Detection And Segmentation of Brain Tumors And Comparing Results For Various Segmentation Techniques

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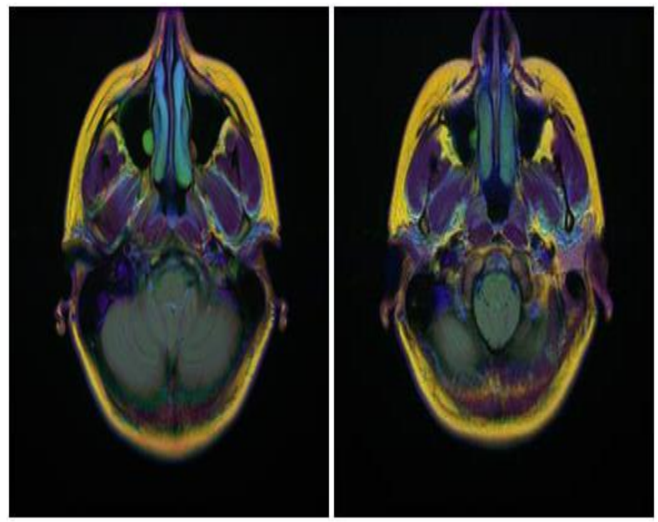
Abstract- *Formation of abnormal cell groups in our brain affect the normal functioning of the person. If proper and timely treatment is not given, this can turn out to be fatal. However, it can be avoided with timely detection and treatment with medical imaging techniques. Many segmentation techniques are used for brain tumor segmentation. Of these techniques, selecting the most accurate one has always been a challenge. In this paper, we have created a comparison between the most used algorithms namely K-means, CUDA k-means, and Gaussian algorithm based on their accuracies. For this, we have used the BRATS2018 dataset. We have mainly used CNN, machine learning and image processing to detect the brain tumor. Our model has preprocessing part(including add weighted Gaussian blur for enhancing the image), skull stripping part(including the erosion operation), image segmentation using K means, CUDA k means and Gaussian algorithm respectively, OTSU method and morphological operations followed by tumor detection and accuracy calculation. The average accuracies of various algorithms will be displayed using a line graph, and the segmented images will be displayed for comparison. Based on these outputs, we will find which algorithm gives the most accurate outputs.*

Keywords- K means, CUDA K means, Gaussian, add weighted Gaussian blur, Skull stripping, Morphological operations

I. INTRODUCTION

With the development of new technologies, the concept of Smart Healthcare has come in existence. The traditional ways of medical practices have now been replaced with automated healthcare. Technologies such as IoT, Deep Learning, Big Data, Cloud Computing, Artificial intelligence etc have changed the old ways of healthcare completely. Using these technologies for Healthcare made it more personalized and effective. It has been used over these years for detection, treatment and avoidance of diseases, prescribing medicines for standard symptoms, scheduling of appointments and hospital management.



(a) (b)

Fig1. a) Brain MRI scan without tumor b) Brain MRI scan with tumor

Providing the needed treatment to the patients at the right time is necessary, else it can be fatal. A large number of patients die due to this fatal disease. However, the traditional method of detecting the tumor is costly and time consuming. Therefore, online software to detect and locate the tumor would make the process a lot easier, accessible and personalized for the patients. This will ensure that brain tumors are detected at the right time ensuring accurate results. The rest of the brain is separated from the tumor region in segmentation of the brain. The exact location of the region with tumor is then displayed along with the tumor size for the doctor's reference.

Machine learning approach that we have used, extracts the basic information from the input image, trains the model and detects the tumor location after morphological operations. We have used CNN exploring small 3×3 kernels. Using small kernel helps create a detailed architecture while helping with better fitting, giving lesser weights in the system. We tried to use intensity normalization as a part of the pre-processing phase. This is not commonly used in CNN based approaches, but turned out to be effective for brain tumor segmentation. To avoid noise and get a variation in gradients, we have used add weighted Gaussian blur approach in our preprocessing part. The imperfections in the image after the applying segmentation algorithm are removed using morphological operations (erosion and dilation).

