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A Hybrid Attention U-Net and K-Means Approach for Multi-View Clustering in Alzheimer's Disease Prediction

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ABSTRACT

Alzheimer's disease (AD) is a catastrophic neurological disorder that progressively impairs memory and cognitive function. Accurate prediction of its progression is critical for early intervention and distinctive treatment. The proposed system outlays the idea of predicting Alzheimer's disease progression using an attention U-net based multi-view clustering model. Attention U-Net is generally a robust deep learning framework that is efficient in image segmentation and classification tasks and extracts intricate spatial details from medical or industrial imaging datasets that are critical for precise analysis and decision-making.Traditional Alzheimer's disease progression prediction models depended on single-view data, restricting their capacity to capture the complexities of the disease's stages. Thus, our model utilizes attention mechanism along with multi-view data to emphasize the salient areas, presents a loss function that combines sparse categorical cross-entropy with focal and dice loss to address the imbalanced datasets, and provides a complete depiction.The results show immense improvement in segmentation accuracy, allowing accurate prediction of AD progression and robust clinical application groundwork. This research paper introduces a new multi-view clustering methodology that combines an Attention U-Net for feature extraction and K-Means clustering for patient grouping according to disease progressionstages Experiments on an Alzheimer's-related dataset demonstrate that the proposed framework improves cluster coherence and offers insightfulknowledgeaboutthediseaseprogression.Theresultsdemonstrate that the multi-view clustering model is superior to conventional single-view models, and it can be a valuable tool for clinical use.

Keywords: *Alzheimer's Disease Progression, Attention U-Net, Multi- View Clustering, K-Means Clustering, Deep Learning, Image Segmentation.*

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressing neurodegenerative disorder that affects millions of people in the world, generally characterized by cognitive decline along with memory loss. For an effective treatment and care regimen, timely diagnosis of underpinning pathology leading the patient to AD and giving a forecasting for the duration of the illness is essential. While many literature explore the deep learning application in prediction of Alzheimer's disease trials, CMC: A Consensus Multi-view Clustering Model for Predicting Alzheimer's Disease Progression model is based on non-negative matrix factorization that intends to incorporate different perspectives of medical data, such as MRI scans, this model demonstrated higher performance compared to state-of-art clustering methods in predicting AD progression by functionally capitalizing multi-view learning and unsupervised clustering**[1]**. Cancer data are increasingly obtained from a variety of biological sources, combining different perspectives can lead to more sophisticated knowledge on patient subgroups, "Parea: Multi-View ensemble clustering for cancer subtype discovery" introduces Parea: a multi-view ensemble clustering method that achieves higher performance in detecting cancer subtype across distinct datasets by employing several clustering algorithms suited to the specific characteristics of each data view**[2]**. "A multi-view concatenated infrared thermal images based breast cancer detection system using deep transfer learning" enhances the detection accuracy and increasing the model's capacity to recognize the cancer- related asymmetries. In this study the deep transfer learning model VGG-16 achieved highest testing accuracy of 99% compared to ResNet50V2 and InceptionV3**[3]**. The research that offers a multi-view hyper-complex learning model uses hyper-complex algebra to capture global and local connections across several mammography views, similar to how radiologists analyse pictures**[4]**. Deep multi-view contrastive learning combines reconstruction,contrastive and clustering losses into a single model to integrate multi- omics data better and identify cancer subtypes, which outperforms previous algorithms on numerous datasets and provides the therapeutic insights for certain tumors, such as liver cancer**[5]**. Single-view mammograms for breast cancer diagnosis limits the detection of abnormalities due to lack of cross-view correlation, but Multi-View Feature Fusion(MVFF) model used four mammography images and incorporates the information retrieved using CNN across all views considerably increasing the classification accuracy, with AUC of 0.932 for mass detection and calcification**[6]**. A Long Short Term Memory(LSTM) model is used for predicting the Alzheimer's disease progression, which contains temporal correlations between clinical variables and future illness stages, delivering a significant boost in prediction accuracy over existing techniques**[7]**. Muti-View convolutional neural network(MV-CNN) model automates the segmentation of eye and tumor in retinoblastoma patients, this model performs the multi-class segmentation in single step with an accuracy of 99% for both eye segmentation and tumor segmentation**[8]**. Tensor Kernel Learning(TKL) combines information several modalities using CP/PARAFAC tensor decomposition and kernel learning to improve the AD classification, delivering greater accuracy (91.31% for CN vs. AD) than individual data modalities**[9]**. Detection of Lung cancer using multi-view image registration and deep learning techniques especially ResNet-18 convolutional neural network classifier achieved 98.2% detection accuracy and 96.4% sensitivity, greatly surpassing the existing methods by minimizing false positives and supporting early-stage lunge cancer identification**[10]**.Multi-View deep forest(MVDF) model overcomes the limitations of traditional methods for predicting overall survival(OS) in cancer by combining several kernels and integrated learning algorithms. This model enables better processing of complicated, high-dimensional clinical data and incorporates a pruning method to minimize the noise and outliers which boosts the reliability of OS predictions**[11]**. Multi-View graph neural network(MVGNN) combines the multi-omics to improve breast cancer differentiation, by using graph convolutional networks(GCN) and attention processes model effectively preserves biological semantics and geometric structures**[12]**.

