BRAIN TUMOR DETECTION USING K-MEAN CLUSTERING AND SVM

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Abstract– Brain tumor classification is an energetic analysis space in medical image process and pattern recognition. Tumor is associate abnormal mass of tissue within which some cells grow and multiply uncontrollably, apparently unregulated by the mechanisms that management traditional cells. The expansion of a growth takes up house inside the os and interferes with traditional brain activity. The detection of the growth is incredibly necessary in earlier stages. Automating this method could be a difficult task thanks to the high diversity within the look of growth tissues among totally different patients and in several cases similarity with the conventional tissues.

This paper depicts a unique framework for neoplasm classification supported gray level co-ocurrance matrix(GLCM) applied mathematics options square measure extracted from the brain magnetic resonance imaging pictures, that signify the necessary texture options of growth tissue.

***Key Words*: Brain, Magnetic resonance imaging, Support vector machine (SVM), LBPH, HOG, GLCM.**

1. INTRODUCTION

Detection of a brain tumour from medical images has been a challenging task. The brain is one of the important organs of the human body as it coordinates each and every action of the human body. The human brain can be affected by many diseases like infections, strokes and tumours. A brain tumour is a cancerous or non-cancerous mass or growth of abnormal cells in the brain. It can be termed as the cells which don't die but grows in size and accumulates as a mass. A brain tumour is classified as a primary and secondary tumour. A tumour that starts in the brain is called Primary Brain a tumour. It can be either malignant (contain cancer cells) or benign (do not contain cancer cells). If a cancerous tumour which starts elsewhere in the body sends cells which end up growing in the brain, such tumour is called secondary or metastatic brain tumour. Image testing of a brain tumour is done using x-rays, strong magnets, or radioactive substances to create pictures of the brain. The brain tumours are generally diagnosed using different types of scans. Magnetic Resonance Imaging, Computer Tomography, Angiogram, Myelogram and Positron Emission Tomography are among the types of scans which are used most often to detect brain diseases. These pictures are so efficient that they can provide with primary information about the presence and location of a tumour.

COMPUTED TOMOGRAPHY (CT) SCAN:

A Computer Tomography (CT) scan uses X-rays to give a three-dimensional image of the brain. CT scan takes many images instead of taking only one image as in x-ray. CT scanner rotates around you while you lie on a table. Later all these images are combined into images of slices of the body. CT scan gives information of the tumour size and any damage to the bones inside the skull .

CT ANGIOGRAM (CTA):

Angiogram uses a series of X-rays to show the arteries and blood vessels of the brain. For the test, you are injected with a contrast material through an IV line while you are in the CT scanner. The scan helps the doctors plan surgery because it can provide better details of the blood vessels in and around a tumour .

MYELOGRAM:

Myelogram makes use of a dye to find out whether a tumour has spread to near parts of the body like a spinal cord. The test is done by injecting the dye into Cerebro Spinal Fluid (CSF) [4].

POSITRON EMISSION TOMOGRAPHY (PET) SCAN:

For the test, a radioactive substance called as FDG is injected into the blood. A little amount of FDG is injected so, it passes out of the body within a day or so. Tumour cells in the body grow quickly, so they absorb larger amounts of the sugar than most other cells. After about an hour, you are moved onto a table in the PET scanner. A special camera creates a picture of areas of radioactivity in the body of the patient.

PET scans are not so detailed but they provide information whether abnormal areas seen on other tests are tumours or not.

PET scan and CT scan are performed in combination to check whether a tumour has been cured or come back after the treatment. The PET-CT scan is generally performed first as a part of treatment.

MAGNETIC RESONANCE IMAGING (MRI) SCAN:

MRI is the basic diagnosed scan among the types of scans.MRI uses radio waves and strong magnetic fields instead of X-rays. The energy from the radio waves is absorbed and then released in a pattern formed by the type of body tissue and by certain diseases. A computer translates the pattern into a very detailed image of parts of the body. The scan uses a dye which is a contrast material called gadolinium that is injected into the patient's veins before the scan for better details .

