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
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.

**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. 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.

**Random forest classifier**
This is one of the learning approaches used for the classification tasks. It is constructed by combining several decision trees. The basic purpose of this ensemble approach is to enhance the training process and classification accuracy. 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.

**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).

**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.
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.

**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

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