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MULTI-VIEW CLUSTERING FOR ALZHEIMER'S PROGRESSION THROUGH DEEP LEARNING

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Abstract : It is difficult to make generalizations about information as its whole since it typically consists of multiple characteristic or multimodal subsets, as is the case in many real-world settings. This sort of information is called "Multi-view" data. Publications, for instance, may be made available in many languages, while photos posted across social media platforms virtually always include both the image and a tag explaining what the image symbolizes. The notion that identical information can be viewed in numerous ways has led to a recent uptick in awareness of Multi-view training. Numerous promising applications exist for the synthesis of Multi-view information, such as multitask learning, clinical applications, object categorization, knowledge representation, clustering, and categorization. Many studies have been conducted in this area, paving the way for the incorporation of Multi-view solutions into a wide range of scenarios; nonetheless, their use in the development of Multi-view clusters of Alzheimer's disease images has been limited. Consequently, researchers have been analyzing a collection of Multi-view classification studies over the last several years to find their weaknesses. Our method for forming Multi-view clusters for Alzheimer's disease is based on the combination of image pair selection, data matrices, fusion, a feature list, and fuzzy classification.

IndexTerms: Image Pair Selection, Data Matrices, Parameter Estimation, Feature List, Fuzzy Classification, Multi-view Clustering.

I. INTRODUCTION

Researchers are concentrating on multi-view documentation since it can be used for a diverse range of tasks, including categorization of standard statistical feature space learning, principal component analysis, extraction of features, and cross-domain progression, and as it persistently can provide complementary knowledge among several different viewpoints. Using the complementary characteristics throughout multi-view information is the primary problem of multi-view cluster formation since it is the only way to identify the underlying clustering method shared by all views. To accomplish this, conventional systems either build a specific deficit that integrates multi-view information even during the clustering procedure or else train a latent feature map to examine the coherence data extending perspectives before clustering. Such methods are quite successful, but they rely heavily on clustering using raw multi-view feedback, missing out on the chance to utilize more generalized documentation to account for differences in local characteristics and subdomains.

Owing to its broad applicability in areas like information retrieval, predictive modeling, and more, multi-view, multitasking, and multifunctional training have subsequently gained a lot of attention. Since it is not possible to completely describe all experimental understanding using just a single input, multi-view learning emphasizes the multi-view records, that is typically collected from several repositories or created from separate subsets of characteristics. For instance, the information that constitutes a web page is often characterized by the text of a website and the keywords of any related sites. It is possible for a single text to have several interpretations, and for image catalogs to be described in a variety of ways, including by histograms of directed gradients with Latent binary patterns.

Since multi-view clustering's inception, it has sought to more reliably assign data points within clusters by combining the data from several viewpoints, which necessitates the challenging issue of identifying how to build linkages amongst some of the different points of view. There have been several attempts to develop algorithms to address this problem. Multi-view data refers to information that has simultaneously been collected from several sources, documented by multiple sensors, or defined by multiple pattern recognition algorithms. This kind of data is widely used in many fields, especially deep learning, statistics, and humancomputer interaction. Several newspapers may report on the exact same news report, the very same person's movements may indeed be recorded on both regular video and sometimes a depth sensor, and the exact same photograph may be concealed using such a huge spectrum of hand-crafted & deep features.

Zhiwen Yu provides a composite hybrid multi-view classification architecture in [1]. The authors proposed a three-pronged approach to improve the generalizability and scalability of the current system. To start, three distinct view modification approaches were used to generate a large set of clustering viewpoints. With a little bit of luck and some bifunctional multi-view retraining, you can use the results of the multi-view grouping to come to an agreement. The second statement is that the construction of a reproducible subspace adaptation increased the variety of the clustering assessments. Finally, a view-based self-evolutionary technique was developed to further improve collections of randomly generated subspaces. It is possible that the proposed framework could efficiently cluster datasets with different attributes if these three elements are coupled in the right way. The proposed technique was shown effective via a battery of tests.