WHY MRI SCANNED IMAGES ARE PREFERRED COMPARED TO OTHER IMAGING TECHNIQUES?

- MRI is non-invasive.
- MRI is cost effective.
- Good contrasts of the tumours that are present in the brain are provided.
- Acquisition time (Total body scan) of MRI is less compared to PET and X-Ray.
- MRI provides better details of bone structure and organs behind them like lungs behind ribs and brain beneath the skull.

2. LITERATURE SURVEY:

KNN is the simple method which required low computational cost. An automatic medical image classification technique KNN classifier is used to classify the medical image into normal and abnormal image this concept Presented by R. J. Ramteke et al.[1]

MRI image classification technique based on SVM classifier proposed by Khushboo Singh etal.[2].Advanced classification techniques based on Support Vector. Support vector machine is a supervised learning algorithm. In SVM, the classification is performed by quadratic programming.

An efficient brain tumor detection algorithm using watershed and threshold based segmentation implemented by A .Mustaqeem, et al [3]. This research was conducted to detect brain tumors using medical imaging techniques.

ANN is a mathematical problem which is inspired by the biological nervous system Priyanka et al.[4] proposed a urvey on the brain tumor detection algorithm and its location in the brain.Shweta Jain et al.[5] extract a feature using GLCM technique and extracted features were classified using the artificial neural network.

P.Vasuda and S.Satheesh [6] proposed a technique to detect tumors from MR images using fuzzy clustering technique. This algorithm uses fuzzy C-means but the major drawback of this algorithm is the computational time required.

Sindhushree. K.S, et al [7] have developed a brain tumor segmentation method and validated segmentation on two dimensional MRI data. Also, detected tumors are represented in three dimensional view. High pass filtering, histogram equalization, thresholding, morphological operations and segmentation using connected component labeling was carried out to detect tumor. The two dimensional extracted tumor images were reconstructed into three dimensional volumetric data and the volume of the tumor was also calculated

Gopal et al [8] proposed a smart system Brain Tumor Through MRI utilizing Image Processing Algorithm, for example, Fuzzy C Means Along with Intelligent Optimization Techniques", diary of IEEE 2010.

It is designed to diagnose brain tumor through MRI using image processing clustering algorithms such as fluffy C Means along with intelligent optimization tools, such as Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The average results classification error of GA is 0.078%. The average accuracy GA is 89.6%. PSO gives best classification accuracy and average error rate. In this the Average classification error of PSO is 0.059% and the accuracy is 92.8% and tumor detection is 98.87%. Therefore, we saw that average classification error is reduced when the number of sample is increased. This report has provided substantial evidence that for brain tumor segmentation of PSO algorithm performed well.

Badran et al [9], proposed an innovative system which can be used as a second decision for the surgeons and were based on adaptive thresholding. It determines whether an input MRI brain image represents a healthy brain or tumor brain as percentage it defines the tumor type; malignant or benign tumor.

HOG descriptors have been introduced by Dalal and Triggs in [10] and [11]. The main idea behind the histogram of oriented gradient is that the local appearance and shape of object in an image can be described by the intensity distribution of gradients or direction of the contours. The implementation of these descriptors can be obtained by dividing the image into small connected regions, called cells. Then, for each cell we compute a histogram of gradient directions or edge orientations for all pixels of the cell. The combination of these histograms is the descriptor.

The HOG descriptor has some key advantages. Since it operates on localized cells, the method maintains the invariance to geometric and photometric transformations.

The method allows a more generic detection, requiring no prior information about the structure of the scene, with a processing time close to the real-time. In 2005, INRIA researchers propose a new technique based on the histograms of oriented gradient (HOG) [12].

Also in 2008, Mu & al. have successfully used local binary patterns (LBP), a type of features that had proven a good effectiveness especially when applied to face detection [13].

