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ALZHEIMER'S DISEASE RECOGNITION SYSTEM BASED ON ATLAS BASED SEGMENTATION WITH U-NET MODEL

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Abstract: The most prevalent kind of dementia, Alzheimer's Disease (AD), is really an incurable neurological disorder that causes gradual mental decline. The majority of an AD diagnosis in practise is dependent on the patient's clinical history or neuropsychological information, such as magnetic resource imaging, despite the fact that an exact diagnosis of AD is challenging (MRI). The effective use of treatment options depends on the early identification of patients with suspected Alzheimer's disease (AD). The most significant advancement in computation in recent years has been in deep learning and machine learning categorization, which meets the physicians' major demand for automatic early prognosis and diagnosis. Moreover, several machine learning techniques are used for automated diagnosis, however they currently have certain accuracy limits. So, the primary goal of this study is to use a preprocessing strategy before a DCNN model to improve classification accuracy. In this research, we suggested an atlas-based segment with U-net model Alzheimer's disease identification system. The dimensions of the feature space were then reduced by using principal components analysis (PCA) to break down a larger collection of features of potentially set of variables into a more manageable group of values of linear uncorrelated variables. According on the current data, our method appears to be more accurate when compared to certain other existing systems.
Keyword: atlas based segmentation, U-net, PCA

I. INTRODUCTION

Alzheimer's disease is among the most well-known types of dementia in people 65 years of age and beyond, in which people's mental abilities gradually deteriorate and reach a point where it is challenging for them all to lead normal lives. Patients become more reliant on their immediate relatives for survival as the disease progresses progressively. By 2050, it's anticipated that one out of every 85 people would be impacted by it, and in the following 20 years, that number will quadruple. In the patient's brain, Alzheimer found two common abnormalities: "1. Thick layers of protein accumulated outside and within the nerve cells. 2. Damaged nerve fibres inside of nerve cells that have gotten knotted rather than being immediately entangled. These plaques & tangles have also been utilized to aid in the diagnosis of AD [1]. Alzheimer's disease (AD) of the dementia kind is characterized by the typical middle- and old-age thinking and learning difficulties. The problematic aspects of this process include neurotic postures and the degradation of certain brain cells. Typically, issues develop gradually until they are serious enough to affect daily living. AD is just an old-age illness, despite the fact that age is the main risk factor. While the patient's ability to communicate and respond is severely compromised in the early stages of the disease, memory loss is minor. Alzheimer's disease (AD) cannot be slowed down by current treatments, but an early diagnosis can lessen the effects of the illness and enable people live better lives. According to estimates, there will be 85 people living with AD in 2050, up from one in the following 20 years [2].

