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AN ADAVANCE DEEP LEARNING BASED BRAIN TUMOR DETECTION

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ABSTRACT:
Brain tumours are dangerous in children and adults. Brain tumours grow quickly and patient lifespan is low if not treated adequately. Early brain tumour detection is crucial. To improve patient life expectancy, treatment planning and diagnostics are paramount. Magnetic resonance imaging detects brain tumours best. MRI images are analysed by radiologist. The complexity of brain tumours and their attributes makes manual inspection risky. Thus, an automated brain tumour detection system is needed to detect early tumours. The unchecked and rapid proliferation of cells can lead to the development of a brain tumour. It is possible to die from this condition if you do not get treatment when you are in the early stages. Accurate segmentation and classification are still a difficult task, despite the numerous important efforts that have been made and the encouraging progress made in this area. The variability in location, shape, and size of brain tumours is a significant obstacle in the process of diagnosing and treating the disease. Helping researchers by providing them with a comprehensive literature review on brain tumour detection by magnetic resonance imaging is the purpose of this survey. This survey discussed the architecture of brain tumours, as well as publicly available datasets, enhancement approaches, segmentation, feature extraction, classification, as well as deep learning, transfer learning, and quantum machine learning for the analysis of brain tumours. In conclusion, this review compiles all of the pertinent literature pertaining to the diagnosis of brain tumours, together with a discussion of the benefits and drawbacks of existing methods, as well as recent advancements and anticipated directions in the field.

KEYWORDS: Deep Learning, Brain Tumour Detection, MRI, Convolutional Neural Networks, Medical Imaging.

1. INTRODUCTION:

The detection of tumours from MRI scans is a crucial task, although one that can be time-consuming and challenging, often requiring manual analysis by medical professionals. Essential work was allocated by radiologists and physicians towards the identification and segmentation of tumours from surrounding brain structures. Nevertheless, the process of accurately classifying brain tumours is a labour-intensive endeavour, and significant differences can be noted among medical professionals.

In recent years, multiple research findings have indicated that the procedure in question is characterised by a significant time need. However, it has been suggested that the utilisation of image processing techniques could potentially accelerate the process. Primary brain tumours have the characteristic of not spreading to distant organs, and they can exhibit either malignant or benign behaviour. On the other hand, secondary brain tumours are always characterised by malignancy. A malignant tumour poses a greater risk to an individual's health and can be more life-threatening compared to a benign tumour. The identification of a benign tumour is comparatively simpler in comparison to that of a malignant tumour. Additionally, it should be noted that the initial stage of a tumour can either be classified as malignant or benign. However, when the tumour progresses beyond the first stage, it undergoes a transformation into a hazardous malignant tumour, posing a significant threat to one's life.

Several brain tumour detection systems have been developed in recent years. The automatic segmentation problem is typically considered to be highly challenging and remains unresolved in a comprehensive and satisfactory manner. This system's major goal is to automatically detect and identify cancers in MRI scans by differentiating them from normal tissue. Taking into account statistical aspects and locating significant feature points results in a representation of brain structure. Early-stage tumour detection and segmentation techniques fall into one of three major categories: region-based, edge-based, or a hybrid of the two.

The K-Means methodology for grouping data, and an unsupervised technique using a neural network classifier are widely recognised and commonly employed segmentation techniques. Additionally, the duration required for tumour segmentation is being reduced as a result of the comprehensive medical image presentation wherein feature points are omitted.

Methods that focus on locating regions as their primary goal that meet specific criteria of homogeneity, while edge-based segmentation techniques focus on detecting boundaries among regions that exhibit distinct traits. Gliomas are a particularly lethal form of brain cancer. Low-grade (LG) gliomas and high-grade (HG) gliomas are the two broad classifications that describe these tumours. When compared to HG Gliomas, LG Gliomas tend to be less invasive and more placid.

Significant findings suggest that those undergoing therapy exhibit a notably low survival rate of merely 14 months following initial discovery. Current therapeutic approaches encompass surgical interventions, chemotherapy, radiation, or a combination thereof. X-ray imaging is particularly advantageous in the identification and characterization of gliomas in routine clinical practise due to its accessibility and the availability of MRI sequences that provide comprehensive information. The accurate segmentation approach of gliomas and their intra-tumoral features is crucial for therapy preparation and subsequent monitoring and assessment. What are the main goals of a

- One major goal of this research is to examine how deep architectures encoded as compact convolutional bits might aid in the segmentation of gliomas in MRI scans.
- Secondly, this study aims to solve the issue of information heterogeneity resulting from the acquisition of MRI images from numerous sites and scanners. This will be achieved by implementing the Depth Normalising technique. Strategic planning is a fundamental aspect of organisational management, involving the formulation and implementation of strategies.

