it easier to interpret the results of a cluster analysis. In hierarchical algorithm large number of objects requires huge I/O cost. In clustering of image dataset using k-means and fuzzy k-means algorithm [5], image is a collection of number of pixels. It is difficult to take account of all pixels for clustering. Image segmentation play very useful role in clustering as it save times and it is efficient too. With the use of k-mean and fuzzy k-means algorithm clustering of large data become easy and time saving. Fuzzy clustering algorithms classify the tissues based on single channel MRI images but after clustering noise and misclassification error may present. The K-means algorithm partitions the data into *K* clusters, represented by their centers or means. The center of each cluster is calculated as the mean of all the instances belonging to that cluster. But in k-means algorithm the clustering quality is greatly dependant on the choice of initial centers. Poor choices of the initial centers can degrade the quality of clustering solution and result in longer execution time.

4. Implementation

A. Existing System

In existing system data object is represented by a multivariate time series. Each dimension is a time series corresponding to the FMRI signal of a specific anatomical brain region. IKM is partitioning clustering algorithm and it is applied to detect clusters of objects with similar interaction patterns. This system finds clusters of objects which are represented by multivariate time series sharing a common cluster-specific interaction pattern among the dimensions. It preserves the information on attribute dependencies. FMRI image is result of simplest kind of FMRI experiment. Time series data is not easily implemented in java. Difficult task in clustering time series is to find appropriate similarity measure. So in proposed system FMRI images are used.

B. Proposed System

Problem Definition: Brain Images which have similar interaction patterns assign to common cluster by using IKM

algorithm IKM (data set DS, integer K): Clustering $\mathcal{C}$
  Clustering $bestClustering$;
//initialization
  for $init := 1 \ldots maxInit$ **do**
    $\mathcal{C} := randomInit(DS, K)$;
    for each $C \in \mathcal{C}$ **do**
      $\mathcal{M}_C := findModel(C)$;
    while not converged or iter $<$ **maxIter do**
//assignment
      for each $O \in DS$ **do**
        $O.cid = \min_{C \in \mathcal{C}} \mathcal{E}_{O,C}$
//update
      for each $C \in \mathcal{C}$ **do**
        $\mathcal{M}_C := findModel(C)$;
      if improvement of objective function
        $bestClustering := \mathcal{C}$;
    end while
  end for
return $bestClustering$;

Figure 1: Interaction K-means Algorithm

algorithm and detects specific cluster names as normal or specific diseased using naive algorithm.

1) Algorithm:

In proposed system IKM algorithm is used. The first step of IKM is the initialization. As a common strategy for K-means, propose to run IKM several times with different random initializations and keep the best overall result. For initialization, randomly partition DS into K clusters. For IKM it is favorable that the initial clusters are balanced in size to avoid overfitting. Therefore, partition the data set into K equally sized random clusters and find set of models for each cluster. For model finding apply greedy stepwise algorithm combination with Bayesian Information Criterion (BIC). After initialization, IKM iteratively performs the further two steps until convergence. After assignment, in the update step, the models of all clusters are reformulated. IKM converges as soon as no object changes its cluster assignment during two consecutive iterations. Pseudo code of IKM is provided in Figure 1.

2) System Architecture:

Login:- In proposed system user first login with valid username and valid password for authentication.
Browse Dataset:- In this dataset of FMRI images stored at specific location. Image histograms values are calculated from FMRI images and stored. Then dataset is browse from stored location and show all images of dataset.

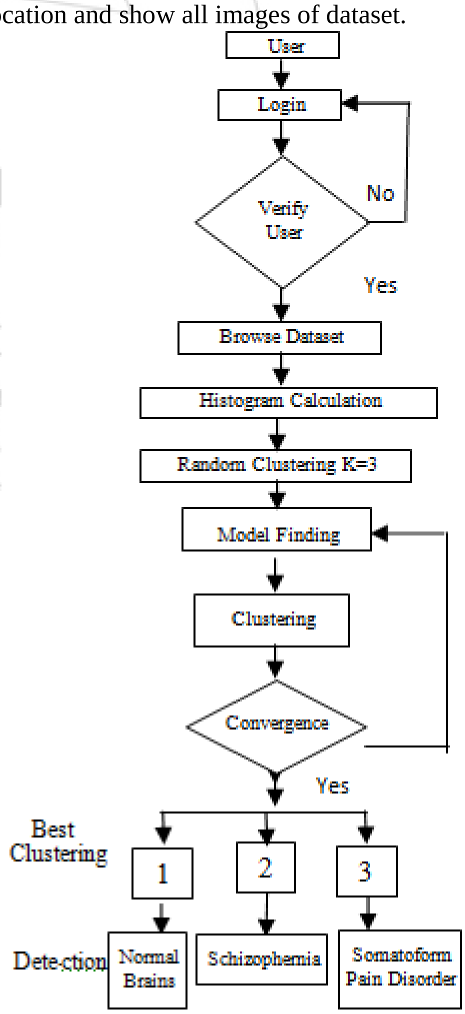

Figure 2: Architecture

IKM algorithm:- Then IKM algorithm is applied on dataset images The image histogram values are taken as input to system.In that first random clustering is done. On that each cluster model finding is applied and clustering is done up to convergence. Then get best clustering. From clustering normal brain images and abnormal brain images evaluates differently. The abnormal brain images consists different clusters of different diseases.