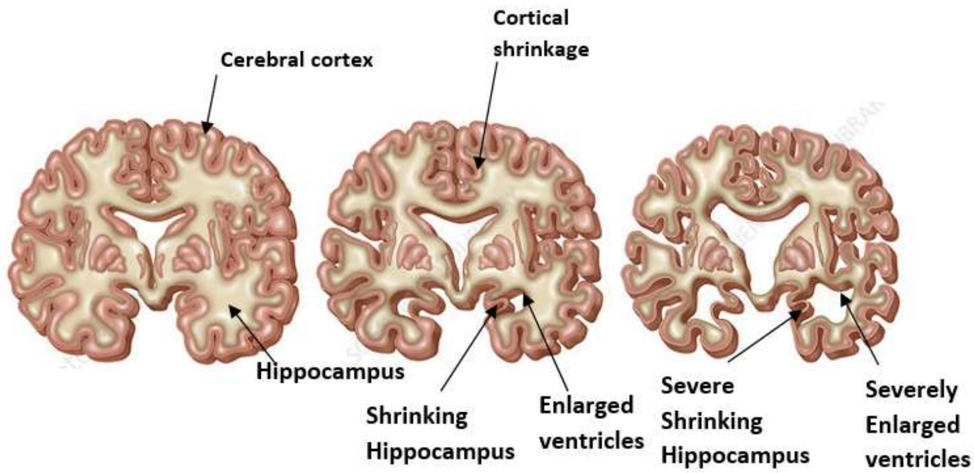

Figure 1. Healthy, Mild Alzheimer's, and Severe Alzheimer's image

Alzheimer's disease is a gradual, neurological brain illness that is irreversible. It is a complex illness that gradually kills brain cells, impairing thinking and memory abilities until eventually even the most basic activities become impossible to do. Dementia is the result of this disorder's effects on cognitive function. For instance, the condition starts off as a modest decline and worsens over time as a neurodegenerative form of dementia. Careful medical evaluations are necessary to diagnose Alzheimer's disease, including patient histories, MMSEs, physicals, and neurobiological tests. In addition to these assessments, resting-state functional magnetic resonance imaging (rs-fMRI) offers a non-invasive way to assess changes in the brain and functional brain activity [3]. AD, a major neuro-degenerative condition in recent years, causes memory loss, confusion, abstract thinking, and other symptoms. As a result, the only approach to manage AD is by early identification, which slows down neuro-degeneration. The biomarker based on neuro-imaging methods including computed tomography, electromagnetic resonance imaging (MRI), diffusion tensor imaging, and magnetic resonance imaging (fMRI) evaluate the metabolic burden using various radioactive tracers that distinguish AD with encouraging findings. Researchers are currently very interested in using machine learning and deep learning approaches to analyse neuroimaging technologies. By utilizing the data that is now accessible, machine & deep learning technologies mitigate the problems with conventional methodologies. Researchers have developed a variety of approaches in recent years, including support vector machines, neural networks, sparse representation, Random forests, linear discriminant analysis artificial neural networks, etc., for the detection of AD. The earlier methods for categorizing the brain pictures are ineffective given the nonlinearities of the retrieved characteristics. In this study, a brand-new framework is put forward for enhancing AD identification and classification performance [4].

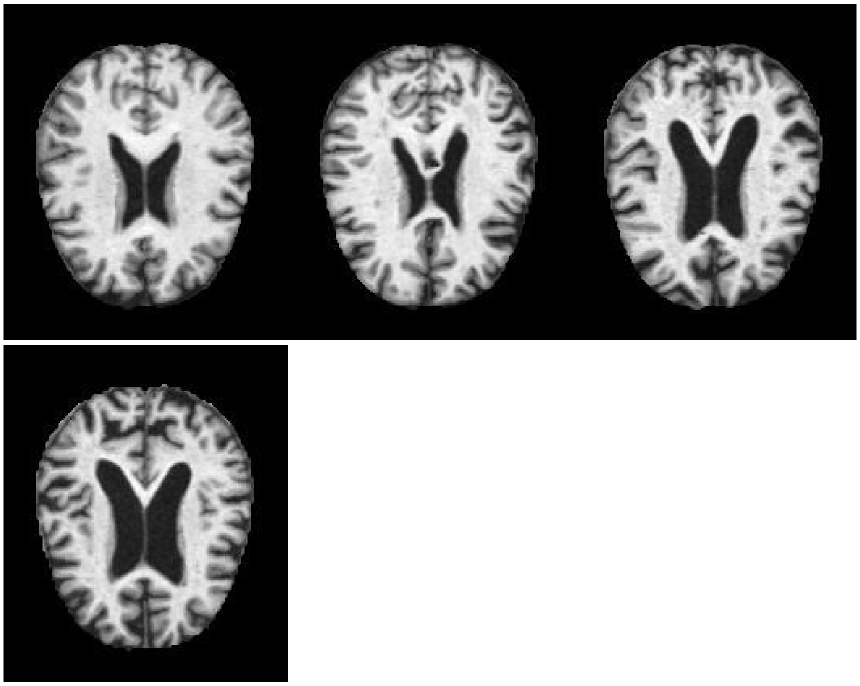

Figure 2. Non Demented, Very Mild Demented, Moderate Demented and Mild Demented

The primary characteristics and elements used to make the diagnosis of AD include demographic and genetic data, results from test performance, cerebrospinal fluid (CSF) biomarker, and findings from brain imaging studies. Furthermore, the change rate of these variables might serve as an additional source of information for the evaluation of the danger of conversions from MCI. Particularly, the research of MCI and AD has made extensive and successful use of neuroimaging technologies including MRI, fMRI, DTI, SPECT, and PET. The choice of neuroimaging modalities depends on the length and severity of the condition; for instance, if MRI failed to detect any changes in the brain, fMRI, SPECT, or PET can detect metabolic abnormalities, and DTI can be used to look for microstructural changes with in white matter (WM) [5].