Image Processing Yardsticks: Metrics that take into account how well different kinds of low-grade Algor's perform on specified assignments are now a vital part of the Machine learning community. These days, Yardsticks methodology has also achieved unquestionable quality in the realm of clinical image diagnosis. Often mislabelled as "defiance," these benchmarks share the common requirement that multiple teams hone their approaches using the same training data provided by the organisers before applying their best work in a coordinated fashion to a standard, independent test set Given that it's possible that this group received instruction that differs from the rest, and that some students may have put in more time and effort towards mastering a Low evaluation algorithm, this condition is not exactly equivalent to many distributed correlations, in which one group implies variant procedures to a dataset of one's choice, which also hinders a sensible finding.

Once Yardsticks have been created, the data used to analyse them creates another standard for determining how best to gauge future development in the image-preparation activity being tested. In addition, the notation and evaluation show can continue as previously even if fresh information is integrated (to prevent the risk of over-fitting this particular database), or if related Yardsticks are initiated. The ability to keep the test set's scores secret makes the online tool for surveying divisions provided by one class a crucial component of Yardsticks. This guarantees that the available outcomes are actually representative of the division performance of the methodology, and not skewed by accidental overpreparation of the procedure being tested. Development of treatment in most cases necessitates the formulation of a goal.

While it is essential to destroy malignant cells, protecting healthy tissue is of equal importance. Life expectancy is shortened for people with HG gliomas, although most treatments aim to extend their lives as much as possible without negatively impacting their quality of life. In this one-of-a-kind situation, tumour segmentation techniques are of high interest for both expediting the delivery of medicine to the tumour and protecting surrounding solid tissues. In addition, the manual outline is still not acceptable because of its low interobserver repeatability and because of the time and effort required to complete it. The arrival of trustworthy and accurate division computations to replace time-consuming manual partitioning and improve focused therapy is much anticipated in light of the growing complexity of multimodality data. As of right now, X-ray brain tumour classification is thought to be the best method available. Very little background work, with only emphasis on the Glio Blastoma Multiforme (GBM) subtype.

A malignant growth in the brain is a condition that can quickly become fatal. Both malignant and benign varieties of tumours can develop in the brain. The buildup of pressure inside the skull that results from the proliferation of tumour cells is what causes damage to the brain.

Primary and secondary brain tumours are the two categories that this disease falls under. Primary brain tumours are a type of tumour that develops in the brain and are considered to be benign. When cancer cells from another organ, like the lung or breast, travel to the brain, a secondary brain tumour can develop. This type of brain tumour is also known as a metastatic brain tumour. Brain tumours are not age-specific and can develop in people of any age. It is possible to successfully treat a brain tumour if it is discovered at an earlier, more treatable stage. There are more deaths among children and people under the age of 40 due to brain tumours than any other cause than any other type of cancer combined.

The incidence of tumours in India ranges from 5 to 10 per 100,000 people, and there is a general upward tendency and in the below section Figure 1 & Figure 2, we have demonstrated the images which is having tumour and without Tumour.