STUDY AREA

The study area for this research focuses on Alzheimer's Disease(AD) progression prediction, utilizing brain MRI scans to analyze structural changes associated with different stages of the disease. The research employs a multi-view clustering approach, integrating axial, coronal, and sagittal views of MRI images to enhance feature extraction and improve the accuracy of disease classification. The Attention U-Net based Multi-view Clustering Model is designed to efficiently capture fine-grained spatial details while selectively focusing on the most relevant brain regions affected by AD. By leveraging multi-view clustering, the study aims to address intra-class variability and enhance patient stratification, ensuring a more precise understanding of disease progression. The findings of this research have significant implications for early diagnosis, monitoring, and personalized treatment planning for Alzheimer's Disease in clinical and medical imaging.

DATA USED

The data used in the present work consist of brain magnetic resonance images, which provide a comprehensive view of structural brain alteration related to the evolution of Alzheimer'sdisease. The total number of samples is 40 and 50 respectively ,the total MRI number in MRI2 and MRI3 for each view1 and view2.AD samples is represented with two views (AXI view and SAG view). Some examples of the AXI and SAG MRI data of the two subjects from MRI2 and MRI3 database and well-labeled database of brain scans. Each scan relates to one of four different stages: Non-Demented, Very Mildly Demented, Mildly Demented, and Moderately Demented. The dataset was split into training, validation, and test subsets, providing a balanced evaluation of the performance of the model..

METHODOLOGY

Alzheimer's disease progression prediction using attention U-Net based multi-view clustering model aims to predict the stages of Alzheimer's disease early. The goal is to improve early diagnosis and clinical decision-making through automated and precise classification. The proposed approach involves several steps Fig.1. shows the complete workflow of the model. The dataset consists of MRI scans which are splitted into train, test and validation sets by maintaining class distribution. The dataset undergoes few data preprocessing steps including image extraction and resizing for uniform input dimensions, normalization of pixel values to the range[0,1] for faster convergence and many augmentation techniques such as rotation, horizontal flipping, zooming, width/height shifts are applied to augment the dataset to greater extent and prevent overfitting. A clustering algorithm is applied on the preprocessed dataset inorder to group the MRI scans based on extracted spatial and intensity-based features which ensures that similar progression stages are grouped together.

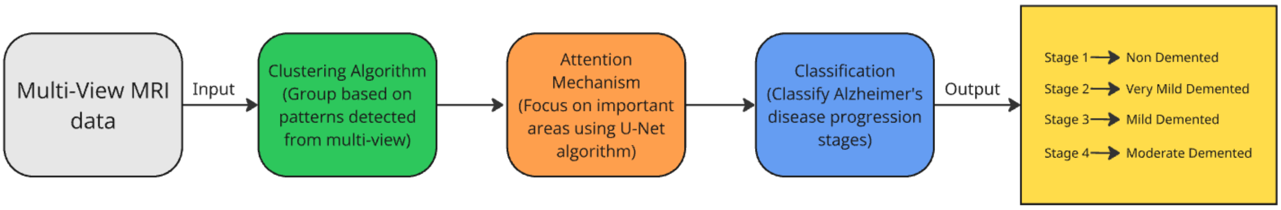

Fig 1. Workflow of the system

In this model, U-Net scales with additive attention operation for segmentation that focusing on disease-specific regions in MRI scans. Attention mechanism includes gating signals to align input feature maps, ReLU activation function to filter significant activations, sigmoid activation to normalize attention weights with in a range[0,1]. U-Net model also utilizes transposed convolutions and skip connections at decoder to reconstruct spatial details for segmentation.

