the operations of the human body. The brain can be affected by several diseases in the life cycle.[1] The brain disorders may sometimes lead to death. So it poses a major challenge for neurologists in the treatment of brain diseases. Brain imaging procedures are adopted in this context. Out of the different imaging techniques, the Magnetic Resonance Imaging (MRI) technique is the noninvasive method used in the analysis and identification of brain diseases in recent days. [2, 3]

The manual study and interpretation of brain MRI images by medical practitioners is infeasible and may lead to erroneous diagnosis. So the computer-assisted methods are beneficial in this context. Various researchers have used machine learning techniques in classifying the brain images as normal and pathological. [4] The authors applied random forest as the classifier for the brain MRI image classification.[5] PCA and neural networks are widely used in the classification of brain images.[6,7] The authors adopted Principal Component Analysis (PCA) for feature selection from the extracted brain images.[8] They applied Multilayer Perceptron (MLP) for the classification purpose that outperformed k-Nearest Neighbor (k-NN) classifier. Independent Component Analysis (ICA) has also been used as dimension reduction technique. [9, 10] From the literature study, the various steps involved in the brain MRI image classification process can be listed as follows:

- o Brain Image dataset collection
- o Data preprocessing with feature extraction and feature reduction
- o Classification and performance measurement.

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The objective of this study is to collect the brain MRI image datasets and then perform data preprocessing. PCA and ICA have been used for dimension reduction purposes. Then three different classifiers i.e. Random forest, k-NN and MLP are applied for the classification purpose. The accuracy values are compared for determining the efficient classifier. This paper is organized as follows. The methodologies are described in the second section. The experimental work is described in the third section. Finally, section 4 discusses the conclusion.

METHODOLOGY

The different feature reduction and classification techniques are discussed in this section.

Independent component analysis (ICA)

ICA is one of the unsupervised dimension reduction strategies used in neuroimaging studies. It groups the original dataset into a set of independent features.[11, 12] These independent components are also most relevant to the classification task.

Principal component analysis

PCA is one of the dimension reduction techniques used frequently in the data science and machine learning field. The high dimensional dataset is reduced to different principal components based on the variance values. [13, 14] No data are lost during the reduction to the low dimensional features. The principal components are the uncorrelated variables and the given initial features are the set of correlated variables.[15]

Random forest classifier

This is one of the learning approaches used for the classification tasks. This is constructed by combining several decision trees. [16] The basic purpose of this ensemble approach is to enhance the training process and classification accuracy. [18] The number of classification trees considered in the random forest approach is chosen randomly.

K-nearest neighbour (k-NN) Classifier

The k-NN classifier is the common classifier used in pattern recognition. The number k is chosen randomly and is very small. The training sample is assigned with the class label that has a minimum distance within the k neighbours. The weights are assigned for different neighbours. It can be stuck at local optima.

Multilayer perceptron (MLP)

MLP is one of the feed-forward neural network structures used for classification purposes. It is completely based on the functionality of the human brain. It belongs to the group of supervised learning. It has one input layer, one or more hidden layers and one output layer. During classification, the number of input neurons will be the number of features. The number of hidden nodes is randomly determined. For the binary classification problems, there is only one output neuron. [16]

Proposed Model

The work proposed in this paper is summarized in figure 1. The brain images of the two diseases are collected and preprocessed using 2D-DWT, PCA and ICA. Then the three different classifiers are used for classifying the brain images into normal or diseased. The accuracy values are recorded for the performance measurement (Figure 1).

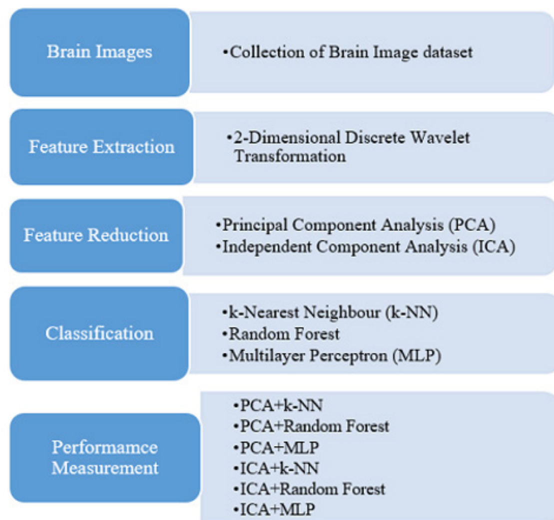
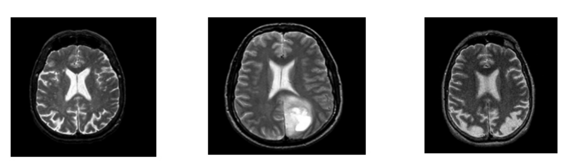


Figure 1: Proposed Workflow.

