IoMT Based Brain Cancer Detection using SVM Classifier

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Abstract.

Early detection of brain cancers with minimum time period through telemedicine principles save the life span of patients concerned. Data collected from MRI consist of noises and have to be removed before the classification process, after classification these data and classified output can be uploaded to internet for analysis and periodic updates through doctors worldwide. The detection and removal of this noise play a vital part in the detection accuracy of tumor. So, here, we propose a Total Variation (TV) homomorphic filter to reduce the noise and enhance the edges of MRI data. SVM classifier is employed for learning and classification. Here the authors propose an intelligent e-health application which will help people with early detection of tumors. For this author's makes use of the possibilities offered by Internet of Medical Things (IoMT). People with internet access can login to the application and upload the MRI scan for diagnosis. Another advantage of the proposed model is its periodic updating capabilities. The uploaded data will be used for training the model only with the consent of the people responsible. The authors hope this platform will give a new dimension of services towards e-healthcare services that improve the quality of medical services.

Keywords: MRI, Total Variation, Machine learning, SVM, IoMT.

1. Introduction.

The Internet of things (IoT) is now often utilized for a wide range of purposes, and its importance in our day-to-day lives is increasing significantly. IoT innovation also the healthcare system is changing to offer patients services that are efficient [1]. As one of the most difficult medical conditions, brain tumour demands special treatment. The kind of the tumour must be accurately and promptly diagnosed before a brain tumour may be classified. Since the choice of effective treatmentmodalities mostly depends on the pathological kind. However, the traditional method for identifyingand categorizing magnetic resonance imaging (MRI) brain cancers relies mainly on human observation and the knowledge of radiologists who research and practice radiology and interpret image. Characteristics and usually give a non-accurate diagnosis. Computer-aided diagnostic methods are highly desirable for these issues [2]. Gliomas are cancerous tumors which can be further classified into high grade gliomas (HGG) and low-grade gliomas (LGG). In these, HGG is deadly com- pared to LGG. HGG can reduce the life span of a person to less than a year even if it is detected [3]. The early detection of cancer will certainly improve the life of an oncology patient, which is a major step of treatment. There are a lot of techniques to detect cancer but most of them detect the cancer in advanced stage, so the chance of recovery of the patient will be less. Due to overlapped structure of cancer cells, the early detection of tumor is challenging. If the affected person is in an advanced stage, Doctors suggest surgery, chemotherapy, or Radiotherapy as treatments to cure the disease.

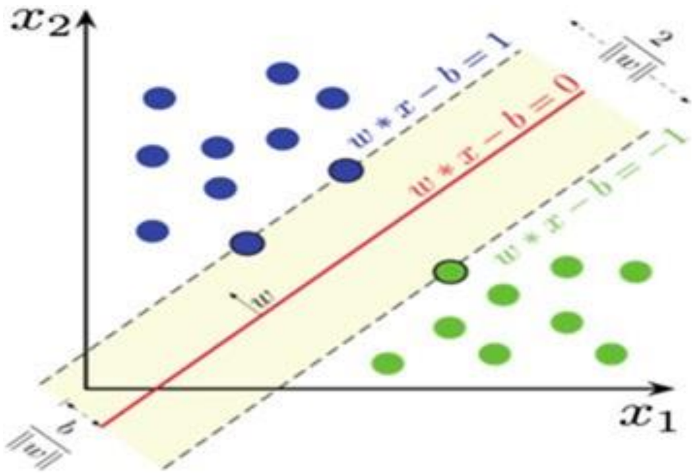
By using magnetic resonance imaging (MRI), early detection of tumor is possible. But the large amount of MRI data to be processed is an overhead. Thus, manual detection will be challenging. Image processing is used to segment the tumor parts in MRI images accurately. For early detection of tumor, we use biopsy, expert’s opinion, etc., human prediction of tumor is less accurate and the existing biopsy test may take one or two weeks to produce the result. Thus, automatic detection of tumor using image processing techniques is getting popularity.

The major benefit of using image processing technique is the time for detection will comparatively much lesser than manual detection. The location of the tumor can be detected by using image processing on MRI data. But the noise produced in the MRI data leads to false identification of tumors [4]. So, to reduce the noise present in MRI data, novel methods have to be used. Anisotropic filters are a good example for noise removal. But here, we took Total Variation (TV) as a method which is better than anisotropic filtering [5]. For detecting and classifying the features in an MRI data, many techniques are used like support vector machine (SVM), nearest neighbor (K-NN) [6], neural networks (NN) [7], deep learning-based convolutional neural network (CNN) [8, 9], etc. Before applying classification techniques, pre-processing techniques should be applied.