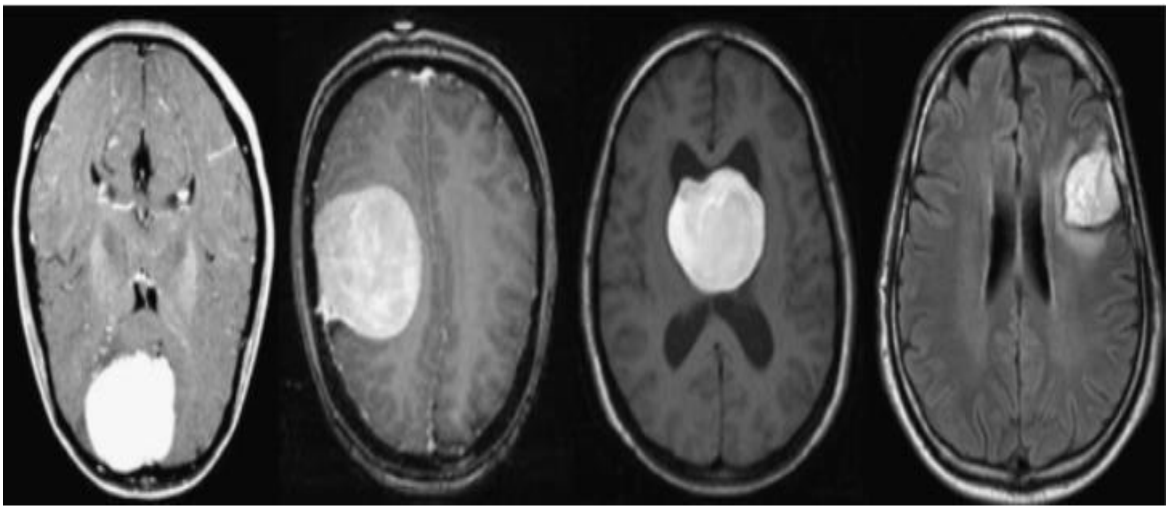

Figure 1: Images with Tumours

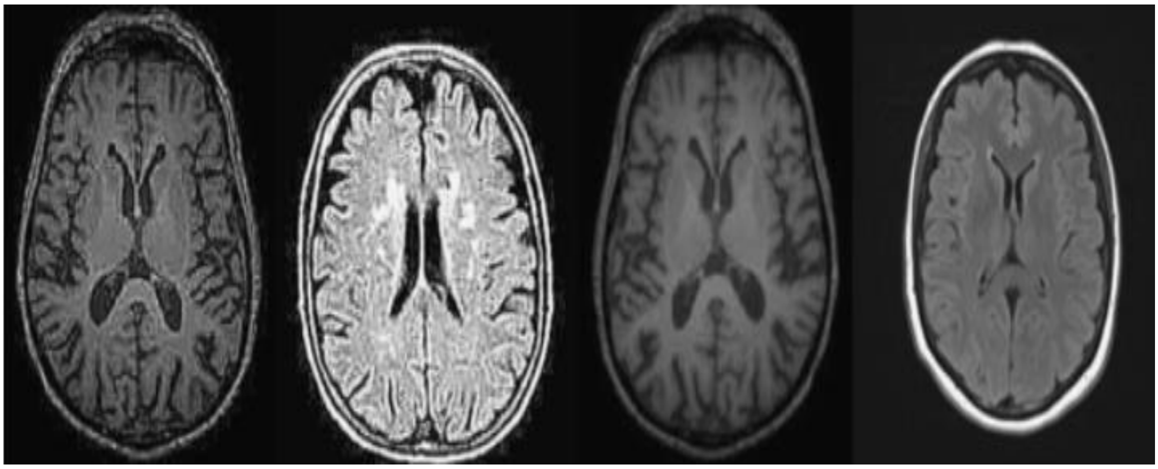

Figure 2: Images without Tumours

The procedure of diagnosing brain tumours can be time-consuming and laborious. Diagnostic procedures for brain tumours comprise imaging techniques such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), and other procedures such as angiograms, spinal taps, and biopsies. The images that are produced by a CT scan are obtained through the use of x-rays. The patients who have CT scans are subjected to ionising radiation. The CT scan exposes the patient to significant amounts of radiation. CT scans are a standard procedure in medical imaging, but a recent This is what a JNCI (Journal of the National Cancer Institute) study found that getting one may raise one's risk of developing brain tumours.

In today's modern medical world, magnetic resonance imaging, or MRI, is an extremely useful tool. This approach does not involve any intrusive surgery or procedures. Imaging of the brain can be produced using MRI by combining a magnetic field with radio waves. MRIs generate images that are richer in detail than CT scans. When screening for brain tumours, magnetic resonance imaging is the test of choice. The objective is to diagnose brain tumours before the onset of any clinical symptoms. The MRI allows for accurate measurement of the tumour’s extent.

Before undergoing an MRI scan, the patient will either have a specific dye known as a contrast medium injected into a vein in their arm or they will be given a pill or liquid to swallow. Cancer can develop in any part of the body that contains aberrant tissue. A radiologist will take a look at the irregularities in the image. A lump or tumour could appear as a concentrated white spot on an MRI. Both malignant and benign types of tumours exist. If a tumour is benign, it poses no threat to the patient's health and is not likely to grow or transform over time. The radiologist is going to look at the pattern and form of it because such features are sometimes indicators of cancer.

The proposed technique has an impressively high accuracy of classification, clocking in at 98.87%. Content-based image retrieval (CBIR)-inspired single-query system was discussed by the authors Amit Kumar Rohit et al., [4]. In the suggested system, preprocessing, the extraction of feature 47, and the detection of tumours are included. The correctness of the approach that was suggested is 98.33%.