The right treatment needs to be given for Brain Tumors at the initial phases of the condition itself. Otherwise, it turns out to be fatal for the patient. Considering the number of image segmentation algorithms used, it is often difficult to find which is the most appropriate for use in Brain Tumor Segmentation. Hence, we figured a need to create a comparison between the various algorithms, and therefore find which of them gives the most accurate results. Also, noise in the final output affects the accuracy of the system making it less reliable. Hence, we have tried to remove any possible noise that could affect the accuracy and used add weighted Gaussian blur to enhance the edges and details of the image.

In this project, our basic objective is to detect the exact size and location of the tumor using all three algorithms (namely K means, CUDA K means and Gaussian). We have changed the basic models a little to avoid noise in the final output, and thus get the maximum accuracies possible for these algorithms. Noise in the final output could hamper the location predicted by the system, hence making it less effective and reliable. We'll then create a comparison between all three algorithms based on their average accuracies and average times taken per image. Based on these observations, we'll try to figure out which algorithm is most suitable and accurate for Brain Tumor Segmentation.

After analyzing the results obtained in this project, we observed that all the three algorithms could predict the approximate location of the tumor. The accuracies of K means, CUDA K means and Gaussian was 79%, 84% and 81% respectively. At all times, we observed that the accuracy of CUDA K means was the highest. Therefore, we came to the conclusion that CUDA K means if the most accurate algorithm considering Brain Tumor Segmentation.

II. RELEVANT WORKS

Annisa Wulandari et al. [1] have used median filter for noise removal. They have then used thresholding followed by watershed segmenatation.

Nishchay Agarwal, Lokesh Kumar, Akansha Singh, Hemant Kumar, Mukul Chauhan, Abhishek Dubey[2] have focused on already existing machine learning and deep learning algorithms fo their system.

Fatih Özyurt,Eser Sert,Derya Avcı[3] have used fuzzy C control algorithm and SqueezeNet architecture for their system.

Mohammad Havaei et al. [4] have used CNN's especially DNN for imaging data.

Asieh Khosravanian et al.[5]have used a novel fuzzy energy functional with a superpixel segmentation for their system.

K.M. Schmainda et al. [6] campared multiset DSC-MR imaging datasets in their paper.

Kai Hu et al.[7] applied CRFs in their system to avoid irrelevant outputs.

Li Sun et al. [8] have used deep convolutional neural network and then extracted the radiomics features to predict the overall survival.

Tiejun Yang, Jikun Song [9] have tried to improve the segmentation results by combining a 1*1 convolution layer to basic model.

D. Suresha et al. [10] have used fusion of K means and SVM to detect brain tumor.

Kaplan Kaplan, Yılmaz Kaya, Melih Kuncan, and H. Metin Ertunç [11] have used nLBP and αLBP procedure to detect and locate tumors.

Hao Chen et al. [12] have used DCSNN for the tumour segmentation process.

Z. Luo et al. [13] have used HDCNet for segmentation of MRI image.

M. Ali, S. O. Gilani, A. Waris, K. Zafar and M. Jamil [14] used a combination of 3D CNN and a U-Net and then compared the results of both.

Jie Xue et al. [15] have used F2 FCN in their system.

Shah Rukh Khan et al. [16] have used a model based on Partial Tree (PART) which classifies the tumors according to severity.

Asieh Khosravanian et al. [17] have used superpixel fuzzy clustering and MMGR for their model.

Mostefa Ben naceur et al.[18] have created a completely automatic CNN based model.

H. Cherguif, J. Riffi, M. A. Mahraz, A. Yahyaouy and H. Tairi [19] have used a deep learning-based U-Net model for automatic tumor segmentation.

Raheleh Hashemzehi et al.[20] have created a system from CNN and NADE and performed the segmentation process on the MRI images.