2. Literature Survey

Natarajan and Krishnan [10] suggest a simple thresholding-based tumor identifica- tion. First, the image is preprocessed to remove noise. Median filtering is employed for noise reduction and edge sharpening is also employed. Simple thresholding is used to segment the image. Morphological operations are also done to fine-tune the result.

Fig. 1 A typical linear SVM classifier



Tumor is identified using image subtraction method. The method fails due to the luminance invariance present in the MRI data.Sahoo et al. [11] use support vector machine (SVM) for tumor classification. SVM is used either as a classifier or it is used for regression. In classification, it creates a hyper plane to separate the features obtained from an image. Figure 1 shows the SVM hyper plane for classification. SVM is also be used for regression. SVM algorithms analyze and recognize the special patterns present in the data. When the data is given, the hyper plane is used to separate the features into two, thus it works as binary classifier [12].The major disadvantages of SVM are the optimal features are not easily identi- fiable when there is nonlinearly separable data is present and the method is likely to give poor performance if the number of features is much less than the number of samples.Arriaga-Gomez et al. [13] proposed k-NN as one of the major distance-based algorithms where given k as a positive integer and a sample feature vector (sample template), the k training features with the smallest distance to the sample is selected. The sample is identified as the most repeated among the selected k feature vector.Ramteke and Monali et al. [14] proposed automatic classification for medical images. Abnormality detection in medical images is performed to classify whether tumor is detected or not. The major advantages of k-NN are simpler to implement and understand. The result will not be accurate always as it determines its class assignment by either getting a majority vote for them or averaging the class numbers of nearest k points.Pereira et al. [15] use convolutional neural networks (CNN) to produce some great results. Convolving an image with kernels to obtain lower level to higher level features is the main application of CNN. In paper [8], single-layered CNN is used so that the features used for classification is less when compared to deep networks. Deep learning methods use highly complex algorithm to extract the features auto- matically from the data provided. The importance is given to developing the archi- tecture of the network rather than finding special features in the data. Thus, here, we propose machine learning-based SVM for classification and Total Variation (TV) filtering for noise removal. The rest of the paper is organized as system model in thenext section and result and discussion in fourth and conclusion.