Tiantian He [2] introduces a novel method named contextual correlation maintaining multi-view featured graph clustering for locating these clusters in AGs. Contextual correlation conserving multi-view featured graph clustering is an improvement over previous methods because it utilizes a multi-view instructional strategy that represents the functional interactions between pairwise vertices by incorporating the latent space information obtained from the attributes of vertices in multiple views. This allows the dormant cluster classification to be investigated jointly from the perspectives of both the graph's configuration and the views. Moreover, contextual correlation conserving multi-view featured graph clustering makes use of semantic similarity cluster inclinations to describe the contextual correlations between pairs of vertex features. Since the learned cluster characteristics and cluster constituents are more potentially similar, the proposed framework is able to find more significant clusters in the Attribute graph. We utilized many large-scale graph datasets to compare contextual correlation-conserving multi-view featured graph clustering to traditional approaches.

To enhance the accuracy of clustering a large amount of partial multi-view data, Liu Yang [3] presented a novel method that incorporates visual sample-level graph conjunction for partial multi-view clustering. In an attempt to determine the basic clustering hierarchy for complete and incomplete datasets, the authors considered a wide range of selected respondents from a variety of angles. This approach was utilized as a guide for clustering incomplete multi-view data. On the other hand, the large number of gaps provided additional context that improved the clustering results. The proposed joint model was resolved using a rapid incremental approach that guaranteed consolidation. Simulations demonstrate that the proposed model surpasses other popular fractional multi-view clustering methods.

Section 2 of this research article presents an analysis of the relevant literature; Section 3 explains the research approach; Section 4 discusses the experimental assessments; and Section 5 closes with suggestions for further study in the future.

II RELATED WORKS

With relation to IMC, Cai Xu [4] introduced an antagonistic incomplete multi-view clustering system that allows for just about any amount of viewpoints to be accounted for. Adversarial fragmented multi-view clustering seeks to create consistent high information and maintain multi-view data that is lacking essential information. Researchers look at two variants of adversarial incomplete multi-view clustering: adversarial incomplete multi-view clustering and generative adversarial incomplete multi-view clustering. The goal of adversarial incomplete multi-view clustering is to reconstruct the underlying patterns of the data corruption utilizing elementwise restitution and a generative adversarial network. Generative adversarial incomplete multi-view clustering implementations are able to learn attributes about the missing viewpoints by examining other incidents inside the same cluster. Six distinct real-world datasets were used to empirically prove the superiority of adversarial incomplete multi-view clustering including generative adversarial incomplete multi-view clustering versus traditional incomplete multi-view clustering techniques.

Qi Wang [5] proposes a Multi-view-based Parameter-Free architecture for cluster discovery. A unique Structural Context identifier is suggested to describe the internal structure of feature extraction. There are two variations of the Self-weighted Multi-view Clustering method that can be employed to combine the feature relationships from the alignments and frame of reference viewpoints into a single model. A tightness-based convergence method is provided for reasonably integrating the coherent local groups. Additional testing on a wide variety of datasets validates the effectiveness of the proposed group identification technique and the multi-view clustering strategy. By tackling surveillance and identification concerns that emerge in crowd settings, the authors hope to greatly boost the achieved effectiveness. Improved skills to decipher the behavior of large groups of people would be very helpful.

Xiumei Wang [6] presented a novel multi-view clustering approach called multi-view clustering predicated on NMF and paired observations. In this paper, we offer a method for incorporating multidimensional batch normalization and bilateral co-regularization into the Nonnegative topic modeling architecture. The system may simultaneously acquire the component-based characterization and preserve the geospatial hierarchy of the data. The researchers use parameters for repeatedly upgrading the answer to the target function in order to rapidly reach a conclusion. The authors argue that the proposed approach to multi-view clustering seems to have a convergent minimization issue, and they present conceptual justification for this assertion. Employing data obtained in the wild, the researchers quantitatively demonstrate the algorithm's higher clustering performance.