Brain tumor classification is very significant phase in the medical field. The images acquired from different modalities such as CT, MR that should be verified by the physician for the further treatment, but the manual classification of the MR images is the challenging and time consuming task [14].

Human observations may lead to misclassification and hence there is need of automatic or semiautomatic classification techniques to make the difference between different tumor types.

3. PROPOSED SYSTEM ARCHITECTURE:

We have proposed segmentation of the brain MRI images for detection of tumors using K-Means clustering technique. A cluster can be defined as a group of pixels where all the pixels in certain group defined by similar relationship. Clustering is also unsupervised classification because the algorithm automatically classifies objects based on user given criteria. Here K-Means clustering algorithm for segmentation of the image is used for tumor detection fromMRI scan .

The proposed system is as shown in figure:

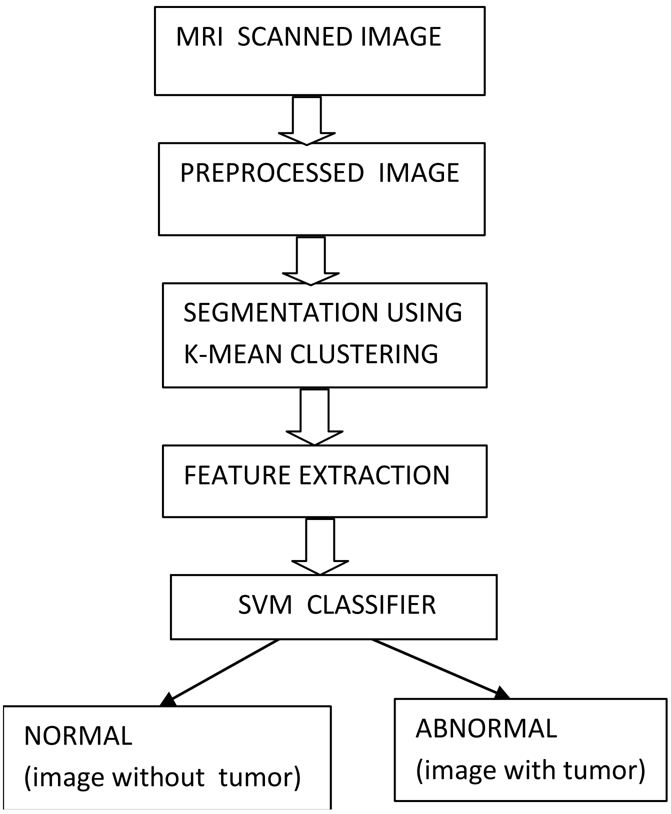


FIG:PROPOSED SYSTEM FOR BRAIN TUMOR DETECTION

3.1 DESCRIPTION

MRI scans of the human brain forms the input images for our system where the grayscale MRI input images are given as the input. Noise present if any, will be removed using a filter. Image enhancement is done for better result. The pre-processed image is given for image segmentation using K-Means clustering algorithm.

3.1.1 Input Image

MRI scan is given as input to the system. MRI scan is preferred as it give the detail picture of nerves tissues and brain in different planes without obstacle and it gives better result than CT(computed tomography)scan.

MRI scanners use strong magnetic fields, electric field gradients, and radio waves to generate images of the organs in the body. MRI does not involve X-rays and the use of ionizing radiation, which distinguishes it from CT or CAT scans.

3.1.2 Pre-processing stage

In this stage image is enhanced in the way that finer details are improved and noise is removed from the image. Most commonly used enhancement and noise reduction techniques are implemented that can give best possible results. Enhancement will result in more prominent edges and a sharpened image is obtained, noise will be reduced thus reducing the blurring effect from the image. Filtering is done to remove noise from the medical images because medical images are somewhat noisy. In proposed work we will use filter to smoothing and removing noise from the image.In addition to enhancement, image segmentation will also be applied. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detection will lead to finding the accurate position of tumor.