The proper design process or pre-processing processes must be set in order to use such machine learning methods. There are typically four processes involved in classification research utilizing machine learning: extraction of features, feature selection, wavelet transform, & feature-based classification method selection. These processes include numerous optimization steps that might take time and need specialised knowledge. It has proved difficult to replicate these methods. To create more insightful combinatorial measures, AD-related features, such as mean subcortical volumes, grey matter intensities, cellularity, brain glucose metabolism, & cerebral amyloid- concentration through regions of interest (ROIs), like the hippocampus, are selected from a variety of neuroimaging modalities, for instance [6].Since therapy may be more effective if diagnosed as soon as feasible, pre-detection for AD stages is considered important. The MCI, which is typically the forerunner to AD, is identified by patterns in brain structure using the MRI's high-dimensional mode categorization. A molecular test for AD can help with improved treatments and rehabilitation, and 18 signalling proteins have been identified that can be utilized to distinguish between AD or healthy controls in samples that have been blinded to their identity [7].

Deep learning (DL) mimics the hierarchical organisation of the human brain by processing input at successively higher levels and eventually assembling an increasing number of semantic ideas. Deep learning has received more attention in the development of big data & artificial intelligence technologies as a new device learning method. Few described a deep learning approach consisting of sparse autoencoders with 3D convolutional networks. Recently, certain algorithms based on deep learning have been suggested to recognise or detect certain objects. Based on an MRI scan, it may forecast the illness condition of a patient. When comparing the brains of AD patients to healthy controls, it had a 95% accuracy rate. A comprehensive imaging extracting features pipeline for the diagnosis of many classes of AD was provided by some. In order to retain all information that may be contained in imaging data, it created a deep-learning framework utilising a zero-masking technique. A maximum precision of 87% was attained. Few have shown how deep learning-based pipelines are used to separate fMRI and MRI data from healthy control data for a certain age group to identify Alzheimer's disease. It virtually completely separated healthy normal brains from those with Alzheimer's disease. Others suggested using a powerful 3D convolutional neural networks to predict AD. The network is based on such a convolutional neural autoencoder that has been specifically trained to recognize changes in anatomical form in structure brain MRI data. Studies on the selected MRI dataset, without any prior skull-stripping preparation, have shown that it performed more accurately than other common classifiers [8].

Deep learning has recently demonstrated superior performance in several computer vision applications due to its strong feature learning capabilities. Several researchers have used deep learning to diagnose and forecast the state of patients up until this point. Some research found that the autoencoder model performed better in diagnosing AD than SVM, logit model, linear discriminant analysis, or other techniques. Others have demonstrated that CNN performs better in AD diagnosis than SVM & sparse autoencoder. These findings show that the deep learning approach has produced positive developments for AD computer-assisted therapy [9].The neural network convolutional (CNN) architecture's atlas-based segmentation enhanced using U-net model is used in this study to separate Alzheimer's brains and healthy brains & create a trained, forecasting models.

II. RELATED WORKS

There have been several studies on AD detection and categorization in recent years. In this section, various recent research studies were examined in terms of database, technique, benefits, and drawbacks.

Using the volumes of 54 brain areas obtained from an autonomous multi-atlas whole brain segmented pipeline, Yuan Luo et al. [10] suggested an automated AD diagnostic method. SVM was used as the classification algorithm, and PCA was used as a dimension reduction approach. The importance of the differences was assessed using Student's ttests, and the AD-versus-control significant variations in each of the 54 ROI volumes were measured. The ideal number of PCs for their categorization was put to the test. Their findings indicate that only the first three PCs are required to get an accuracy level of 96.08%. Given the limited quantity of data available, the efficiency of their method in this instance may be seen to be pretty good. Although their preliminary results are encouraging, a bigger dataset will be required for a complete study to see whether it is feasible to use this strategy in a clinical environment. It's also feasible that employing whole-brain segmentations carried out at different granularities may improve their outcomes, and such alternatives will be taken into consideration for subsequent research.