Table 1: Comparison between properties of all research papers

Ref no.	Technique	Dataset	Advantages	Limitations
1	Watershed segmentation	14 MRI scan images from different sources was used	Time taken is less	Error while finding tumor area is high
2	CNN, Fuzzy C means and SVM		Accuracy is high	Does not find the location of the tumor.
3	Fuzzy C-means, SqueezeNet		Performance is high	Speed can be further enhanced
4	Cascaded convolutional neural networks, CNN,	2013 BRATS	System is really fast	Accuracy can be improved
5	Lattice Boltzmann an d Fuzzy C means clustering	BRATS 2017	System is fast and immune to noise	Accuracy can be improved
6	DSC-MR	Six datasets were used: i) T1C ii) DSC-MR iii) AIF iv)Brain mask v) NAWM vi)brain tumor	Effective for both LGG and HGG	Preprocessed stage can be automated
7	CNN, multi-cascaded convolutional neural network	BRATS 2013,2015,2018	The system has been tested on a large dataset	System is not that effective
8	CA-CNN, DFKZ Net, 3D U-Net	Brats 2018	Performance is enhanced	Accuracy is less
9	U Net model	Brats 2015	Model gave better results than the present segmentation models used; time taken has reduced	Accuracy can be enhanced
10	K-Means and support vector machine		Accuracy is high	They do not find the tumor location
11	nLBP, αLBP, KNN, ANN and Linear Discriminant Analysis (LDA)	Database collected from various hospitals and colleges in China from 2005 to 2010	Low cost and high accuracy	Only a few types of brain tumors have been considered
12	Deep Convolutional Symmetric Neural Network (DCSNN)	BRATS 2015	Speed is high	Accuracy is less
13	HDCNet	BraTS 2018 and 2017	Less parameters needed	Accuracy is less
14	3D-CNN and U-Net	BraTS-19	Difference combinations have been used	Accuracy is less
15	F^2 FCN	BRATS2013, BRATS2015 and SC dataset	Used a huge dataset	Model quality is bad
16	Partial Tree (PART) and 10fold cross-validation	Used dataset from different online sources	Low cost and higher accuracy	Performance can be enhanced
17	Superpixel fuzzy clustering objective function, multiscale morphological gradient reconstruction (MMGR) and lattice Boltzmann method (LBM)	BraTS 2017	Accuracy is high	Many parts of the image have not been segmented
18	Deep CNN	BRATS-2018	Automated system	CNN performance degradation is seen during training.

2.1 Gap Analysis

While researching on all these research papers, we figured out that most of the models either had low accuracy or time taken was more. Hence, figuring out the model which is best suited for Brain tumor segmentation of MRI scanned images was difficult. Also, noise removal and edge detection were major issues faced in all these models. In our project, we have changed the basic algorithm and focused on better edges and noise removal. We have created a comparison between three methods of segmentation to find which is the most reliable, accurate and takes the least time.

III. PROPOSED SYSTEM

3.1 Pre-processing phase

The noise removal and enhancement of the grayscale image is done in this part of the system. Various techniques are implemented for the same. To give best results, noise needs to be removed, thus removing the blurring effect in the output. Enhancement helps in sharpening the edges and giving best image output. After this, segmentation of the image is done. These result in sharper edges and enhanced quality helping in finding the exact location of the tumor.

i. The MRI scan is taken as input and stored in the database.
ii. It is converted to grayscale image(255*255 size)
iii. Any noise in the image is then removed.
iv. For better edges, this image is then passed through a high pass filter.
v. Using Add Weighted Gaussian Blur, this image is then added to the original image for enhancement.