3.1.3. Segmentation using K-Mean clustering :

Segmentation is an essential process to extract information from complex medical images. The main objective of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze and the pixels within the region are homogeneous with respect to a predefined criterion. Clustering is division of data into groups of alike objects. Each group consists of objects that are comparable between themselves and dissimilar to objects of other groups.

K-Means algorithm :

The purpose of k-means algorithm is to cluster the data. K-means algorithm is one of the simplest partitions clustering method. K-Means is the one of the unsupervised learning algorithm for clusters. Clustering the image is grouping the pixels according to the some characteristics. In the k-means algorithm initially we have to define the number of clusters k. Then k-cluster center are chosen randomly. The distance between the each pixel to each cluster centers are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centers using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids. The process continuous until the center converges.

$$W(C) = \frac{1}{2}\sum_{k=1}^{K}\sum_{C(i)=k}\sum_{C(j)=k}\left\|x_i - x_j\right\|^2 = \sum_{k=1}^{K} N_k \sum_{C(i)=k}\left\|x_i - m_k\right\|^2$$

For a given cluster assignment C of the data points, compute the cluster means For a current set of cluster means, assign each observation as:

$$C(i) = \arg\min_{1 \le k \le K} \left\|x_i - m_k\right\|^2, \; i = 1, \ldots, N$$

- Iterate above two steps until convergence
- For a current set of cluster means, assign each observation as:
- Iterate above two steps until convergence

Algorithm:

1. Give the no of cluster value as k.

2. Randomly choose the k cluster centers

3. Calculate mean or center of the cluster

4. Calculate the distance between each pixel to each cluster center

5. If the distance is near to the center then move to that cluster.

6. Otherwise move to next cluster.

7. Re-estimate the center.

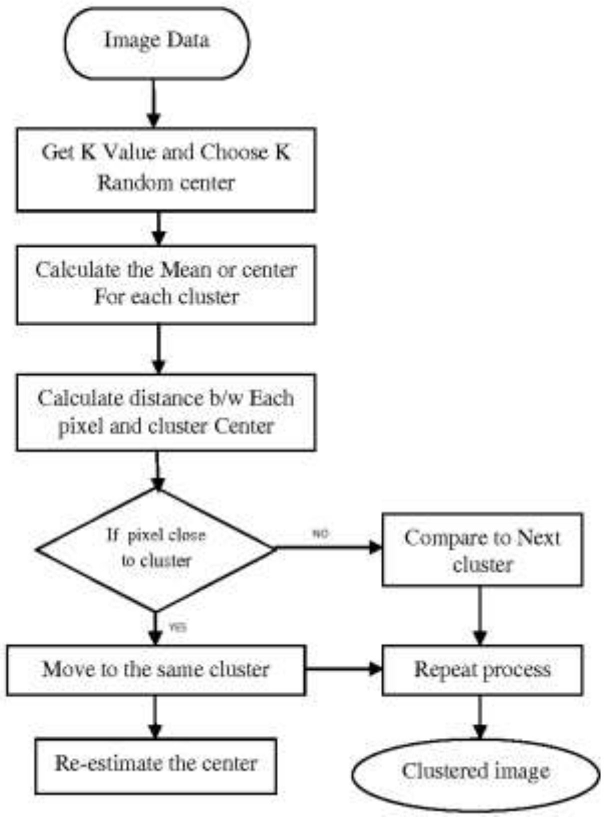


FIGURE: FLOWCHART OF KMEAN ALGORITHM

K-MEANS SEGMENTATION :

Image segmentation is typically used to locate object and boundaries in image. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Segmentation is an important process to extract information from complex medical image. Segmentation has wide application in medical field. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion.

3.1.4. FEATURE EXTRACTION

In this stage we need to retrieve the valuable information from the MRI images after pre-processing. It is the process of collecting higher-level information of an image such as shape, texture, color, and contrast. In fact, texture analysis is an important parameter of human visual observation and machine learning system. It is used effectively to improve the accuracy of diagnosis system by selecting important features.For texture feature glcm is used,for shape HOG is used and for intensity LBPH is used.