Here, Bach CuadraM.et al. [11] examined the methods currently in use for volume registration-based atlas-based segments in medical imaging. When substantial space-occupying lesion are present in an MR image of the brain, they specifically discussed the issue of employing atlas data for pathological image processing and suggested their approach for atlas-based segmentation. They also highlighted potential future research areas that attempt to combine segmentation and registration procedures to overcome the present drawbacks of atlas-based segmentation systems based only on registration.

When combined with MRI, ApoorvaSikka et al[12] .'s U-Net design was investigated to estimate PET modality, which increases classification accuracy above the state-of-the-art. The cross-modal estimate is carried out via a 3D architecture that uses the entire MRI volumes as an input and produces an associated PET scan in a single pass. In an encoder-decoder setup, the model may capture both non-linear & non-local correlations due to the presence of skip links. By doing multi-modality classification with both the actual MR and the artificial PET scan, they were able to show the applicability of the created scans. In situations when recording PET scans is not practical, synthetic data can be employed, according to the higher joint classification accuracy. Moreover, it may be applied as a missing information technique to estimate Imaging techniques that have been skipped for a variety of reasons.

The usage of 3D-UNet, a end-to-end deep learning-based segmented technique for skull stripping, was suggested by Hyunho Hwang et al. [13]. The technique is totally automated and has successfully stripped skulls from actual brain MRI datasets. The most well-liked traditional approaches and one deep learning-based method have been contrasted with the offered method. In terms of Dice coefficient, sensitivity, and specificity, 3D-UNet fared better than the traditional approaches. Moreover, it displays equivalent outcomes using a deep network created especially for the issue.

The introduction of Alzheimer's disease by Kadhim et al.[15] is shown and explained, and then the relevance of diagnosis detection for MRI images is discussed. The several kinds of Alzheimer's disease are explained, as well as numerous treatment options. This paper's primary goal is to offer research on all latest quantitative comparative investigations diagnosis reviews of Alzheimer's disease MRI techniques from 2017 to 2020. The challenges for the research include that diagnosis is a key component in the detection of brain illnesses, however for Alzheimer's disease, this is challenging to recognize physically in the initial stages of the disease because the brain's changes are difficult to detect.

Jordan Bhai et al [16] proposed an approach for mouse brain segmentation with multi-atlas LDDMM methodology. The precision of the mouse brain delineation can be increased by adding more complexity to the registration or segmentation models. However, MRF to nonlinear register (Demons or LDDMM) didn't perform better than the multiatlas segmentation method, indicating that further research is required to fully understand the essence of the segmentation model & registration before they can be integrated into the segmentation of the mouse brain.

A U-Net having multi-scale foreground highlighting was proposed by Gilsoon Park et al. [18]. (HF). According to their numerous tests, the suggested strategy enhances, as expected, the detection of WMH voxels with ghosting effects. For their system to maintain high accuracy and recall, though, is still a challenge. This problem could be resolved by attention-based models that successfully pick up crucial traits of a structure for segmentation. The integration of an attention-based model into deep networks is thus recommended in the future to enhance WMHs segmentation. The therapeutic usefulness of their strategy is shown by their clinical evaluation. Nevertheless, the clinical criteria is not met for the individual diagnostic of people who have not been visited. To enhance individual diagnosis, a subsequent research would combine other WMH data, such as the position or dispersal of WMH volumes or the longitudinal trajectories of WMH volume changes. In Dockerhub, you can find the implementations of their suggested technique.

Golrokh Mirzaei and others [19] In this article, various imaging & machine learning methods for AD diagnosis were examined. There is no definite method for correctly diagnosing AD. The sensitivities of the biomarkers has a significant impact on how accurately a detection can be made using all methodologies. The majority of the studies' biomarkers in the neuroimaging context concerned hippocampus volumetry and other kinds of brain tissue. In order to identify the interest area (ROI) in various types of pictures, several segmentation approaches were applied. The total brains, hippocampus, GM, WM, & CSF are the primary ROIs. One of the primary duties in all processing techniques is segmentation. Although adaptive thresholding may be used to enhance the segmentation process, not all types of photos may be suitable. The ROI is classified using classification algorithms, but a database of data points (training set) is required first. SVM appears to have a greater overall accuracy in the AD experiments when compared to the other classification algorithms examined.