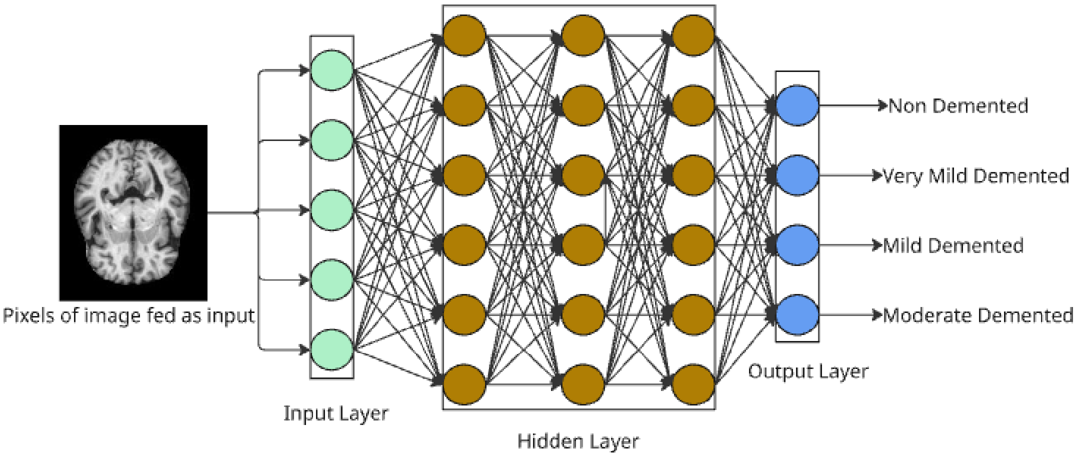

Fig 2. Architecture of Convolutional Neural Network(CNN)

Following segmentation, a Convolutional Neural Network(CNN) is used to classify the stages of Alzheimer's disease where segmented output is processed through convolutional layers to extract hierarchical features. Global Average Pooling(GAP) layer converts spatial features into feature vector, followed by softmax classifier that gives the probability score for different stages of AD. Sparse categorical cross-entropy optimizes multi-class classification, reducing the computational complexity. Adam optimizer with an initial rate of 10^{-4} ensures fast convergence. Model checkpoint saves the best model, the early stopping prevents overfitting. The model proposed, based on an Attention U-Net Based Multi-View Clustering approach, combines deep learning-based feature extraction and clustering techniques to efficiently analyze the staging of Alzheimer's disease. The approach ensures both elemental pixel-level information and complex deep features maximize disease staging accuracy and clustering efficiency. The approach is implemented via four major steps: Data Preprocessing, in which MRI images are gray-scaled, resized, and normalized; Feature Extraction using Attention U-Net, which enables spatial feature learning using attention gates without losing informative data for classification; Multi-View Feature Representation, in which raw pixelinformationandfeature-extracteddeepfeaturesarecombinedtoforma dense feature space; and finally, Clustering & Classification, in which K-Means clusteringisusedtoclassifypatientsbasedondiseaseseverity,usingpixel-based anddeepfeaturerepresentations.Theend-to-endpipeline,asdepictedinFig. 1,demonstrateshowthesestepsworkinsynergytoenabletheunderstandingof Alzheimer's disease staging, thus ensuring strong and accurate patient stratifi- cation.