Lei Xing [7] proposed 2 novel multi-view subdomain grouping techniques, one utilizing a pairwise-based regularization tactic and the combination of the following employing a centroid-based regularization strategy, to learn a joint subdomain characterization across all viewpoints by incorporating the Frobenius norm with such a correntropy-induced metric. The authors also suggested strategies focused on HQ and the alternate orientation technique of integrators for fixing the correntropy-based multiple-feature subspace segmentation minimization problem. Extensive testing on six real-world multi-view datasets demonstrates that correntropy-oriented multi-view subspace clustering significantly exceeds traditional multi-view clustering techniques. With minimal energy expended on tuning, correntropy-based multi-view subdomain clustering could well be brought to excellent use. This is because it iterates rapidly and is not excessively sensitive to its parameters within a reasonable range.

Shaoguang Huang introduces a novel multi-view subspace clustering approach to hyperspectral image classification in [8]. As a result, researchers develop an original information integration architecture to make the most of the complementary data offered by multi-view data. This framework separates the subspace representation for every perspective as an engagement of a multilateral coalition low-rank matrix that's also conveyed by every one of the perspectives and a view-specific sparsity matrix, with the goal of establishing a preferential clustering technique in the low-dimensional subspaces with adaptable recognition to the data modeling tool in each point of view. In addition, a composite hypergraph within the subdomain representation is used to propose a manifold-based spatial normalization. In this paper, researchers demonstrate that the proposed regularization effectively captures the local and nonlocal spatiotemporal contexts of complicated processes. The authors have come up with a brilliant strategy for dealing with the resulting model.

Kun Zhan [9] claims that combining multi-view features for the purpose of clustering is a significant challenge in the study of data. Here, researchers suggest a new multi-view clustering technique employing graph framework integration, which finds a worldwide network with accurately connected components expressing cluster suggestions. The authors employ the Hadamard commodity as a regularization to each of the source graphs prior to actually building the global graph, which preserves the underlying structure of the input networks. To create the fundamental graph, the authors provide a proposition that asserts the number of connected nodes in the graph matches the multiplicity of zero, which acts as a kind of eigenvalue for either Linear combination. Each connected part of the fundamental network has vertices that all map to the identical cluster, therefore no further computation is required to get the clustering indicators. An efficient method is provided for doing this.

Shirui Luo [10], who recently proposed a novel MvSDc method, proposed using multi-view data for multimodal clustering. The dual-clustering structure and the data's integrated architecture, which is predicated on many views, were both decided upon at the same time. The proposed method was developed to distinguish between two distinct, high-quality clusterings that are sensitive to rank limitations and individually unique features. The resulting optimization problem was best addressed by using an inconsistent optimization strategy. Since multi-clustering information does exist, it is interesting to look at plural clustering, some of which have superfluous conceptual matrices while others have different and incompatible counterparts.

As Xia Ji [11] notes, several clustering techniques have been published and the imperfect multi-view clustering problem has been studied at length recently. Traditional procedures, for instance, have too much of a time overhead or have too many parameters to be capable of being extended to encompass more beyond two ways. To address some of the shortcomings of prior methods, this study introduces a proactive anchor-based incomplete multi-view clustering strategy. Experimental results verify the design's efficacy. If the dynamic anchor-based strategy can be expanded to the partial multi-view classification problem, where no constituent from the many views captures all the perspective attributes, that would be exciting. Additionally, like the vast range of current options, our technique necessitates knowing the complete number of clusters in preparation.

Zhiqiang Tao [12] created a novel method for improving the efficiency with which marginalization denoising, consensus reinforcement learning, and route coefficients segmentation may all be run in parallel. The clustering aim is best served by a multilayer framework, which is constructed by stacking blocks of minimized multi-view ensemble clustering. Simulations on 8 data sets from the actual world show that the recommended minimized multi-view ensemble clustering beat several existing state-of-the-art multi-view and EC methods. In addition to a case study illustrating how to employ marginalized multi-view ensemble clustering with limited multi-view data, the authors presented in-depth papers analyzing the approach from a variety of perspectives.