Summary:

- Investigating dimension reduction & classification methods besides PCA and SVM may result in further performance improvements.
- With U-Net architecture, stronger adversarial training may be conducted.
- While being a bit slower than current non-deep learning algorithms, the given deep learning-based approach performs so well that it should be used for skull stripping.

III. PROPOSED METHOD

A contemporary subset of computer vision that draws inspiration from the human brain is called hierarchical or organized deep learning. This method was created on the basis of intricate algorithms that represent high-level characteristics or extract those abstraction from data by employing a neural network design that is comparable to but considerably more intricate. In order to interpret sensory inputs, the neocortex, a region of a cerebral cortex that controls hearing and sight in mammals, propagates the impulses via a complicated hierarchy through time, as revealed by neuroscientists. This was the main driving force for the development of deep machine learning, which concentrates on computer modelling for information representation that show traits resembling those of the neocortex [3].

AD is a type of neuro-degenerative condition that affects the brain's synapses, causes structural changes, and impairs cognitive performance over time. The recognition algorithm, in particular, begins with MRI information as input, pre-processes the information to enhance recognition accuracy, and then finish the recognition using atlas-based segmentation with U-net. These stages are explained in the subsections that follow. Four processes, including picture capture, image preprocessing, feature extraction, and segmentation, are part of the suggested framework. Fig. 2 depicts the suggested framework's Block Diagram architecture.

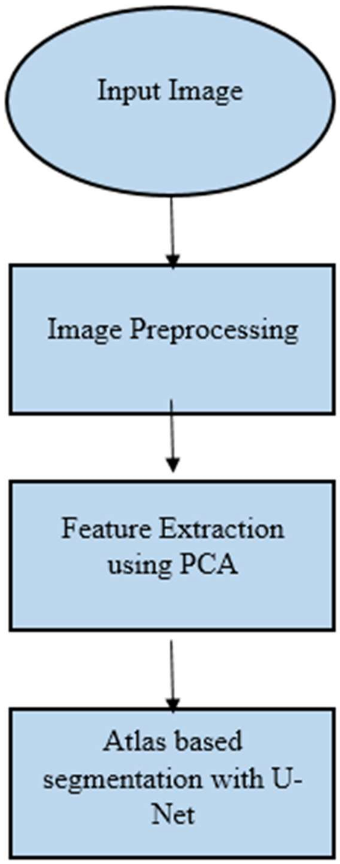

Figure 3. Block Diagram

i. Dataset

The MIRIAD dataset consists of 708 MRI images from 23 patients who are healthy and 46 subjects who have Alzheimer's disease [4]. Brain scans are recorded in this database at periods between 2, 6, 14, 26, 38, & 52 weeks following the baseline. Also, the MIRIAD dataset includes data on the subject's age, gender, and results of the Mini Mental State Examinations (MMSE).

Figure 4. Input image

ii. Preprocessing

Data preprocessing is required in machine learning to standard the data into a similar range. This is crucial when working using MRI data whose brightness does not fall inside a set range. Different MRI acquisition techniques, scanner types, calibration settings, etc., result in variations in the intensity range. Filtering and diffusion of the image are the preprocessing steps carried here

Figure 5. Preprocessed image

iii. Atlas-based segmentation with U-Net architecture

a. Atlas-based segmentation

In an atlas-based segmentation approach, the subject image is coregistered with an extra reference image known as the atlas image, in which the structure of value has been manually demarcated (see Fig. 1). The structure's coordinates are transferred from the coordinate space of the atlas image to the subject image as a result of the spatial transformation. Because this technique is presented in terms of image-to-image registration, it benefits from methodological developments in registrations that are driven by a wide range of application domains, such as visualization, image-guided surgery, & voxel-based morphometry. The client just needs to match the atlas with the topic photographs, making atlas-based approaches among of the easiest to use [17].