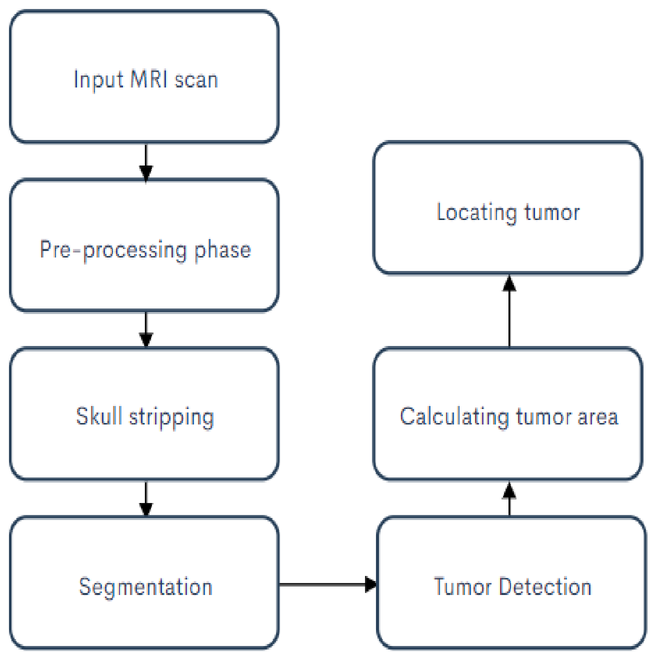


Fig.2 Flowchart of Brain tumor segmentation

3.2 Skull stripping phase

This is one of the major processes used. This is only needed for brain segmentation and is not necessary for heart, lung scan etc. All the non brain tissues (such as skull, skin, and fat) are removed for the brain scan in this step. Skull stripping can be done by many techniques. However considering the need for this paper, we have used threshold value technique to remove the non-brain tissues. The threshold values of the skull and normal brain tissues considered.

i. Convert the given image to grayscale
ii. Convert the image to binary
iii. Remove any noise present in the image
iv. Apply erosion operation to this image

3.3 Image segmentation phase

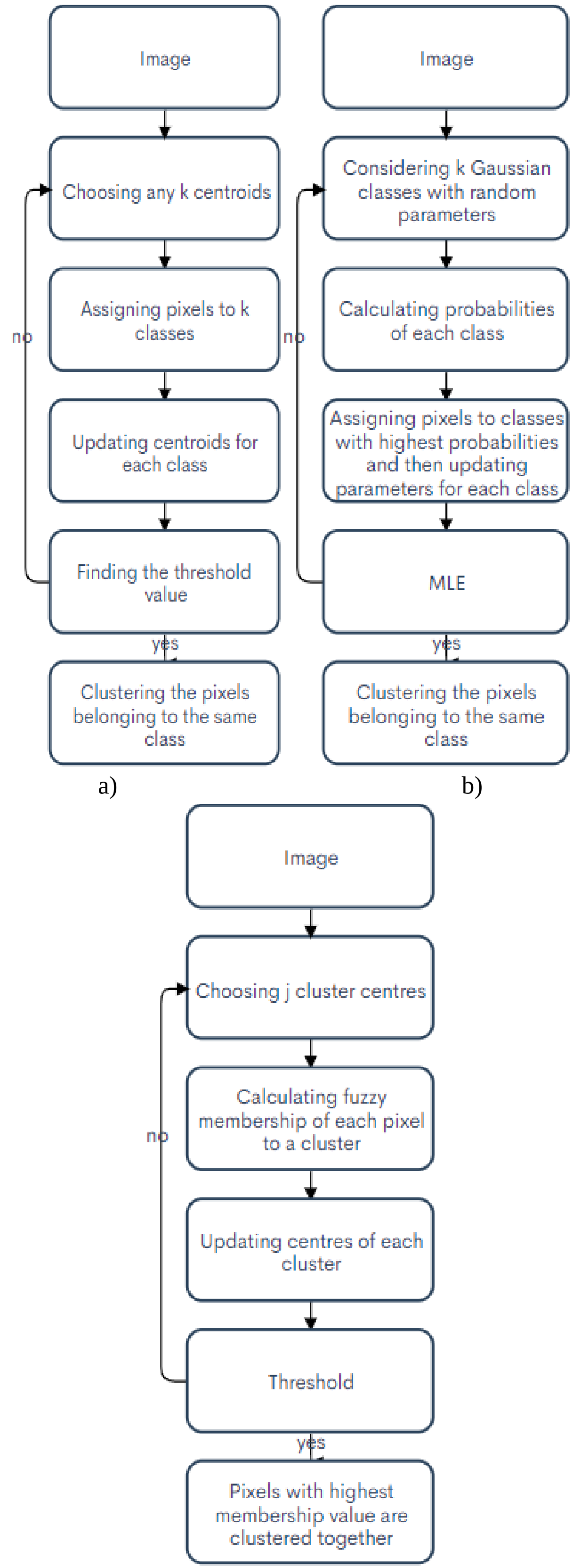
Segmentation is defined as the method of converting the image into pixels that are easy to work with. It is mostly used to extract the object f4rom the input image. Segmentation is done in two parts, first is finding the size, shape and other dimensions for the image. Other is examining the part of the image that need to be extracted from the original image.

Of the several image segmentation techniques developed over the last decade, we have created a comparison between k means, CUDA k means and Gaussian.