HOG

Dalal and Triggs first introduced Histogram of Oriented Gradients to recognize a person in an image. HOG is a feature descriptor used in image processing for object detection purpose. The purpose of the feature descriptor is to generalise the object in an image such that this object produces the same feature descriptors in the images, containing that object, acquired under different conditions like different angle, illumination, distance etc.,. The HOG descriptor technique counts occurrences of gradient orientation in localised portions of an image - detection window, or region of interest (ROI).

1. HOG initially divides the images into cells. Cells can be either rectangular or radial.

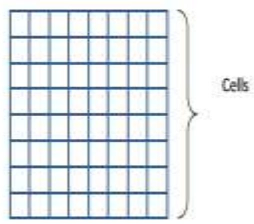
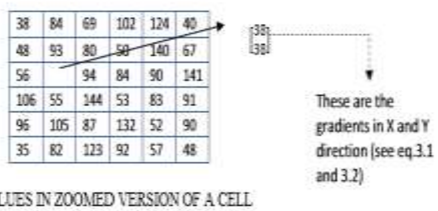


FIGURE DIVISION OF IMAGE INTO CELL

2. For every pixel in the cell, gradient vector is calculated [17].



38	84	69	102	124	40
48	93	80	58	140	67
56		94	84	90	141
106	55	144	53	83	91
96	105	87	132	52	90
35	82	123	92	57	48

FIGURE PIXEL VALUES IN ZOOMED VERSION OF A CELL

APPLICATION OF GRADIENT VECTOR:

1. Edge detection

2. Feature extraction

Gradient vector at a particular pixel is calculated by taking the difference of neighbourhood values in both horizontal axis and vertical axis. Gradients can be subtracted from left to right or right to left in horizontal and top to bottom or bottom to top in vertical

X-axis: 94-56=38

Y-axis: 93-55=38

After calculating the gradient vectors for each and every pixel, magnitude is found out

$$\text{Magnitude}=\sqrt{X^2+Y^2}$$
$$=\sqrt{38^2+38^2}$$
$$=53.74$$

Orientation plays a key role in HOG. Orientation can be termed as a change in direction, in which pixel intensity value changes. The change in direction can be along X-axis or Y-axis. The orientation of a gradient vector is calculated as

Orientation = $arc\ (Y/\ )$

= arc (38/38)

= 0.785 $radians$

= 45 $degrees$

38	84	69	102	124	40
48	93	80	50	140	67
56		94	84	90	141
106	55	144	53	83	91
96	105	87	132	52	90
35	82	123	92	57	48

Orientates to 45 degrees

FIGURE: ORIENTATION OF PIXELS IN CELL

The orientation of each and every pixel depends on the value of the gradient vector. The gradients are placed into bins of the histogram as per its orientation.

10	30	50	70	90	110	130	150	170

FIGURE: BINS IN HISTOGRAM

In the figure the gradient vector has an angle of 45 degrees. We add 1/4th of its magnitude to the bin centred at 30 degrees, and 3/4ths of its magnitude to the bin centred at 50 as there are no 45 degrees bin the histogram [17].

NORMALISATION:

The magnitude of the gradient vector for pixels in an image varies. To have the same value, normalisation is done. Normalisation is defined as dividing the vector by its magnitude. Magnitude gets affected by normalisation whereas orientation is unaffected .

CELL REPRESENTATION:

The image is divided into cells of $m \times n$. The size of the cells can be taken as 2×2, 4×4, 6×6 and 8×8 pixels. The main reason for dividing the image into cells is compact representation.

BLOCK NORMALISATION:

Grouping of cells into the block is the basis for grouping and normalisation of histograms. Block histogram is the normalised group of cells. The main advantage of the calculating histogram on the blocks of an image is that it makes the image more robust to local variations in illumination.