III PROPOSED METHODOLOGY

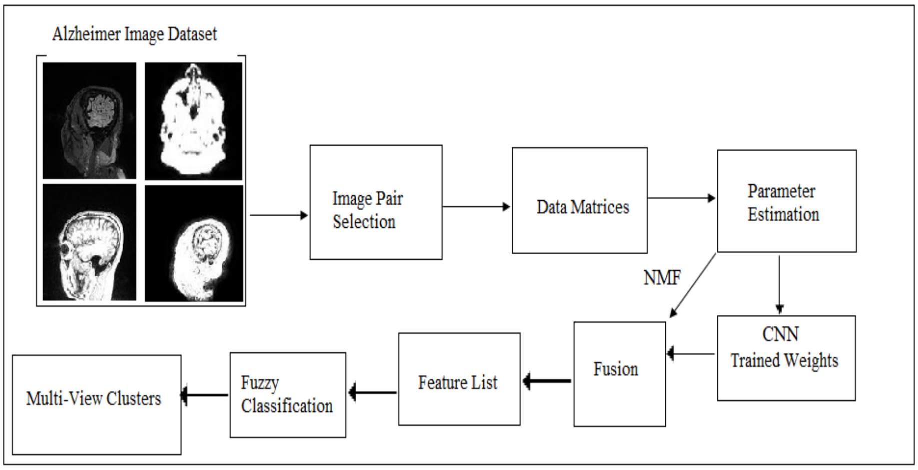

Figure 1: Proposed Methodology for Alzheimer's disease multi-view clustering

The presented techniques for the purpose of achieving the multi-view cluster formation for Alzheimer's patient MRI images have been depicted in Figure 1 above and the steps taken to achieve this system are elaborated below.

Step 1: Dataset – The proposed model of multi-view clustering for Alzheimer's disease images is accomplished by downloading the image dataset for two views, auxiliary and sagittal. These images are being downloaded from the Alzheimer's Disease Neuroimaging Initiative (ADNI) site URL https://adni.loni.usc.edu/, by creating an account. A total number of 3199 images are downloaded for the axial view images from the ADNI site for six stages of Alzheimer's disease. On the other hand, 8737 images are downloaded for the sagittal view from the ADNI site for the same six stages of Alzheimer's disease. These six stages of the disease are named CN, SMC, EMCI, MCI, LMCI, and AD from stage 1 to stage 6, respectively. All these images are downloaded in. dcm format, and they need to be converted into a proper image format in the next step

Step 2: Image Conversion an Preprocessing – The downloaded .dcm images cannot be processed for the clustering process. Hence, they need to be converted to a proper image format like.jpg. So the "pydicom" library is installed in the Spyder IDE to do the program in Python. After this, by iteratively traversing all the folders in different stages of two views, the images are successfully converted into jpg format. Before converting the images into jpg format, they are resized, and then they are converted into absolute grayscale.

All the images are rescaled to a dimension of 128 X 128 using the resize function of the Image class, which belongs to PIL(Python image library). After this process, the resized image is subjected to the absolute gray scaling process. In this process, each pixel of the image is read in the RGB color channel. Then these values of RGB are averaged to set them back in the place of RED, GREEN and BLUE to get the absolute grayscale image. This process can be viewed in the below-mentioned algorithm 1.

ALGORITHM 1: Absolute Gray scaling

// Input: Resized Image R_{IMG}
//Output: $GRAY_{IMG}$
// function: absoluteGrayScaler(R_{IMG})
Start
ROI_{IMG} = Ø
for i = 0 to the size of Width of R_{IMG}
for j=0 to the size of Height of R_{IMG}
color[] = $R_{IMG\,[i,j]}$ RGB
R= color[0]
G= color[1]
B= color[2]
AVG=(R+G+B)/3
$GRAY_{IMG\,[i,j]}$ =[***AVG, AVG, AVG]***
end for
end for
return $GRAY_{IMG}$
stop

Step 3: CNN Training

Weights - Images from the converted dataset are separated into train and test data for the Alzheimer's image, respectively, and are used to train the dataset. 8323 train images and 4996 test images are used to train the convolutional neural network.