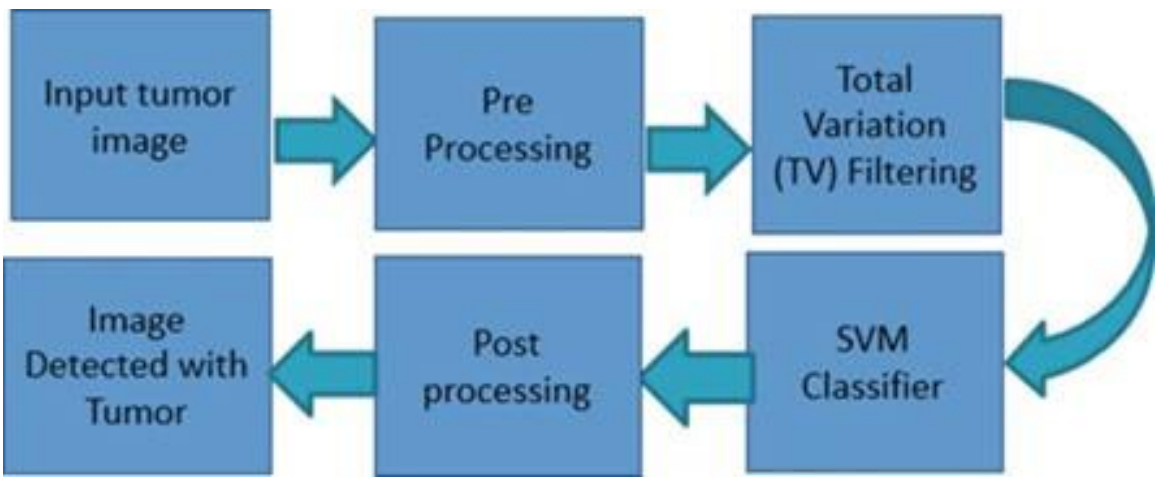
3.**System Model**

Noise in MRI images is due to the malfunction of the equipment and the environ- ment in which it is placed. The MRI equipment noise is caused by field strength, RF pulse, RF coil, voxel volume, and receiver bandwidth. The most common noise which affects an MRI image is Gaussian or salt and pepper. Both of these noises reduce the tumor detection performance of SVM classifier. Several de-noising tech- niques are available. The most common methods are median filtering, histogram equalization, and anisotropic filtering. But for de-noising and to enhance MRI data, we propose Total Variation (TV) filtering. Method like median filtering or linear smoothing reduces the effect of noise but affect import details such as edges. But TV filtering is based on the fact that images affected by sharp or spurious noise will have high variation. So the absolute gradient of the image will be high on these regions. In order to reduce the affect noise, the gradient is to be minimized. This reduces the noise but also keeps edge information than ordinary noise removal algorithms.
The Total Variation de-noising is expressed as
$y = x + n; \quad y, x, n \in Rn \quad (1)$
where x is the original image and y is the image corrupted by noise n. To estimate x from y is by minimizing the objective function
$E(x) = \min\|y - x\|2 + \lambda\|\nabla x\| \quad (2)$
where λ is called the regularization parameter which controls the smoothing operation performed on the image and is the gradient operator.

3.1 Tumor Image

A publicly available dataset is used for training and testing. The database contains 789 tumor images of four different categories. The images are in ordinary PNG format and can be easily processed.

Fig. 2 Block diagram of proposed method



3.2. **Preprocessing.**

Medical data is difficult to obtain. Also, the data obtained will be taken by MRI machine using different conditions. So, illumination variation is inherent. Preprocessing of the images reduce the illumination variation.

3.3. **Total Variation,**

Total Variation filtering is performed on the normalized image using Eq. 2. It is based on the principle that images having spurious noise have high total variation. So the gradient of the image is high. Reducing the gradient also minimize the total variation, hence noise.

The process is iterative. We did 100 iterations per image. Noises like Gaussian and salt and pepper are successfully reduced. Here, λ is the regularization parameter controlling the amount of de-noising, smaller value implies more aggressive de- noising and hence smoothed results. Some examples on tumor images have shown below. Fig. 3 is the noisy MRI image.Figure 4 clearly shows a smaller value of λ 0.01 with 100 iterations reducing the Gaussian noise considerably.

Fig. 3 Noisy image

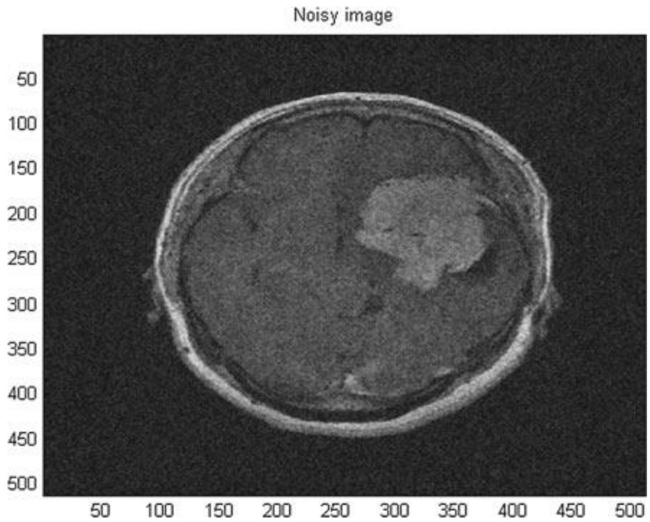


Fig. 4 Total variation de-noising with $\lambda = 0.01$

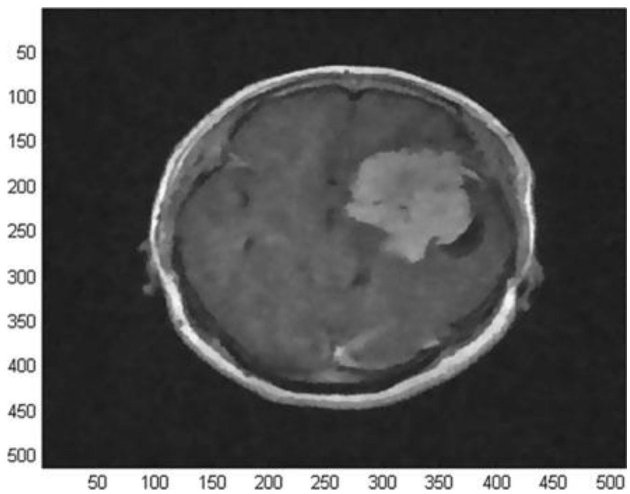


Fig. 5 Tumor area detected using TV de-noising, and SVM classifier

3.4 SVM Classifier

Machine learning is an application of artificial intelligence which learns from the observed data rather programed for finding a result. Machine learning makes use of patterns in the data for learning and classification. Machine learning can be classi- fied into supervised learning and unsupervised learning. In supervised learning, a previously learned data and their labels are used for the future events prediction. But in unsupervised learning, there is no previous data or labels. Unsupervised learning is mainly used for regression analysis.