The single-atlas approach, which employs image registration to transfer structural tagged data from an atlas picture to a subject's image, is one of the oldest techniques. Without a doubt, registration accuracy has a big influence on how well the segmentation succeeds. Moreover, it has been established that the choice of atlas biases segmentation accuracy.

b. U-Net architecture

Skip connections or a U-shaped structure with symmetric encoders & decoders are two of a U-net neural network's key features. U-net uses the encoder to execute downsampling operations to extract high-level semantic features or the decoder to perform up-sampling operations to symmetrically restore the high-level semantics map to the quality of the original picture. Simultaneously, the network topology leverages skip-connections to combine the recoverable feature with low-level data, aiding the model in learning not only the semantic information of MRI scans but also the initial subtle features [9].

Both classification & segmentation tasks are performed using CNNs. One of their finest qualities is that trained networks may be used to data that has never been seen before thanks to its generalizability. When examining MR pictures from several scanner manufactures or with varied image dimensions, this flexibility can be necessary. The most often used CNNs are 2D U-Nets since they need less compute than higher-dimensional variants. Nevertheless, the volumetric data that is present between slices cannot be processed by 2D U-Nets. The most computationally intensive 3D CNN systems have this processing built in [20].

The network design has a significant impact on a CNN's ability to recognize the pattern necessary to accomplish a given goal. ResNet containing hidden units (ResNet152), EfficientNet versions B0 (EfficientNetB0), or two VGG-based architectures were examined (VGG16 and VGG19). For feature extraction from medical images, all four techniques are often utilised [20].

Five-fold cross-validation was employed. Our model was trained using 1,000 epoch iterations with a learning rate of l0 = 5 104. For both 2 and 3D semantic U-Nets, we used a sigmoid-shaped non - linear activation but also divided the output at 0.5. Slices taken from 3D volume in the x, y, & z directions served as the inputs for 2D models. We average the outputs from the three simulation results (axial, coronal, and sagittal) for the 2.5D U-Net after dichotomizing at 0.5.

Because to the U-Net architecture's good advantage regardless of the types of targeted objects, it is employed in many picture segmentation investigations. Bio-medical image segmentation is more difficult than natural picture segmentation since there is frequently not enough training data available. U-Net overcomes this difficulty by densely predicting the input picture utilizing up-sampling layers that result in input and output of the same size. Fully convolutional networks served as the inspiration for this method. In U-Net, features are back by max-pooling layers during the encoding phase, and are up-sampled to their original size during the decoding phase. Using the contraction path, which joins the feature maps kept in the encoding section with the decoding part, it keeps the localization accuracy. When the extracted features is up-sampled with in decoding part, these retained high resolution features aid in the restoration of the localization information that the max-pooling layer had previously lost [14].

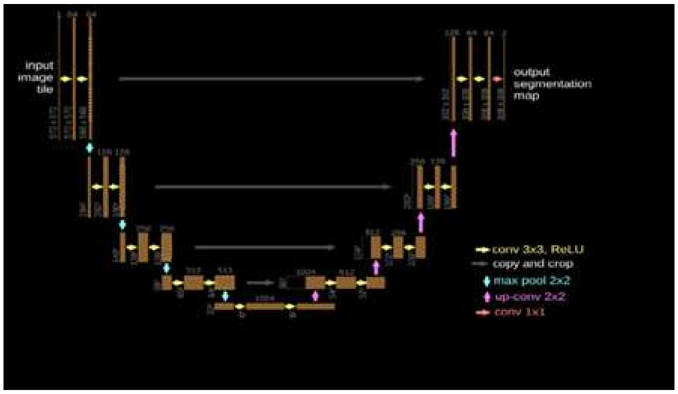

Figure6. U-Net architecture [21].

Deep learning techniques also make use of the applications that lie beneath picture segmentation, including speech recognition, object detection, classification, and genotype detection. Popular deep learning techniques include stacked auto-encoders, neural networks, CNNs, and deep Boltzmann machines.