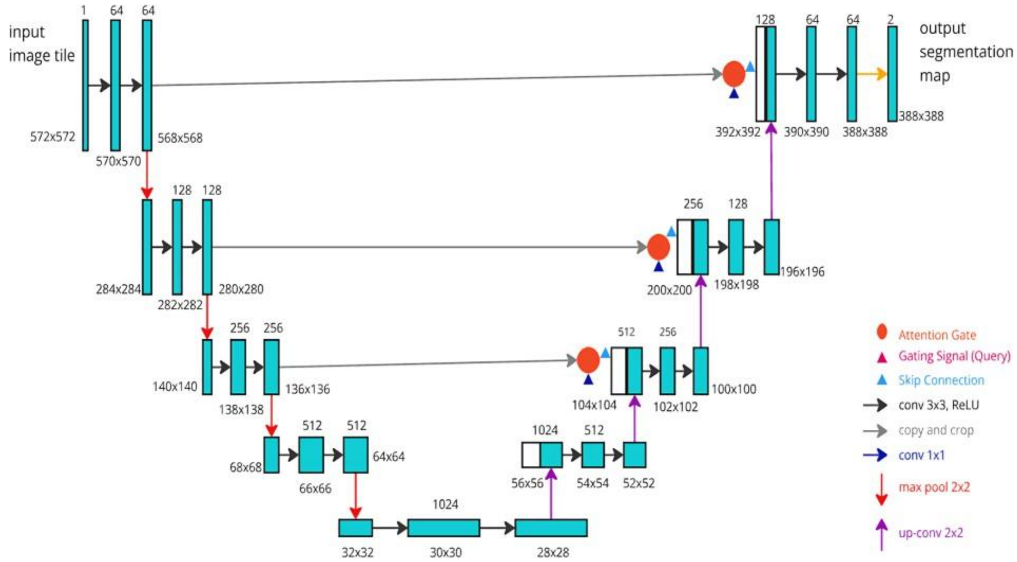

Fig.3:U-Netarchitecturediagramwithattentiongatesandskipconnections

The Attention U-Net Model (shown in Fig. 3) is used to extract deep and meaningful features from MRI Images. It is different from standard U-Net models as it hasattentiongateswhichemphasizetheimportantregionsandreducetheeffect of the background noise. This helps in better segmentation and classification at different levels of dementia.

Multi-ViewClusteringApproach

To improve clustering performance a multi view is constructed by combining complementary feature sets. View 1 is raw pixel intensity values which preserve the spatial details of the MRI scans capturing structural informationdirectlyfromtheimages.View2isdeepfeaturerepresentationsfromtheglobalaverage pooling layer of the Attention U-Net which encodes high level abstract features relevant to disease progression. By concatenating these two views the model uses both low level spatial features and high level learned features to create a more complete feature space which improves disease stage differentiation and clustering accuracy.

2. RESULTS AND DISCUSSION

The proposed model successfully classifies the stages of Alzheimer's disease progression. Fig 3. Shows the classification result which identified a MRI scan as Moderate Demented with a confidence score of 94.03%, which illustrate the strength of CNN classifier. The model effectively performs for Demented category with 264 correctly classified cases but some misclassifications occur in Very mild demented cases that is disclosed by Fig 4 confusion matrix.

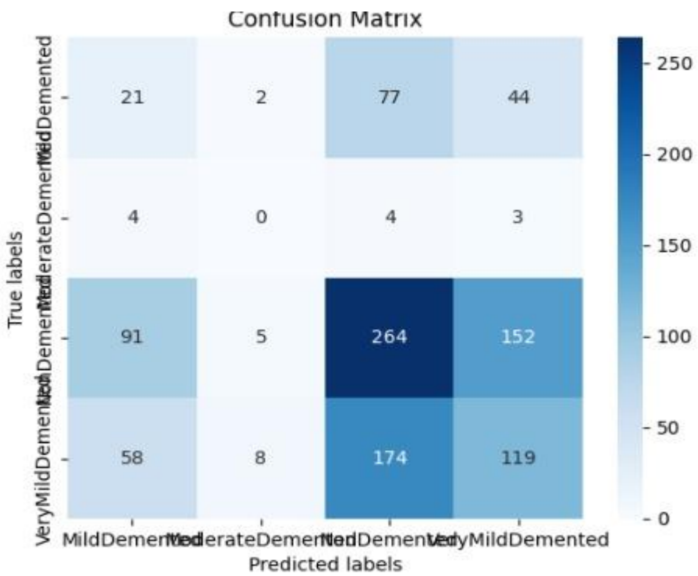

Fig. 4. Confusion matrix

Fig . 5 Loss Plot and Accuracy Plot

Fig 5 The training and validation curves shows the accuracy reaching 98-99% and validation loss stabilizing over epochs that indicate the rapid convergence and generalization of the model. The slight fluctuation in validation loss imply minor overfitting which can be mitigated using advanced augmentation techniques and refines feature selection. Empiricalresultsshowthat multi-viewclusteringcanbeusedtoimprovefeaturerepresentation,improve classificationaccuracy,andallowformoreaccuratestagingofdisease[13].