According to the survey mentioned above, many of the works still do not follow a straightforward database that is nice to users and easily accessible. For the benefit of the community of biomedical engineering researchers, this study presents a proposal for the creation of a database of MRI scan pictures that we have dubbed the "BRAMSIT Database." The lack of a medical rationale and a plan for tumour diagnosis presents a significant challenge for the ongoing investigation and growth of this group. Even while several pertinent studies have talked about localization problems, these papers do not give databases that are user-friendly for scholars.

Because of this, the primary contributions that we have made to this body of work are as follows:

- You will need to develop an inclusion of 319 MRI scan images to the existing ground truth images in the new BRAMSIT database.
- Include an annotation of all 319 subjects' biological data as well as their axial location in the presentation.

For the objective of isolating gliomas from other anatomical structures in MRI scans, the application of deep figures with light convolutional sections has been investigated as part of the proposed technique. This research was prompted by the ground-breaking work that has been done on deep CNNs. It is possible to stack a bigger number of convolutional bands using lighter parts and still have the same responsive field as larger bits by making use of smaller CNN portions that are 3x3 in size. This can be accomplished by using smaller CNNs to build more CNNs.

It has been proposed that brain cancers be divided automatically using deep convolutional neural networks.

There has to be more research done on the force standardisation technique's potential application as a pre-handling step. It is intended to draw attention to the information heterogeneity that arises as a result of acquiring MRI pictures using numerous scanners at multiple sites. The benefits of the system that was suggested

2. LITERATURE SURVEY:

The Segmentation, method suggested for detecting brain tumours, works by breaking down an image into its constituent parts. To correctly interpret an image & label its contents, image segmentation must first separate the foreground from the background. In this setup, edge detection was crucial for cutting apart images. The authors of this research set out to compare and contrast some of the most popular edge detection methods used in picture segmentation and report their findings [1].

An approach is proposed for identifying Brain MRIs using a probabilistic neural network and spider web visualisations based on wavelet entropy. The proposed method involves extracting features using a Wavelet entropy-based spider web plot and then classifying those features using a probabilistic neural network [2].

Wavelet transform was used for feature extraction from the acquired brain MRI, and We calculated the entropy as well as the spider web plot's surface area. In a probabilistic neural network, the entropy is employed for classification purposes. With an accuracy of close to one hundred percent, the probabilistic neural network provides a one-size-fits-all answer to the pattern categorization problem.

The combined wavelet statistical characteristics (WST) with co-occurrence networks. when sorting aberrant brain materials into benign and malignant categories, researchers used the a two-stage wavelet transform producing a wavelet texture feature (WCT). The proposed system has four steps: segmenting the region of interest; disintegrating the region into discrete wavelets; abstracting features; selecting features; and organising and evaluating them. For this reason, we used a support vector machine to segment the tumours in the brain. Tumour characteristics were extracted using a discrete wavelet transform with two levels, and WST and WCT were used for this purpose. From the pool of mined features, the best texture features were chosen using a genetic algorithm. The performance of the probabilistic neural network (PNN) was evaluated by comparing its classification result with that of classifiers based on neural networks that are already in use to determine if abnormal brain tissue is benign or cancerous. The suggested system has a high rate of correct categorization (97.5%) [3].

The technique utilises medical picture information (area of interest) to dramatically increase processing speed for tumour segmentation findings. It was suggested that a method based on significant feature points could be used to segment primary brain tumours. Brain MR images that were T1-weighted and contrast-enhanced were analysed in axial slices. Applied a morphological and wavelet-based feature point extraction methodology that uses a fusion of edge maps to isolate important image features. Feature points acquired in this manner have been evaluated for geometric changes and image scaling. Finally, the tumour region was cut off using a region growth algorithm. Using our method, we were able to successfully segment data in early tests. A lot of maths was spared thanks to this strategy as well. The significance of the technology as implemented in medical image retrieval applications will be studied in future work, as will its use in automated 3D tumour segmentation & region-of-interest extraction from other medical images [4].

3. METHODOLOGY:

Algorithm:

Data Collection and Preprocessing:

- Acquire a labelled dataset of brain MRI images with annotations indicating the presence and location of tumours.
- Separate the dataset into three groups: training, validation, and test.
- Preprocess the images:
- Resize images to a consistent size.
- It is recommended to "normalise" pixel values to a standard range (such [0, 1] or [-1, 1]).
- To make the model more stable, it is recommended to: • Rotate, translate, and invert the training data

Model Architecture:

- Select a deep learning architecture that works well with picture categorization problems. Many people choose for CNNs, or Convolutional Neural Networks.
- You can use and fine-tune models that have already been pre-trained, such as VGG, ResNet, or Inception.
- Adjust the architecture to include a classification layer for tumour detection.