Convolutional neural network libraries from Keras and Tensorflow are installed and imported before the training phase begins. To be able to generate an object for the images, an image data generator class is used for both the training data and the testing data. A ratio of 1:255 is then set to learn the pixel in depth. The batch size is then set to 64 for the dataset images. The form "categorical class" mode is set to "grayscale" color mode.

A sequential neural network model is subsequently configured to construct its object when all the initial phases are completed. As the initial layer of the neural network, a convolution layer is inserted with 32 kernels of size 3 X 3 with the "Relu" activation function. The convolution neural network's first layer is finished with a color channel of one and a dimension of 128 X 128.

In the convolution neural network's second layer, 64 3 x 3 kernels with the "Relu" activation function are used. A max-pooling 2D layer is then added with kernel size 2 X2 after that, the Droput function engages a 25% dropout rate.

128 kernels of size 3 X 3 are added to the Third and Fourth Layers, followed by the "Relu" activation function. A maxpooling 2D layer with a kernel size of 2 X 2 is added after each layer. Finally, a dropout layer with a 25% percentage is added. After the neural network has flattened, the tensors are collected employing an activation function of "Relu" and a size of 1024. A dropout layer of 50% is implemented at the model's conclusion to collect the trained data in 12 classes such by using the "Softmax" activation function. These 12 classes are made up of 6 from auxiliary views and 6 from sagittal view for stages like CN, SMC, EMCI, MCI, LMCI, and AD.

The "Adam" Optimizer is then used to optimize the generated neural network model, running it for 100 epochs for the Alzheimer's dataset images. The gathered information is stored in a file with the extension ".h5 for use during the fusion of the weights.

The used Softmax and Relu activation functions are depicted in equations 1 and 2.

$$\sigma(Z) = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \quad \_\_\_\_\_\_(1)$$

$$Relu=max(0,x) \quad \_\_\_\_\_(2)$$

Where
x= neuron value
σ = softmax
z = input vector
e^{zi} = standard exponential function for input vector
K = number of classes in the multi-class classifier
e^{zj} = standard exponential function for output vector

The designed neural network's architecture for CNN is shown below.

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 12	Softmax
Adam Optimizer	

Figure 2: Model Architecture

Step 4: Non-negative Matrix Factorization (NMF)- The non-negative matrix factorization is the process is used to optimize the two random images of the different views, which belong to different stages of the multi-view clustering of Alzheimer's disease. Here the first image is considered as the original image, for which a B_{mat} matrix of size 128 X 128 is created, where each matrix element consists of an array of RGB. In the same way, another image is considered as the feature image, and a feature matrix A_{mat} is created like the previous way. These obtained two matrices are used to create the fusion of the parameters of the data matrices to optimize the multi-view clustering process.

In this process initially, two matrices are multiplied to obtain a product matrix C_{mat} as shown in equation 3.

$$C_{mat}=B_{mat} X A_{mat} \quad \_\_\_\_\_\_(3)$$

After this process inverse of A_{mat} is estimated as shown in equation 4

$$D_{mat}= A^{-1}_{mat} \quad \_\_\_\_\_\_\_\_\_\_(4)$$

Then an optimized matrix is obtained by multiplying the C_{mat} and D_{mat} as shown in equation 5

$$O_{mat}= C_{mat} X D_{mat} \quad \_\_\_\_\_\_\_\_\_\_\_(5)$$

The obtained matrix O_{mat} contains the feature list to cluster the multi-view data as explained in the next step.

Step 5: Multi-view clustering – In this process, the user initially gives the input of images contained in a folder by giving the folder path. Once the folder path is given, then a half-number of iterations are executed for the given number of input images. This is because for every iteration, two random images are being selected from the input folder to cluster them based on two different views. The selected two images are first fed to the NMF process to optimize each of the images one after another. After this, these images are estimated with respect to the CNN weight factor to get a prediction score.