SVM comes under supervised learning models. Here, we used a binary SVM classifier which makes use of pixel intensity for classification. A threshold value is used for labeling the pixels either as tumor pixels or non-tumor pixels. The dataset contains 789 tumor images and training of SVM classifier is performed on 600 images. To get more images, data augmentation can also be performed.The learned model is applied on the remaining images and got good results. Along with total variation de-noising, SVM performs better than common methods like median filtering and machine learning. The training is done with fivefold cross- validation for better accuracy. Some of the results obtained are shown below.

The above results in Fig. 6 show the need for removing the noise present in the MRI data before going for tumor detection. Figure 6 leads to inaccurate results in the presence of noise. Figure 5 shows better tumor segmentation with TV de-noising. Some morphological operations are performed if required after the classification. Figure 7 shows the classifier result for TV de-noising.

Fig. 6 Tumor area detected in the presence of noise and SVM classifier

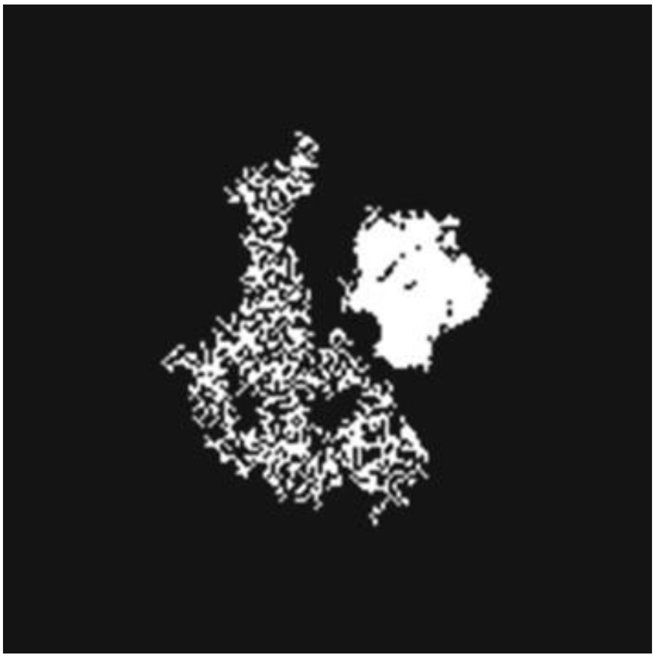


Fig. 7 SVM classification.

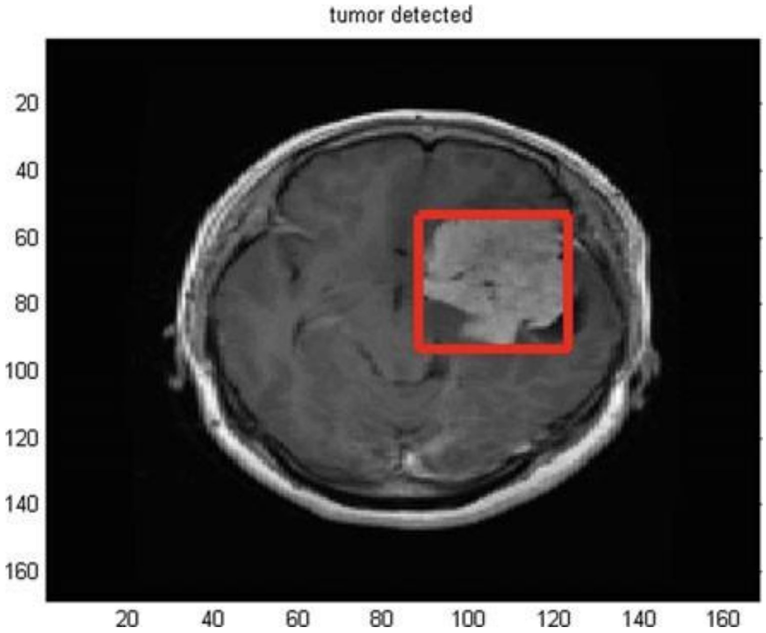


Table 1 Comparison of SVM with de-noising and without de-noising along with median filtering and anisotropic filtering.