Model Training:

- Initialize the model with appropriate weights (transfer learning if using pre-trained models).
- Define a loss function, typically binary cross-entropy, as you're performing binary classification (tumour or no tumour).
- Choose an optimizer like Adam or RMSprop.
- The model should be trained using the training data while its performance is tracked using the validation data. Early stopping should be used to avoid overfitting.
- Tune hyperparameters (learning rate, batch size, etc.) as needed.

Model Evaluation:

- Evaluate the trained model on the test dataset to assess its generalization performance.
- Calculate standard evaluation metrics like accuracy, precision, recall, F1-score, and ROC-AUC.
- Generate confusion matrices and ROC curves for a more in-depth analysis.

Post-processing and Visualization:

- Apply post-processing techniques to refine the model's predictions if necessary.
- Visualize the model's predictions overlaid on MRI images for clinicians to review.

Deployment:

- Deploy the trained model in a clinical environment, which may involve integration with a healthcare system.

- Ensure security, privacy, and regulatory compliance (e.g., HIPAA, GDPR).

Continuous Improvement:
- Continuously monitor and update the model to account for new data and improved techniques.
- Collaborate with medical experts to improve model accuracy and clinical relevance.

This research aims to identify and diagnose tumour regions for cancer treatment. Here we detail the suggested system. The threshold is an intensity value that delineates the foreground from the background in an image. Its range is from 0 to 255. Non-brain tumour tissue makes it difficult for threshold-based clustering algorithms to effectively detect tumours in MRI scans. We propose employing K-Means and Object Labelling algorithms, along with median filtering and morphological operations, for tumour detection.

Preprocessing: Various methods, including brightness, threshold, and Filtering, are used to alter grayscale images in the course of image processing. The contrast between white and grey or light and dark elements that makes up the image. Tumour detection in an MRI picture can thus be facilitated by adjusting the image's contrast [5].

Through the use of a threshold, we may separate the interesting from the uninteresting elements in our environment. In addition, thresholding changes the image from a grayscale one (where pixels can have values between 0 and 255) to a binary one (where pixels can only have the values 0 or l). Pixels whose intensities are displayed in red are within the cutoff range. A value of 1 is assigned to them by the threshold operator. The greyed-out pixels have values that are too high or too low. Their values are all reset to zero by the threshold operator. The initial stage of our planned method is preprocessing of brain MR images. Skull masking and picture filtering are examples of preprocessing steps. The goal of preprocessing is to improve image quality and streamline subsequent processing and more reliable to locate the tumour.

The following are the procedures for preprocessing:
- Grayscale image is created.
- Noise in an MR picture of the brain is reduced by using a 3x3 median filter.
- A high pass filter is applied to the resulting image to identify sharp contours. Applying a mask of a high pass filter. If you take the original image and add it to the edge-noticed version, you get the improved picture. To prevent further loss of local detail, a damaged image should have its median filter applied, which will only adjust the degree to which faulty pixels shine. fortunately, fixed-valued impulse noise (sometimes called salt-and-pepper noise) must be present in order for the faulty pixels in this image to be identified.).

Skull Masking: The item's boundaries are managed by the skull detection system. Finding the ROI, or the area of the image containing the tumour, is facilitated by edge information. To accomplish this, the middle of the image must be located. Brain tissue is "stripped" from MR images in a procedure known as "skull stripping".

This is a crucial part of many imaging experiments involving neurons. In this situation, the threshold value was chosen instantly by using an automatic threshold value selection [6]. Then, suitable images of the brain after removal of the skull are obtained by performing a series of mathematical morphological operations on a binary image.