38	84	69	102	124	40
48	93	80	50	140	67
56		94	84	90	141
106	55	144	53	83	91
96	105	87	132	52	90
35	82	123	92	57	48

FIGURE: BLOCK REPRESENTATION

FEATURE DESCRIPTOR:

The set of these block histograms represent the feature descriptor. Technically, a feature descriptor represents an image or a part of an image that simplifies the original form of an image by extracting the important information. The distribution of orientation of gradients is taken as features in HOG. Consider an image of size width × height × channels, feature descriptor coverts the size of the image into feature vector/length of the array.

GLCM:

GLCM points to Gray level Co-occurrence matrix. It is of 2nd order statistics, so information with regards to pixels of pairs are collected by GLCM.GLCM exhibits how the pixel brightness in an image occurs..A matrix is built up at a distance d=1 and at angles in degrees(0,45,90,135) .Haralick also offered different measures i.e. entropy, energy, contrast, correlation etc. These dimensions calculate at different angles.[1] GLCM is texture character profile and this profile mention to touch i.e. smooth, silky and rough etc. The order of character profile statics are: First order texture measures are statistics declared from the original image values, like variance, and pixel neighbour relationship are not implemented. Second order measures defines the relationship between groups of two (usually neighbouring) pixels in the original image. Third and higher order textures (noting the relationships among three or more pixels) are theoretically possible but practically/ commonly not implemented due to calculation time and interpretation difficulty. GLCM texture picks up the relation between two pixels at a time, called the reference and the neighbour pixel. GLCM expounds the distance and angular spatial relationship over an image sub- region of specific size. GLCM is prepared from gray scale values. It is taken into account how often a pixel with gray level(gray scale intensity or gray tone) values come either horizontally, vertically and diagonally to levelled the pixels with the value j. GLCM directions are:

Horizontal(0)

Vertical(90)

Diagonal

a)bottom left to top right(-45)

b)top left to bottom right (-135)

They are announced as P0, P45, P90 and P135 respectively.[1],[2]

The properties of GLCM are:

1. GLCM is of square in shape because the reference and neighbouring pixels have same range of values.

2. Number of rows and columns equal to the quantization level of the image. The test image consists of four gray level values that is 0,1,2 and 3.Eight bit data consists 256(2^8) possible values,256X256 matrix would be obtained,65536 cells.16 bit data having matrix of 65536X65536,having cells 429,496,720.

3. It is symmetrical about the diagonal. The diagonal elements pairs having no gray level difference(0-0,1-1,2-2,3-3etc). Most pixels are identical to their neighbouring cells,very less contrast is there in the image.If there is a difference of 1 cell away from the diagonal,one level gray difference is there(0-1,1-2,1-3 etc).More the distance from the diagonal,more the gray level difference.[1],[2]

GLCM CALCULATION:

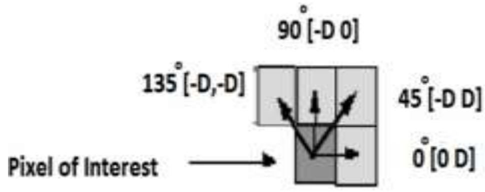
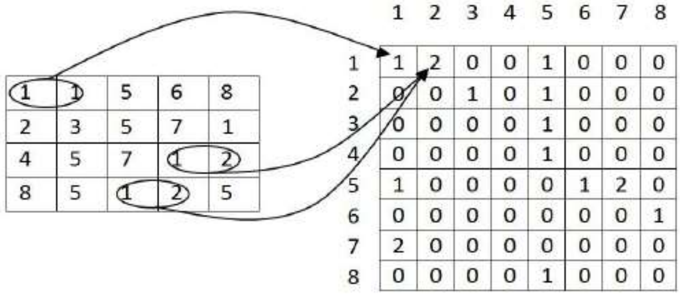