Method	Sensitivity	Specificity	Accuracy
SVM with noise	0.85	0.75	0.75
SVM + TV-proposed	0.90	0.98	0.92
SVM + Median Filter	0.75	0.78	0.78
SVM +Anisotropic	0.90	0.95	0.90

4.**Experimental Setup and Discussion**

The proposed method is validated on a publicly available database. The dataset contains around 3000 tumor images along with the ground truth data. The proposed method is validated on the first dataset contains 766 images with tumor. Table 1 shows the average value of evaluation parameters for 769 images. Six hundred images are used for training the classifier and 169 images are used for testing. The result obtained is compared with SVM classifier. Figure,8 represent the proposed IOMT based E-HEALTH detection of brain cancer.

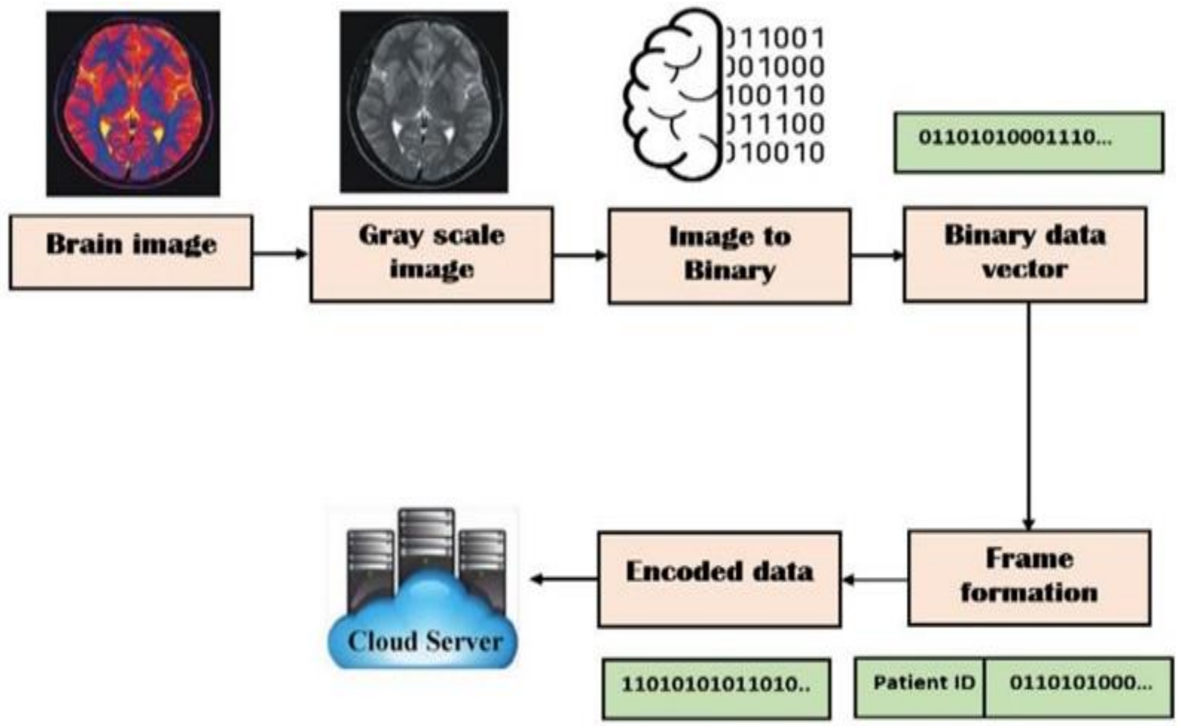


Fig.8. Dataflow of the prposed IoMT system

Mode of Registration Any new user just needs to use the registration mode once. When a patient first registers, their ID number is given to them so they can readily access their account in the system. Operating Style The authentication mechanism is initially used in this mode to identify the registered user. Following that, image preparation is carried out to get the picture ready for the following steps. To cut down on noise, use the Weiner filter. The scaled data is then applied to the specified CNN model, in feet. The SoftMax classifier is then utilized to detect brain tumours after the suggested CNN model extracts features from the processed pictures. The patient can finally use his or her database to locate the classification outcomes. Figure.9 shows the registration modes.