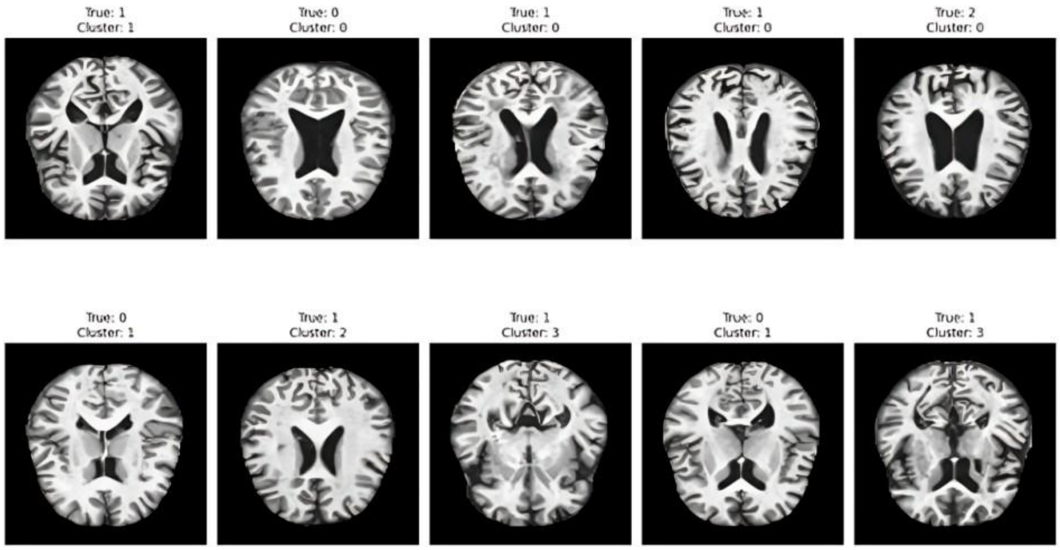

Fig.6:VisualizationofClusteringResults

The multi-view clustering is shown in Fig. 6 which is the clustering visualization.Themulti-viewrepresentationwhichcombinesrawpixelvalues(View 1) and deep features from Attention U-Net (View 2) is able to separate different disease stages better than single view clustering