FIGURE: CO-OCCURENCE MATRIX DIRECTIONS FOR EXTRACTING FEATURES



1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

FIGURE: GLCM MATRIX

Firstly fetch angle at 0 degree (horizontal).In the GLCM output, the element(1,1) has value1 because in the input image, there is only 1 opulence where two horizontally near to pixels of distance 1 having values 1 and 1.GLCM(1,2) has value 2 because in the input image there are two opulences where two horizontally near to pixels of distance 1 having value 1 and 2. GLCM(1,3) has value 0 because in the input image there are no opulence where two horizontally near to pixels of distance 1 having value 1 and 3.The procedure is repeated for the whole GLCM matrix at different angles.

LBPH:

Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets.

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.

- Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).

- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.

- Optionally normalize the histogram.

- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector will currently be processed victimisation the Support vector machine, extreme learning machines or another machine learning algorithmic rule to classify pictures. Such classifiers may be used for face recognition or texture analysis. A helpful extension to the first operator is that the alleged uniform pattern[8], which may be wont to scale back the length of the feature vector and implement a straightforward rotation invariant descriptor. this idea is intended by the very fact that some binary patterns occur additional normally in texture pictures than others. an area binary pattern is named uniform if the binary pattern contains at the most 2 0-1 or 1-0 transitions. to Illustrate, 00010000(2 transitions) could be a uniform pattern, 01010100(6 transitions) isn't. within the computation of the LBP bar graph, the bar graphe compasses a separate bin for each uniform pattern, and every one non-uniform patterns ar allotted to one bin. victimisation uniform patterns, the length of the feature vector for one cell reduces from 256 to fifty nine.

The 58 uniform binary patterns correspond to the integers 0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31, 32, 48, 56, 60, 62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 207, 223, 224, 225, 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254 and 255.

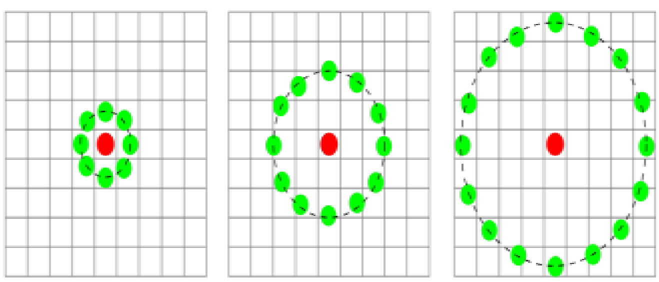


FIGURE: Three neighborhood examples used to define a texture and calculate a local binary pattern (LBP)

4.CLASSIFICATION:

Support vector machine(SVM) is the linear learning algorithm used for classification. The process of classification forward through training and testing. Support vector machine (SVM) is the linear learning algorithm used for classification. SVM will classify the image into normal andAbnormal.

SVM is a powerful supervised classifier and accurate learning technique that has been introduced in 1995. SVM has proven its efficiency over neural networks and RBF classifiers.SVM uses an optimum linear separating hyper plane to separate two set of data in feature space. This optimum hyper plane is produced by maximizing minimum margin between the two sets. Therefore the resulting hyper plane will only be dependent on border training patterns called support vectors.SVM operates on two mathematical operations-

- Nonlinear mapping of an input vector into a high dimensional feature space that is hidden from both the input and output.

- Construction of an optimal hyper plane for separating the features .

SVM maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed .

The data with linear severability may be analyzed with a hyper plane, and the linearly non separable data are analyzed with kernel functions such as Gaussian RBF.