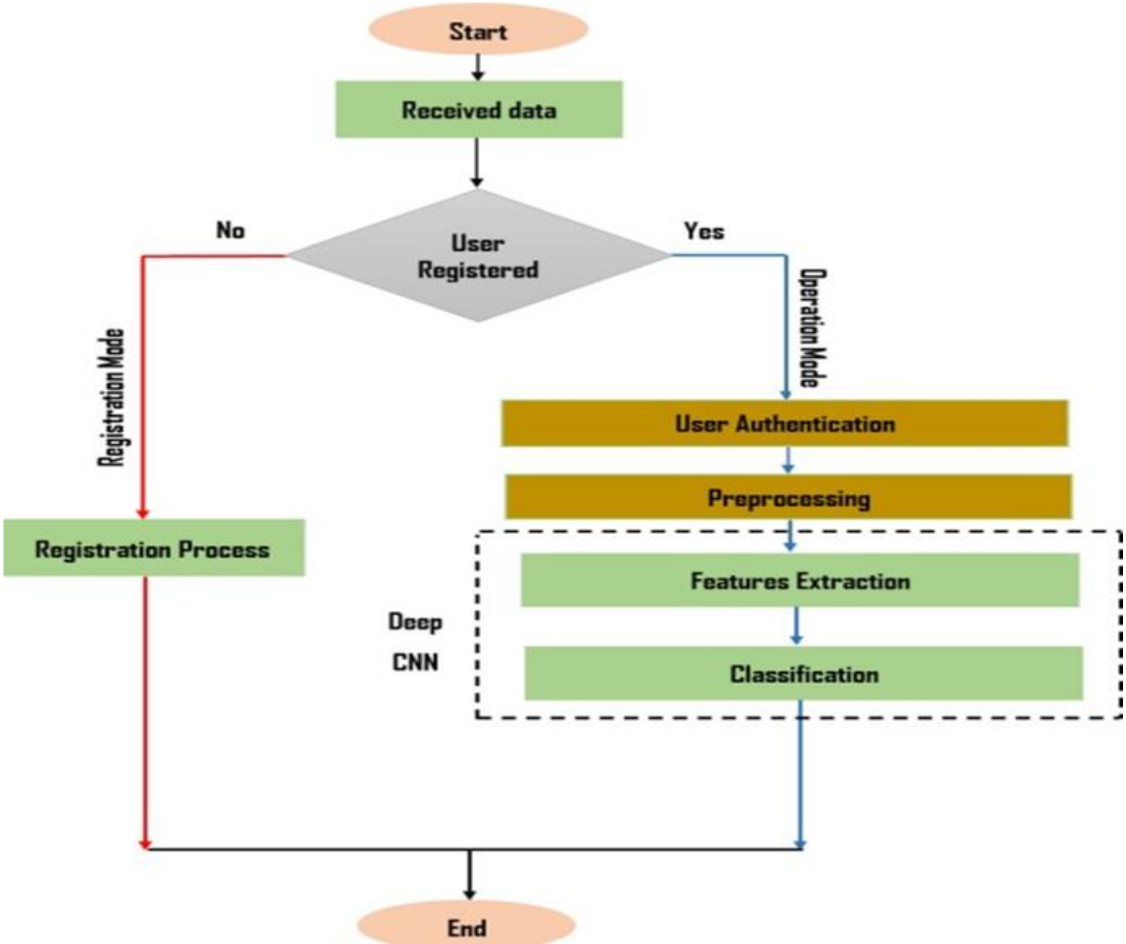


Fig.9. Flowchart of data receiving part.

5.Conclusion

Here we propose a cloud based IoMT architecture for brain tumor detection. The advantage of the proposed method over the existing deep learning techniques is its user accessibility, continuous updating capability and reliability. The user can choose a wide range of models training the data. The authors hope this platform will give a new dimension of services towards e-healthcare services that improve the quality of medical services The factors causing MRI noise is mainly due to the hardware. So it cannot be avoided. Noisy data can lead to false tumor detection and leads to inaccurate results. The only method is to reduce the noise before going for tumor classification. Since SVM is a pixel-based binary classifier, each pixel is important. The proposed method outperforms the commonly available noise reduction methods like median filtering, anisotropic diffusion, etc. The obtained result clearly shows the advantage of the proposed method.

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