Many segmentation techniques, such as cascaded, multi-modality, single-modality, update, & semantic-wise, can be used with the CNN architecture. We rely on semantic-wise segmentation in our work because of its advantages over alternative techniques. Because each pixel is predicted from the entire input picture, semantic-wise segmentation is also known as the dense prediction method. It correlates each pixels of the image pixels with its class label. Its key benefits include minimising the loss function, producing segment maps for any picture size, and having a lower computing complexity than previous approaches [21].

Algorithm1. segmentation using the U-Net architecture and the Atlas

1. Start
2. Using the training information set as an input, A and B
3. a test of the input test dataset
4. for r in active_ Columns(l)
5. Forecast is untrue
6. when u = 0 and cells per column are -1
7. If the predictive state (r, u, and l-1) equals true,
8. "p" is equal to "get active segment" (r, u, l-1, active State)
9. When choosing an atlas, Pearson's correlation is calculated between the segmentation scan or the training scans. In this manner, the best atlases are selected.
10. Given a sample of n observations on a vector of p variables.
11. Use the linear combination to define the first PC.
12. While exercise (U-net)
13. If (network training performance!= network test performance), then
14. Then
15. There are issues with the network, such as overfitting, underfitting, or other issues.
16. After modifying the suggested models, repeat the previous procedures.
17. Else
18. Keep working out until you obtain high performance metrics.
19. End

Magnetic resonance image (MRI) scans have been used to improve the performance & accuracy of diagnosing Alzheimer's disease using deep learning algorithms. Studies that have using this methodology have produced generally reliable findings.

Input Image	Ground Truth	Segmented image Binary	Segmented image Gray scale

iv. Feature Extraction: Principal component analysis (PCA)

A well-known multivariate methodology for reducing dimensionality and extracting features is principal component analysis. High-dimensional data are converted into low-dimensional space using PCA. PCA symbolises information into a place that best reflects the variation by lowering its degree of freedom & complexity of time and space. In order of decreasing of variability, the PCA determines the PCs that really are basis vectors [7]. Not only does PCA decrease the number of dimensions, but it also removes noisy data to facilitate pattern detection [10]. A process known as a Kosambi-Karhunen-Loeve transform (KKLT) is used by PCA to mathematically transform a data X of dimensions p to a new dataset Y with reduced dimension l:

$Y = U^t X,$ (1)

U is just an orthogonal matrices where

PCA involves a number of phases, including: Divide by the standard deviation after deducting the mean. Also, it is common practice to standardize each variable to a unit norm. This may be accomplished by multiplying each variables by its norm, which is the total of all its squared parts [26]. As a result, the data set will have a zero mean or unit norm, which simplifies the calculations that come next. Next, calculate the covariance matrix, and then find its eigenvectors and eigenvalues. It's crucial to remember that these eigenvectors must have units norms (i.e., their lengths are all 1). The matrix X has the singular value decomposition as follows (SVD).

$X = P\Delta Q^T ,$ (2)

where P stands for the left input image of X, which are also known as the eigen values of the matrices XXT (i.e., PTP = I). The these really vectors of X are denoted by Q, which stands for the eigen values of the matrices XTX (i.e., QTQ = I). The singular values' diagonal matrix is written as. SVD is identical to eigen decomposition when X is a negative semi-definite matrix; find PCs. Components for PCA are derived from of the SVD of a dataset X. The first PC in the data set is the eigen value with the highest eigen value. The values of the linear function of the components are provided by the matrix Q. These component are the PCs that we choose if the percentage of the sum of the constituent coefficients in Q approaches 95%; (5) Provide updated info to the chosen Computers [10].

IV. RESULT AND DISCUSSION:

In this work simple predictions are established with four Alzheimer affected image using our proposed technique. Implementation has been built for four categories of images among which three are affected by Alzheimer's mildly, moderately and severely and the rest is normal dataset.

The formulae below are used to generate pixel accuracy, mean accuracy, mean IoU, and frequency weighted IoU. (FWIoU).