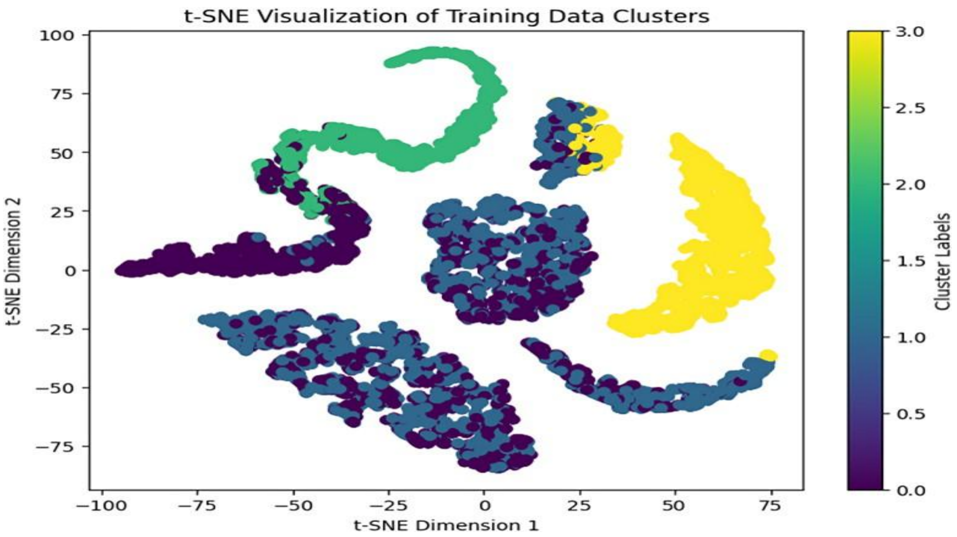

Fig.7:t-SNEVisualizationofTraining Data Clusters

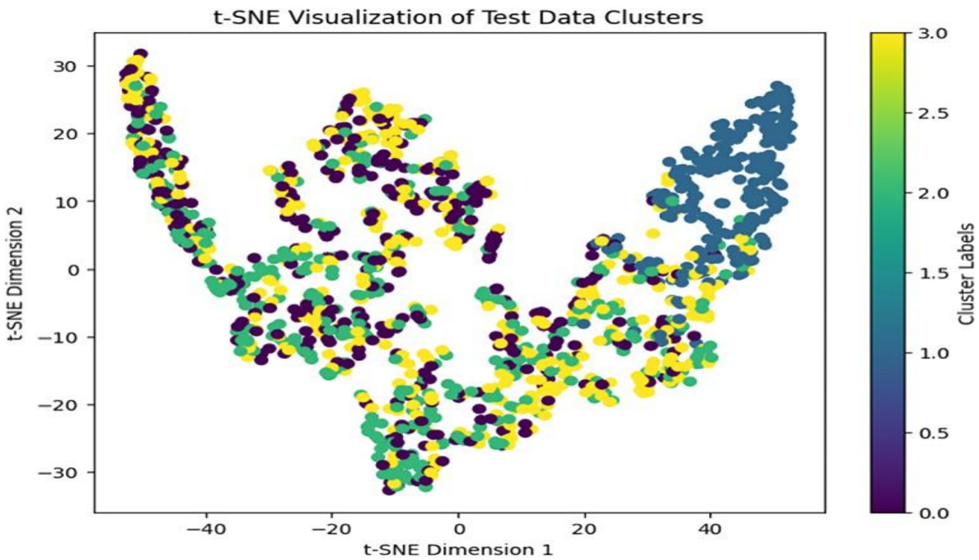

Fig.8:t-SNEVisualizationofTestData Cluster

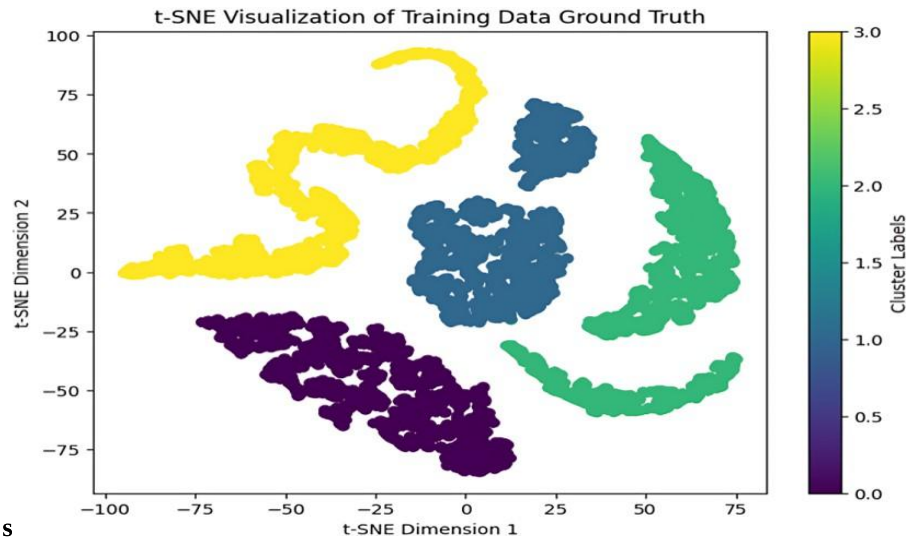

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Fig.9:t-SNEVisualizationofTraining Data Ground Truth