In k means algorithm, the image is divided in k pixels based on the similarity in pixels of the clusters. In brain tumor segmentation, it helps to detect the shape and location of the tumor.

In CUDA k means algorithm, the two steps (i.e. assigning data points to clusters according to centroid and finding the new centroid based on new assigned cluster points) are done in parallel.

In Gaussian algorithm, every cluster in the image is considered as a generative model. Parameters such as mean and variance are used to detect the tumor location.



c)

Fig. 3. Block diagram of a) K means b) Gaussian c)CUDA K Means

3.4 Morphological Operation phase

Operations related to dimensions and morphology are performed in this section. This converts the image into an image with non-zero pixel value. Erosion has been used in this paper find if the MRI image has tumor region or not.

Erosion section of morphological operation is been applied on Ax by Bx:

$$Ax \ \Theta \ Bx = \{(ix, jx): Bx\ (ix, jx)\} \quad (1)$$

Ax= image after converting into binary
Bx= structuring element of the image
(ix, jx)= center pixel of the structuring element of image

3.5 Area calculation and location detection of the tumor in the brain

Area calculation of the tumor region in brain MRI scanned image, we have used the following approach.

Area of tumor in the MRI scanned image =Ax * number of pixels in the tumor area (2)

$$Ax= Vx * Hx \quad (3)$$

Where, Ax=one pixel area
Hx=image horizontal dimension
Vx=image vertical dimension
Hx=inverse of the horizontal resolution of image
Vx=inverse of vertical resolution of image after segmentation

3.5.1 Tumor Area

1. The MRI scan image is inputted in jpeg format
2. If it is in RGB format, convert it to grayscale
3. Calculate the tumor area using the formula
4. Display the tumor stage and condition

3.5.2 Tumor Location

1. Read the input image
2. Convert to grayscale
3. Calculate the number of rows and columns in the image
4. Divide them in two parts
5. Label this result as left and right hemisphere

IV. IMPLEMENTATION

In this paper, we have taken MRI image as an input to perform our algorithms on. We considered MRI images because it gives us detailed information about the tissues and conditions of the brain. We start with checking if the patient have tumor or not. The tumor region is extracted and the number of pixels is calculated. If it is zero, image of the brain without the tumor is displayed.

After this, we remove the noise from the image. Of all the filters used for the same, we have use average filter. On this smoothened image, we perform skull stripping to avoid wrong classification. We have used threshold values based skull stripping in our paper. In this process, all the unnecessary tissues are removed, gaps are filled and the skull tissues are displayed. We then convert this into binary image. The binary image is then added to the original image. On the image without skull borders, we perform image segmentation. The image after skull stripping is the segmented using all three methods i.e. K means, CUDA K means and Gaussian.

After segmentation, final tumor image is displayed after morphological operations. We perform erosion operation on the mage obtained after segmentation. We separate the white and gray matter from the image. We then find the values of the regions (gray and white separately). These values are then compared and the one with more intensity is found out

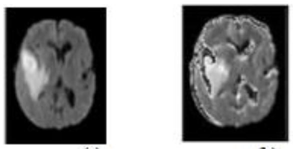
After separating, we find the total area of the tumor in the brain region. The area of one single pixel in the brain image is found out and multiplied with the total number of pixels.

We divide the tumor detected image in parts to locate the tumor. We name these parts as left and right hemisphere (The left part is right hemisphere and visa verse). Based on the number of pixels in each side on the brain, we find where the tumor might be located (right hemisphere, left hemisphere or the center of the brain).

V. RESULTS

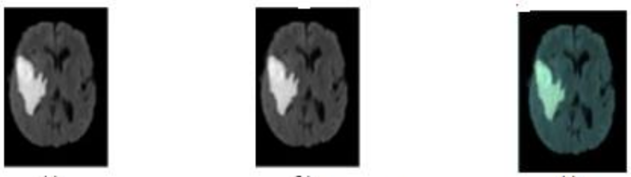
We tested all the three segmentation methods namely K means, CUDA K means and Gaussian on BRATS2018 dataset. The main aim behind this research is comparing the results and accuracies of three segmentation techniques and finding which is the most effective. Fig 4 shows the input image and the image after skull stripping. In skull stripping phase, all the noise and unnecessary parts of the image were removed and the edges were sharpened. When comparing Fig

4.a and Fig 4.b, we can clearly see that the edges are clearly distinguishable and the image got sharpened on performing skull stripping.