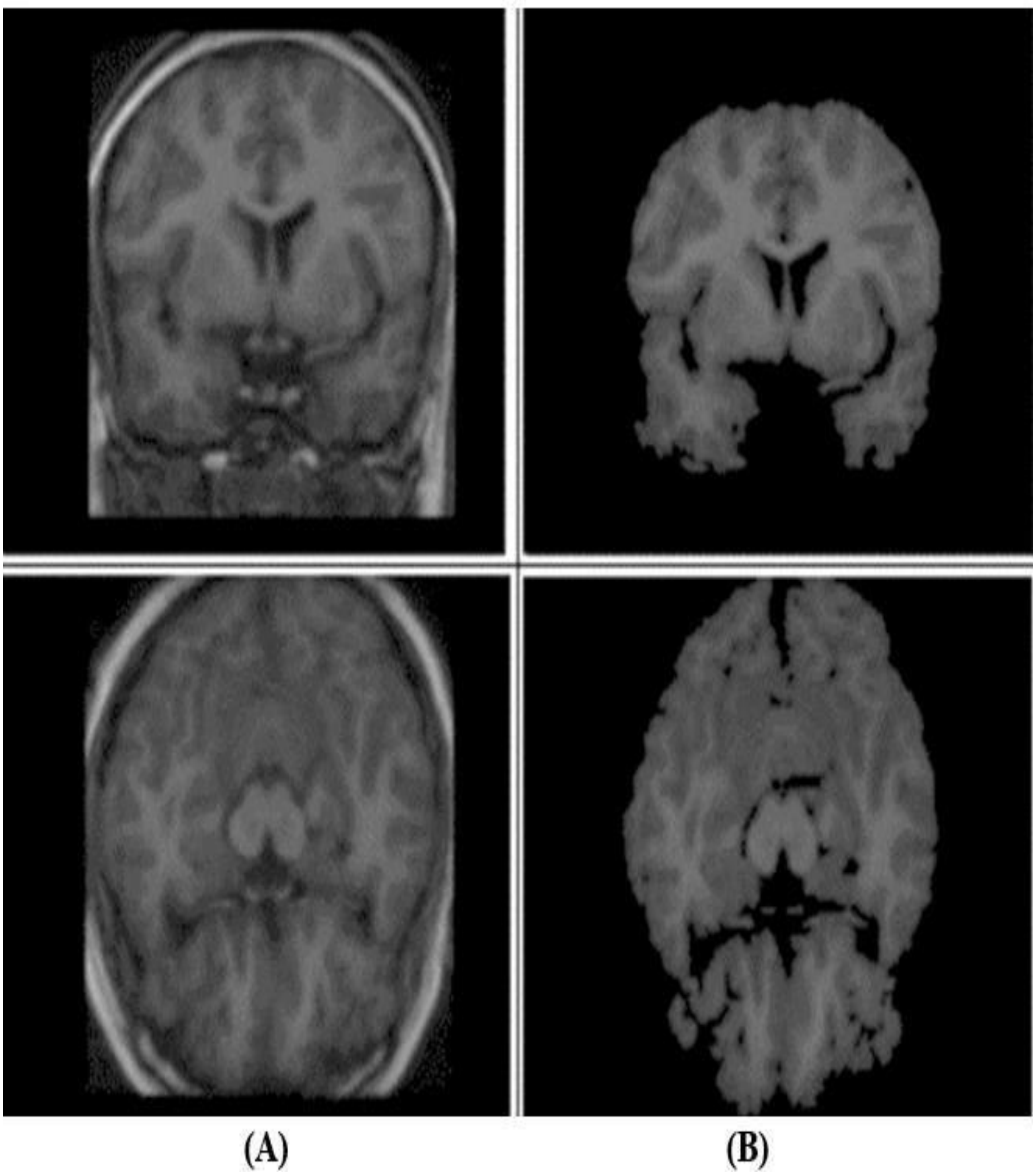

Figure 3: Removal of the skull (A) input (B) removal of the skull.

The above Figure 3 shows the Removal of the skull an input, removal of the skull. The suggested method for removing a skull has four steps. To begin, we apply a threshold to the image, creating two distinct halves are taken out of the two parts using morphological opening. Then, the brain, which is the most connected structure inside the head, is chosen as the biggest connected part of the binarized image and the flow diagram of the proposed system is shown in Figure 4.