These prediction scores are used to segregate them into six classification boundaries between 0 and 11, which eventually indicate the six stages of the Alzheimer's disease. To segregate the scores, the proposed model uses the fuzzy classification process. Here scores are segregated into six stages, as depicted in algorithm 2.

ALGORITHM 2: Fuzzy Crisp Value Generation

//Input : Size S, Number of stages N
//Output: Index List IN_L
1: Start
2: $IN_L = \emptyset$
3: DIV= S/N
4: begin=0, end=0
5: ***for*** i=0 to size of N
6: R_{LST} [Range List]
7: ***if*** (i==(N-1))
8: $R_{LST[0]}$ = begin
9: $R_{LST[1]}$ = S-1
10: $IN_{L=} IN_{L+} R_{LST}$
11: ***else***
12: $R_{LST[0]}$ = begin
13 : end=begin+DIV-1
14: $R_{LST[1]}$ = end
15: $IN_{L=} IN_{L+} R_{LST}$
16: begin=end+1
17: ***end for***
18: *return* IN_L
19: ***Stop***

The obtained prediction index is used to determine the stage of the disease and cluster the images efficiently using the ranges of the fuzzy classification. The formed clusters of the images are stored in a folder properly for viewing by the user, along with the distribution graph, which is also shown.

IV RESULTS AND DISCUSSIONS

The core i5 processor and 8 GB of RAM Windows laptop that is used to build the designed approach for clustering the multi-view Alzheimer's image. The proposed model is created using the Python programming language and Spyder IDE. As previously noted, Auxillary and sagittal Alzheimer's image datasets are downloaded for the experiment from the Alzheimer's Disease Neuroimaging Initiative (ADNI) website at https://adni.loni.usc.edu by creating an account.

For the axial view images for the six phases of Alzheimer's disease, a total of 3199 images were retrieved from the ADNI website. On the other hand, 8737 images for the sagittal view of the same six phases of Alzheimer's disease were downloaded from the ADNI website. From stage 1 to stage 6, the six stages of the illness are referred to as CN, SMC, EMCI, MCI, LMCI, and AD. The images are all downloaded in the.dcm format and then converted to.jpg. In order to get the final 8323 training images and 4996 for the testing phase images are considered, the majority of the undesirable and subpar images are manually removed.

While clustering the images, a set of 100, 200,400 and 500 images is being created and given as input to the system. The obtained distribution of images in six stages for the input of 100 images and 500 images clusters is represented in the below-mentioned graph in figure 3 and 4.