(a) (b)

Fig 4. a) Input MRI scan b) result after skull stripping



(a) (b) (c)

Fig.5. Segmentation results after (a) Gaussian (b) K means (c) CUDA K means

Fig 5 shows the results in all three cases after segmentation. The time taken to perform segmentation and display results was least in CUDA K means, and really long for Gaussian segmentation. Fig 6 we have displayed the average times taken for each image in all three types of segmentation in a line graph. As we can clearly see in the graph, the time taken for Gaussian was much higher compared to other two segmentation techniques. Fig 7 displays the average accuracies per image for each type of segmentation technique. In this, we can see that the average accuracy for CUDA K means at all times was higher than the other two segmentation techniques.

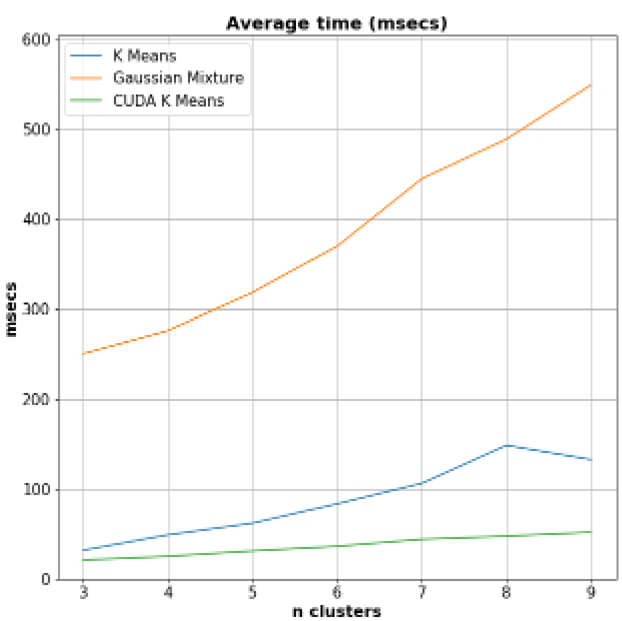


Fig 6. Average time comparison graph between the three segmentation techniques

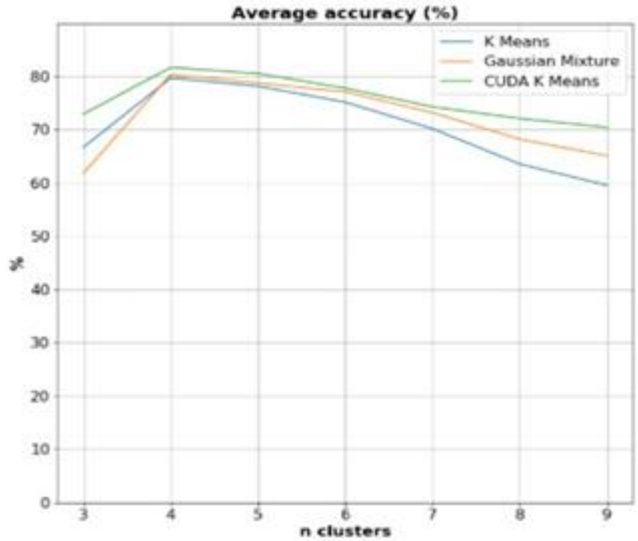


Fig 7. Average time comparison graph between the three segmentation techniques

VI. CONCLUSION AND FUTURE WORK

In this paper, we have compared the results for three types of segmentation techniques. We have used add weighted Gaussian blur and various noise removal techniques for get better accuracies. The accuracies we got for K means, CUDA K means and Gaussian was 79%, 84% and 81% respectively. We observed that CUDA K means gave better accuracy and took the least time, giving the best results possible for convex images. Hence, of these three methods of segmentation, we found CUDA K means to be the most effective for Brain Tumor Segmentation.

This is continuous research and in future we would compare other segmentation techniques along with these. We are also planning to further improve our algorithm to get better accuracies.

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CAPTION LIST