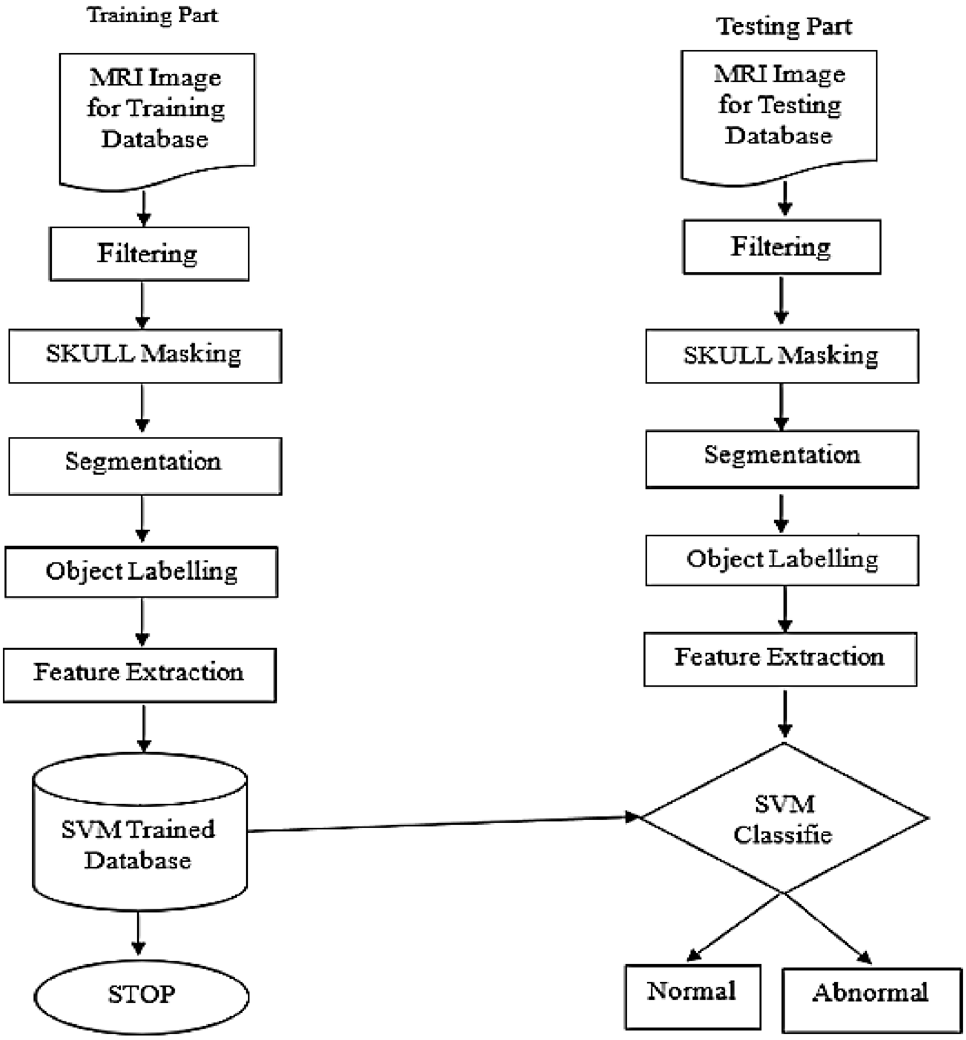

Figure 4: A flowchart of the Proposed System

Create images and masks: The image's region attributes are utilised in this case. A line is created through the empty space in the skull by making use of the image's centroid feature. As a result, the skull is now in half. The comparison is made among the experimental and control images. Finding the limits of the tumour. Each axial slice (left-right view) of input MR data has a left-right symmetry axis. A brain tumour is an aberration that throws off this equilibrium [7].

Although they share a common axis, the left-hand rectangle is very different from its mirror image on the right. Two rectangles' intensity histograms are very different, but their borders share a similar pattern. It is anticipated that the malignancy can be contained to one cerebral hemisphere by using one of the rectangles.

B. Segmentation: Segmenting an image involves dividing it into many sections or sets of pixels. Images are partitioned into items with similar textures or colours. Image segmentation yields zones covering the entire image and extracted contours. Pixels inside a region share properties including colour, intensity, and texture. Regional differences exist among neighbouring regions with the same uniqueness. Methods for determining region boundaries include:

- Thresholds dependent on pixel properties.
- Abrupt changes in intensity levels.
- Directly identifying regions. Thus, the chosen image segmentation technique relies on the situation at hand. Methods based on region continuity.

Techniques divide images into subregions according on rules, such as ensuring all Grayscale consistency between adjacent pixels. Methods based on location use similar patterns in intensity levels among neighbouring pixels in a cluster. The simplest segmentation method is threshold. Using threshold transforms an input image into a segmented binary image. Segmentation methods that draw attention to regions reveal sudden changes in intensity. These are Edge or Boundary-based approaches. Edge detection algorithms are commonly used to identify interruptions in grayscale images. The common strategy in edge detection is to find discontinuities in the grey level image. Detecting discontinuities in images requires segmentation techniques that use boundaries.