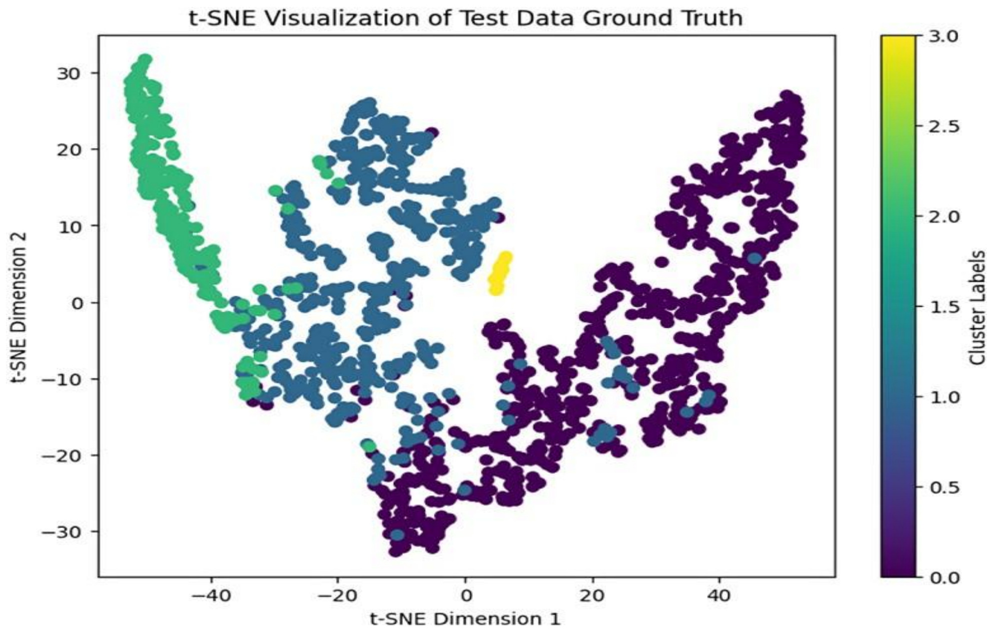

Fig.10:t-SNEVisualizationofTestData Ground Truth

The multi-view clustering is shown in Fig. 7 which is the clustering visualization.Themultiviewrepresentationwhichcombinesrawpixelvalues(View 1) and deep features from Attention U-Net (View 2) is able to separate different disease stages better than single view clustering.

The tSNEvisualizationoffeatureembeddingsprovidesfurthervalidationofclustering.Fig.8andFig.9showsthet-SNEprojectionsoftrainingand test data clusters. The clusters are well defined and corresponds to the four Alzheimer's disease stages. But the minor overlaps between VeryMildDemented and MildDemented clusters need additional clinical data integration to separate better.For comparison with ground truth, Fig. 9 and Fig. 10show t-SNE of training and test data ground truth labels. The proposed framework agrees with actual dementia stage distributions. Multi-view clustering provides a more structured and meaningful separation of Alzheimer's disease stages which helps in better disease progression analysis.Future work would be to further improve feature representation,improverecallforborderlinecasesandincorporatemorepatient data to boost classification. multi-view clusteringframeworksprovideaconsensusrepresentationintegratingcommon and complementary knowledge from multiple sources of data. Deep learning methods, specifically convolutional neural networks (CNNs), are widely used in the analysis of medical imaging.But classical CNN models have limitations in maintainingspatialaccuracyandcontextperception.Inanefforttosolvethese problems,theAttentionU-Netarchitecturewasproposedasamoreenhanced form of the U-Net model with specific intent towards segmentation applications [14].

3. CONCLUTIONS

The experimental results show that the proposed Attention U-Net Based Multi- View Clustering Model is able to extract meaningful features from MRI scansand stratify patients. The combination of deep learning feature extraction with multi-view clustering improves both classification and clustering performance and is suitable for Alzheimer's disease progression analysis. The proposed framework agrees with actual dementia stage distributions. Multi-view clustering provides a more structured and meaningful separation of Alzheimer's disease stages which helps in better disease progression analysis .Future work would be to further improve featurerepresentation,improverecallforborderlinecasesandincorporatemorepatient data to boost classification. This paper introduces a new multi-view clustering methodology that combines an Attention U-Net for feature extraction and K-Means clusteringforpatientgroupingaccordingtodiseaseprogressionstages.The proposed framework employs deep learning for extracting robust imaging featuresandclusteringmethodstoexaminesimilaritiesbetweenvarious patient groups. Experiments on an Alzheimer's-related dataset demonstrate that the proposed framework improves cluster coherence and offers insightfulknowledgeaboutthediseaseprogression.Theresultsdemonstrate that the multi-view clustering model is superior to conventional single-view models, and it can be a valuable tool for clinical use.