Detection:- To detect which cluster is for which specific cluster comparison is done. The known disease images are stored already as training data which are comparing with clusters and get result. The system architecture shown in figure 2.

5. Mathematical Model

Image clustering using IKM algorithm clusters brain images into normal and diseased.

Assumptions:
L : Login into system
DS: Browse Dataset
HC: Calculate histogram
CL: Make clusters
DT: Detect cluster names

1. User can login into system with valid username and valid password.
2. User can give dataset of brain images as input.
3. Image histogram values are taken as input by system.
4. Output is set of clusters each cluster contain similar interaction pattern images.
5. Considering training data specific cluster names detected.

C. Model Finding

For model finding apply greedy stepwise algorithm combination with Bayesian Information Criterion (BIC). In proposed system linear model used because of images are in sequentially format. They are interpretable and computationally efficient. And also applied for efficient compression and classification respectively.

The greedy stepwise algorithm [6] starts with an empty set of relevant dimensions. In each step, either one dimension is added or removed, depending on which of these two actions is judged superior by the evaluation criterion. The algorithm terminates if none of the two actions leads to a further improvement. BIC [7] which determines a balance between goodness-of-fit and complexity of the model and is defined by:

$$BIC\ (M_a) = -2 \cdot LL\ (a, M_a) + \log(m^*)(|V| + 1).$$

The first term represents the goodness-of-fit, where $LL\ (a, M_a)$ denotes the log-likelihood of dimension a given the model. The second term punishes overly complex models.

D. Detction

The naive algorithm is used for comparison. At the detection known disease structure images are compare with clusters. The type of disease images are predicted by finding similarity difference.

6. Results and Discussion

In proposed system FMRI images dataset is considered. A database contains normal brain images and different diseased brain images for example here proposed system considers Somatoform Pain disorder and Schizophrenia disease brain images. There are two algorithms for clustering K-means algorithm and Fuzzy K-means algorithm. Clustering is either hard clustering or soft clustering. In hard clustering, data is divided into distinct clusters, where

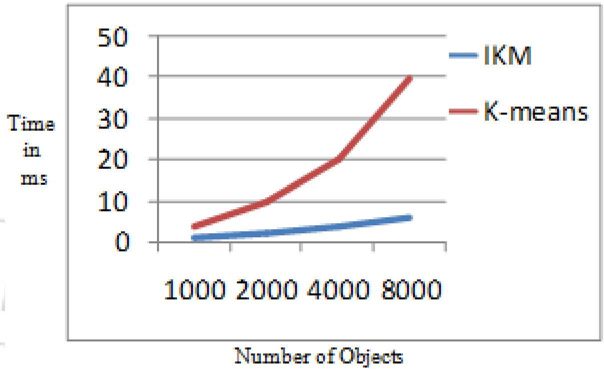

Figure 3: Scalability w.r.t. objects/time

each data element belongs to exactly one cluster. K-means algorithm is hard clustering. In fuzzy clustering it is also referred to as soft clustering, data elements can belong to more than one cluster. K-means clustering produces fairly higher accuracy and requires less computation. Fuzzy K-means clustering produces close results to K-means clustering, but it requires more computation time than K-means. So K-means algorithm is better than Fuzzy K-means.

So K-means algorithm is compared with IKM algorithm. Fig.3 shows comparison between those algorithms.

IKM algorithm achieves significantly faster response time than K-means algorithm. Efficiency is correctness of output. It is number of images which are properly clustered to number of input images. The scalability in terms of number of objects is shown. The number of objects that means images increases then time required for clustering is increases, the clustering time measured in millisecond. Also IKM algorithm achieves better clustering accuracy than K-means algorithm. Best clustering is done using IKM algorithm. For detection training data is compared with clusters using Naive algorithm. It detects normal brains and diseased brains separately. Naive algorithm achieves better accuracy and efficiency.

7. Conclusion

In this paper, novel cluster notion proposed for FMRI image data. Cluster defined as a set of objects sharing a specific interaction pattern among the dimensions. Interaction K-means (IKM), an efficient algorithm for interaction-based clustering is used. The specific cluster for specific diseases detected that means normal brain images, psychiatric disorder images differentiates.

8. Acknowledgment

This is a great pleasure & immense satisfaction to express my deepest sense of gratitude & thanks to everyone who has directly or indirectly helped me in my project work successfully. I express my gratitude towards project guide Prof. S.A.Bajpai, and Prof. G.M.Bhandari, Head of Department of Computer Engineering, Bhivarabai Sawant Institute of Technology and Research College of Engineering, Pune who guided & encouraged me in my project work in scheduled time. I would like to thanks our Principal Dr. T.K.Nagraj, for allowing us to pursue my project in this institute.

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