$P_{acc} = \frac{n_{ii}}{\sum_i t_i}$ (3)

$M_{acc} = (\frac{1}{n_{cl}}) \sum_i \frac{n_{ij}}{t_i}$ (4)

$M_{IoU} = (\frac{1}{n_{cl}}) \sum_i \frac{n_{ii}}{t_i + \sum_i n_{ji} - n_{ii}}$ (5)

$FW_{IoU} = \left(\sum_k t_k\right)^{-1} \sum_i \frac{t_i n_{ii}}{t_i + \sum_i n_{ji} - n_{ii}}$ (6)

$$P_{acc} = Pixel\ Accuracy$$
$$n_{ij} = number\ of\ pixels\ in\ class\ i\ classified\ to\ class\ j$$
$$t_i = total\ number\ of\ pixels\ in\ class$$
$$n_{cl} = total\ number\ of\ classes$$

Table –I Results obtained during our first iteration of training using 20 epochs

Data	Pixel Acc (%)	Mean Acc(%)	Mean IoU (%)	FWIoU (%)
Image1	96	88	89	97
Image2	96	79	87	96
Image3	97	85	85	98
Image4	98	80	82	96

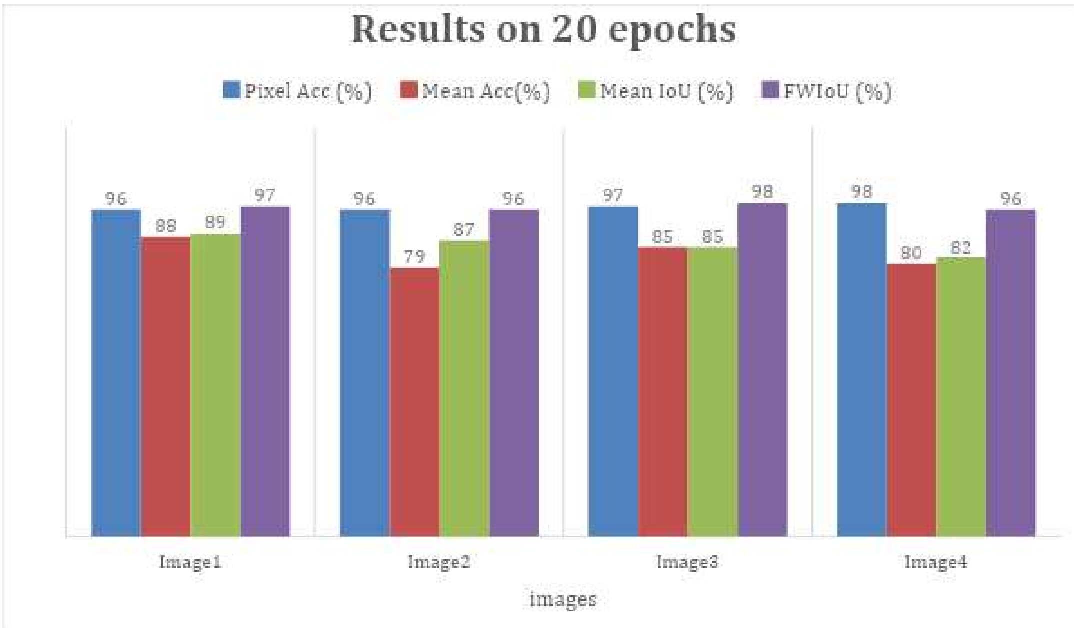

Figure 7. Results obtained during our first iteration of training using 20 epochs

Table 1 and Figure 7 demonstrate the results of our initial implementation of the proposed U-Net, which was trained on 20 epochs for sample four image among which each depend on different class [22].

V. CONCLUSION

Alzheimer's disease is one of the most common diseases in the world (AD). While Alzheimer's disease (AD) accounts for 60 to 80% of dementia cases, it is not the most common cause of the disorder. Memory loss and a variety of other intellectual capacities, such as clear thinking, are by definition part of the dementia diagnosis. Alzheimer's disease (AD) is a long-term, incurable illness that causes brain shrinkage, memory loss, and cognitive impairment.In this study, we suggested a method to recognise Alzheimer's disease utilising atlas-based segmentation and a U-net model to forecast the progression of AD illness. For feature extraction, we used principal component analysis (PCA). According on the current data, our method appears to be more accurate when compared to certain other existing systems.

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