REFERENCES

[1] Xiaobo Zhang, Yan Yang, Tianrui Li, Yiling Zhang, Hao Wang, Hamido Fujita, CMC: A consensus multi-view clustering model for predicting Alzheimer's disease progression, Computer Methods and Programs in Biomedicine, Volume 199, 2021, 105895, ISSN 0169-2607.

[2] Bastian Pfeifer, Marcus D. Bloice, Michael G. Schimek, Parea: Multi-view ensemble clustering for cancer subtype discovery, Journal of Biomedical Informatics, Volume 143, 2023, 104406, ISSN 1532-0464.

[3] Tiwari, D., Dixit, M., Gupta, K. (2021). Deep multi-view breast cancer detection: A multi-view concatenated infrared thermal images based breast cancer detection system using deep transfer learning. Traitement du Signal, Vol. 38, No. 6, pp. 1699-1711.

[4] Eleonora Lopez, Eleonora Grassucci, Martina Valleriani, Danilo Comminiello, Multi-View Hypercomplex Learning for Breast Cancer Screening, Computer Vision and Pattern Recognition (cs.CV), Submitted on 12 Apr 2022 (v1), last revised 4 Mar 2024 (this version, v3)

[5] Wenlan Chen, Hong Wang, Cheng Liang, Deep multi-view contrastive learning for cancer subtype identification, Briefings in Bioinformatics, Volume 24, Issue 5, September 2023, bbad282.

[6] H. Nasir Khan, A. R. Shahid, B. Raza, A. H. Dar and H. Alquhayz, "Multi-View Feature Fusion Based Four Views Model for Mammogram Classification Using Convolutional Neural Network," in IEEE Access, vol. 7, pp. 165724-165733, 2019, doi: 10.1109/ACCESS.2019.2953318.

[7] X. Hong et al., "Predicting Alzheimer's Disease Using LSTM," in IEEE Access, vol. 7, pp. 80893-80901, 2019, doi: 10.1109/ACCESS.2019.2919385.

[8] Strijbis, V.I.J., de Bloeme, C.M., Jansen, R.W. et al. Multi-view convolutional neural networks for automated ocular structure and tumour segmentation in retinoblastoma. Sci Rep 11, 14590 (2021).

[9] Vu Duy Thanh, Thanh Trung Le, Pham Minh Tuan, Nguyen Linh Trung, Karim Abed-Meraim, Mouloud Adel, Nguyen Viet Dung, Nguyen Thanh Trung, Dinh Doan Long, Oliver Y. Chén, Tensor Kernel Learning for Classification of Alzheimer's Conditions using Multimodal Data, July 22, 2024.

[10] Nazir, Imran, Haq, Ihsan ul, AlQahtani, Salman A., Jadoon, Muhammad Mohsin, Dahshan, Mostafa, Machine Learning-Based Lung Cancer Detection Using Multiview Image Registration and Fusion, Journal of Sensors, 2023, 6683438, 19 pages, 2023.

[11] Li, Qiucen, Du, Zedong, Chen, Zhikui, Huang, Xiaodi, Li, Qiu, Multiview Deep Forest for Overall Survival Prediction in Cancer, Computational and Mathematical Methods in Medicine, 2023, 7931321, 12 pages, 2023.

[12] Ren Yanjiao , Gao Yimeng , Du Wei , Qiao Weibo , Li Wei , Yang Qianqian , Liang Yanchun , Li Gaoyang, Classifying breast cancer using multi-view graph neural network based on multi-omics data, Frontiers in Genetics, Volume 15, 2024.

[13] Zhang, X., Yang, Y., Li, T., Zhang, Y., Wang, H., Fujita, H.: CMC: A consensus multi-view clustering model for predicting Alzheimer's disease progression. Computer Methods and Programs in Biomedicine,vol.199,2021,105895.

[14] Nguyen, M., He, T., An, L., Alexander, D.C., Feng, J., Yeo, B.T.T.: Predicting Alzheimer'sdiseaseprogressionusingdeeprecurrentneuralnetwork.NeuroImage, vol. 222, p. 117203, 2020.