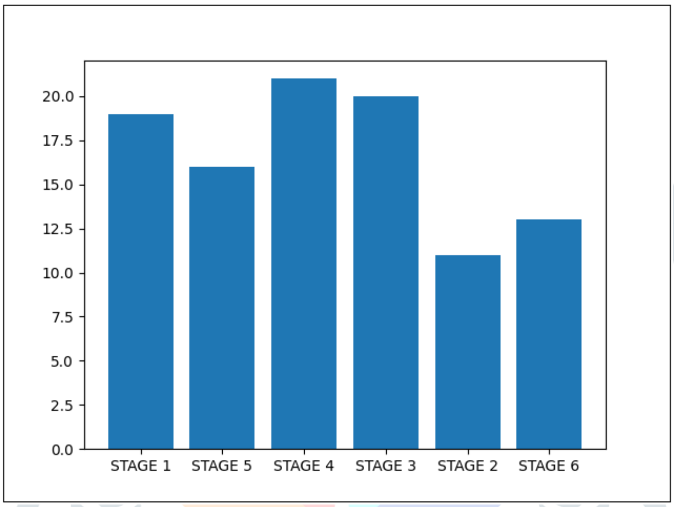

Figure 3:The result of Clusters for input of 100 images

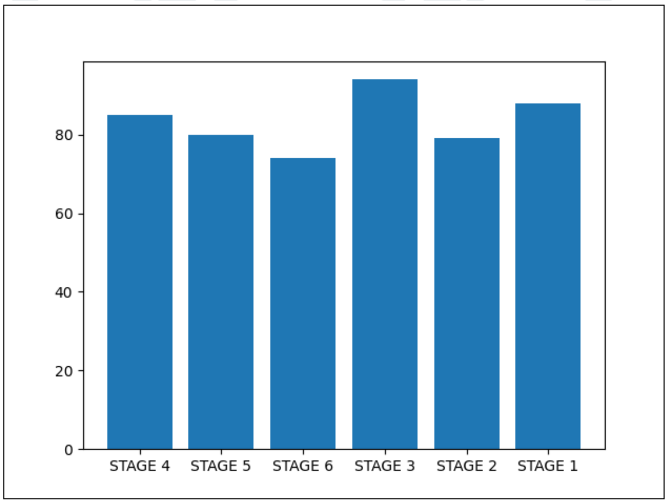

Figure 4: The result of clusters for input of 500 images

To evaluate the system, five experiments are conducted with 100, 200, 300, 400, and 500 input images. Then the obtained multi-view clusters are subjected to estimate their accuracy in percentage with respect to the belonged clusters. The obtained results are tabulated in Table 1, and the respective graph is shown in Figure 5.

No of Input images	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6
100	100	90.9	100	90.47	100	100
200	100	100	100	88.57	100	100
300	98.113	97.91	98.33	86.95	100	100
400	97.26	97.95	100	89	100	100
500	96.59	96.2	100	88.23	98.75	100

Table 1: Accuracy in percentage

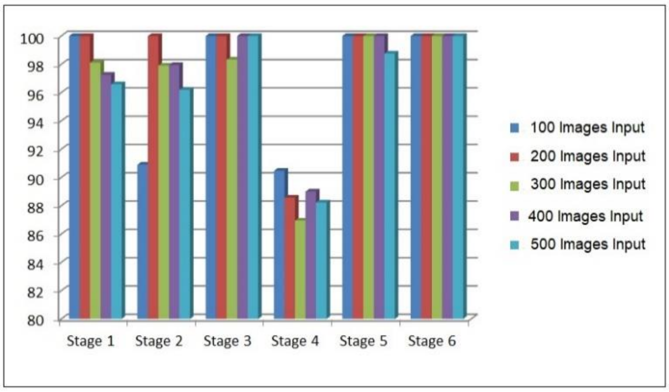

Figure 5: Accuracy for Different sets of Input

The above table and the graph clearly indicate that the proposed model provides an average accuracy of 97.1741 % which is the best result obtained in the first attempt using the hybrid model of CNN and NMF for multi-vie clustering of Alzheimer's disease.

V CONCLUSION AND FUTURE SCOPE

The presented techniques for the purpose of achieving the multi-view cluster formation for Alzheimer's patient has been elaborated in this research paper. This research utilizes a large collection of Alzheimer's images as an input to provide the input data for the multi-view clustering mechanism. The collected dataset with the plethora of images is effective in the realization of the clustering that can considerably improve the diagnostic capabilities of this disorder and improve the lifestyle of the individuals. The input Alzheimer's image dataset is provided as an input to the methodology and the image pair selection is performed. Once the image pairs are selected these are utilized for the generation of the data matrices which will be utilized for the parameter estimation module. The parameter estimations are then effectively segregated into the next two modules, the training weights and fusion. The trained weights and fusion of the parameter estimations are then supplied to the next component for feature list creation. The feature list will then be classified using the fuzzy classification subsystem that effectively provides the multi-view clusters as the output to the user. This methodology has been exposed to numerous tests that have been crucial in the realization of the performance metrics of the proposed multi-view clustering approach. The proposed model obtained an average accuracy of 97.1741 % which is one of the best results in multi-view clustering models.

The proposed model can be enhanced to work on the other disease images. And the model can be enhanced to work as the API in the deep learning segment.

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