SIMULATION STUDY

The experimental study is conducted on MRI image datasets of two brain diseases i.e. Glioma and Alzheimer. These two datasets are collected from the Website of Harvard School of medicine. The Glioma dataset contains 122 images and the Alzheimer dataset contains 100 images where each image is of size 288 X 288. The sample MRI images of these two brain diseases are shown in Figure 2-(b) and 2-(c) respectively. Figure 2-(a) shows the normal brain MRI image.



(a) (b) (c)

Figure 2: Sample (a)-normal, (b)-Glioma, (c)- Alzheimer brain images.

2D DWT is used for feature extraction. Using this procedure, 1296 features are extracted.

FEATURE REDUCTION

In this work, two feature reduction techniques i.e. PCA and ICA are used. The number of reduced features are shown in Table 1 and Table 2 for PCA and ICA respectively.

Table 1: Feature Reduction using PCA

Brain diseases	No. of Samples	Total Features	Reduced Features
Glioma	122	1296	30
Alzheimer	100	1296	34

Table 2: Feature Reduction using ICA

Brain diseases	No. of Samples	Total Features	Reduced Features
Glioma	122	1296	122
Alzheimer	100	1296	100

CLASSIFICATION

The datasets are divided into train and test datasets for supervised learning. In this work, the Glioma and Alzheimer data sets are divided as 75% for training and 25% for testing purposes. The three types of classifiers i.e. random forest, k-NN and MLP classifiers are considered for the experimental study. [15,16]

The loss occurred during training of the datasets using PCA+MLP and ICA+MLP classifiers for the Glioma and Alzheimer datasets are shown in Figure 3 and 4.

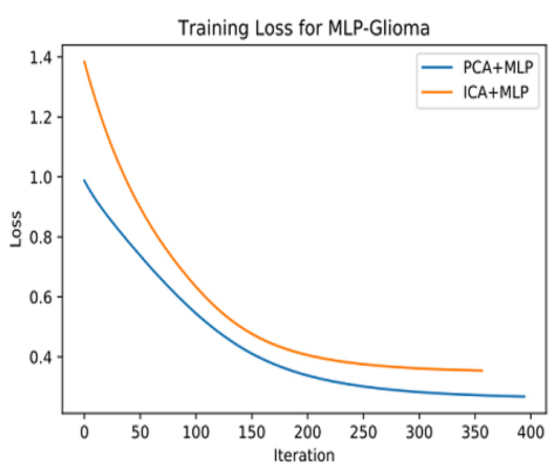


Figure 3: Training Loss using PCA+MLP for Glioma Dataset.

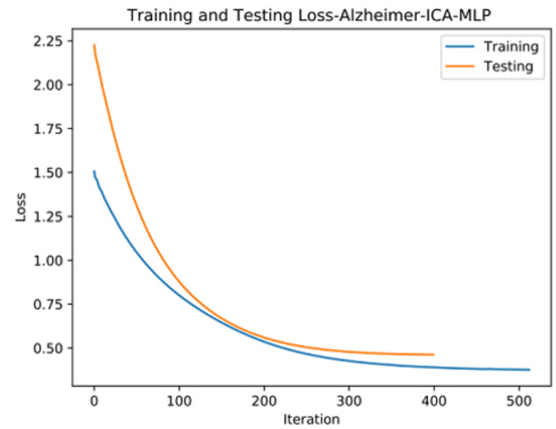


Figure 4: Training Loss using PCA+MLP for Alzheimer.

The accuracy values found during the classification of the brain diseases are stored in Table 3 and Table 4 for Glioma and Alzheimer image datasets.

Table 3: Accuracy values for Glioma

Models	Accuracy (%)
PCA+ Random Forest	90.023
PCA+ k-NN	92.68
PCA+ MLP	92.68
ICA+ Random Forest	60.37
ICA+ k-NN	46.37
ICA+ MLP	70.73

From Table 3, it is found that PCA with MLP and PCA with k-NN classifier has same accuracy values i.e. 92.68% for classification of Glioma images into normal and pathological brain.

Table 4. Accuracy values for Alzheimer

Models	Accuracy (%)
PCA+ Random Forest	81.81
PCA+ k-NN	75.75
PCA+ MLP	90.023
ICA+ Random Forest	66.66
ICA+ k-NN	45.46
ICA+ MLP	57.57

From Table 4, it is found that PCA with MLP classifier has highest accuracy i.e. 90.023% values for classification of Alzheimer images into normal and pathological brains.[14,15]

CONCLUSION

This work focuses on the experimental study on the performances of different standard classifiers i.e. random forest, k-NN and MLP classifiers for the brain MRI image classification of Glioma and Alzheimer datasets. The 2D DWT is used to extract the features from the brain images. Then two different feature reduction techniques i.e. PCA and ICA are employed in this work to reduce the feature sets. The experimental results suggest that the PCA with MLP produced the highest accuracy values and hence outperformed the other models for the classification of brain images for these two brain diseases.

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Conflict of Interest

NIL

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NIL

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