5. RESULT:

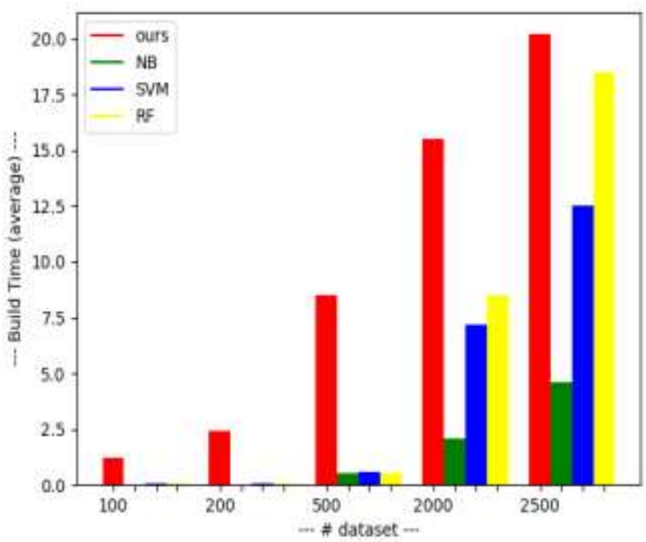


FIG:RESULT FOR TIME

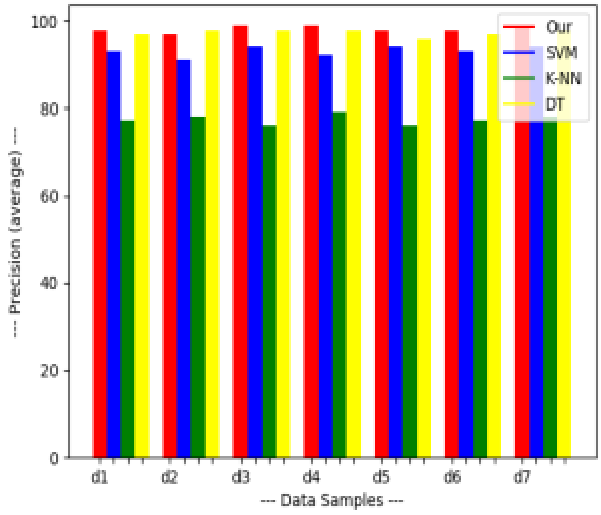


FIG: RESULT FOR ACCURACY

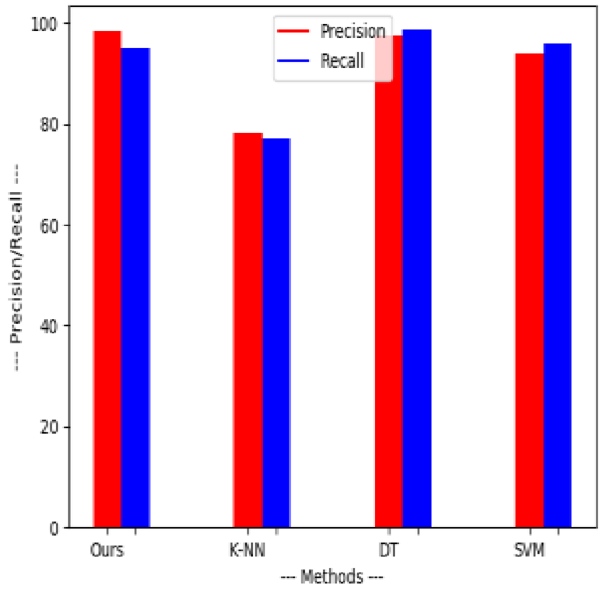


FIG: RESULT FOR OVERALL PERFORMANCE

5. CONCLUSIONS

This paper proposes a work on brain tumor detection system based on kmean clustering and machine learning algorithms.

The texture based features are extracted using Gray Level Co-occurrence Matrix (GLCM). The texture features of the image considered in this proposed work include energy, contrast, correlation, homogeneity.

Along with texture based features intensity features also used with the help of LBPH(local binary pattern histogram).

For the classification purpose, support vector machine machine learning algorithm is used and the maximum accuracy 98.6% is achieved by considering around 250 training samples and 100 test samples of brain MR images.

This accuracy can probably be increased by considering a large data set and implementing other recursive pre-proccessing algorithmic steps.

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