K-Means based segmentation: Similar objects are grouped together as a cluster & distinct from those in other clusters. It focuses on identifying organisation in unlabelled data. A loose definition of clustering is grouping objects. Its members are comparable. Using qualities and features, the K-Means algorithm classifies data into clusters of size k. The Euclidean distance between the data and the cluster centre is minimised to complete the clustering. Therefore, data can be clustered using K-Means. Random Partition is a popular way to initiate a partition table.

The Forgy method takes the averages of the first k randomly chosen data points. Each observation is randomly assigned to one of several clusters, and the initial mean is determined by taking the centroid of these clusters. The starting means are dispersed in the Forgy method but grouped together in the middle of the data via Random Partition. Algorithms like the K harmonic means and the fuzzy k-means, according to Hamerly, benefit most from the Random Partition approach. The Forgy initialization method is recommended for use with standard K-Means algorithms and expectation maximisation.

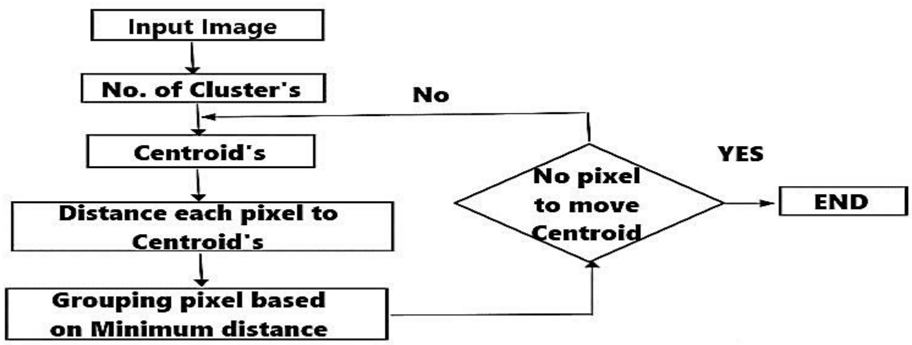

Figure 5: K-Means work flow.

In the Figure 5 above, you can see how the K-Means method works. The first block shows the picture that was sent in. The picture is then divided into groups. Then it locates the middle of each group and how far each pixel is from the centre will keep grouping images until it gets to the last one, at which point it will stop.

SVM: An example of supervised learning is the support vector machine (SVM). It works well for both analysing data and organising it into categories. Even when presented with a big amount of data, the SVM classifier has a rapid rate of learning. For situations involving the categorization of two or more classes, SVM is utilised. The idea of decision planes is the fundamental building block of Support Vector Machine. A decision plane is a type of aircraft that differentiates between a set of objects that belong to different classes in a collection. The method known as Support Vector Machine was utilised both for the classification and the detection of brain tumours. The image is then classified in order to determine the type of tumour that is present in it. Training and testing are the two fundamental procedures that are required when using an SVM.

Linear SVM: There is a linear division between the training patterns. In other words, one can define a linear function f(x) as w T x + b (1). where f (xi) = +1, y, and f (xi) = 0 if x = 0 for all xi in the training set. For a more precise classification flat function F(x) = wT + b=0, where b is an invariant and w is the unit vector, hyper-separation between the two classes of training instances is preferable. The SVM classifier uses the hyper plane that most effectively maximises the separation between the two classes for a given training set, even if there may be numerous hyper planes that do so. The hyper plane that yields the highest difference in decision function values is determined using SVM for "borderline" samples that might go either way. This support vector machine (SVM) classification approach employs a hyper plane to reduce the discrepancy between the two classes. A training set's support vectors are its elements that lie along the hyper planes dividing the two categories Fig.6..

Non-Linear SVM: The SVM classifier was used in the aforementioned examples, as depicted in figure 7. A hyperplane or straight line can be used to make a clear distinction between two groups. However, you can't always tell which classes a dataset or data point belongs to by drawing a straight line between them. The points in Figure 7 below are an illustration. None of the aforementioned support vector machines can be used to separate it. For this reason, the SVM classifier makes use of Kernel functions. The kernel function is the key that unlocks the door from nonlinear to linear analysis.

Using a kernel function is based on the premise that it can map information from a lower-dimensional space onto a higher-dimensional feature space in which the points of the information are linearly separable. The network used to discover appreciation patterns is a feed-backward tan sigmoid network, which consists of a hidden layer and an output layer. The network takes in 24 vectors as input but only generates a single neuron as output. The hidden layer consists of 100 neurons, and the learning rate is 0.1. The momentum factor is 0.9, and the number of epochs is 500. The efficiency of the classifier is determined by its accuracy, which is maximised to within a margin of error of 0.001.

4. RESULTS:

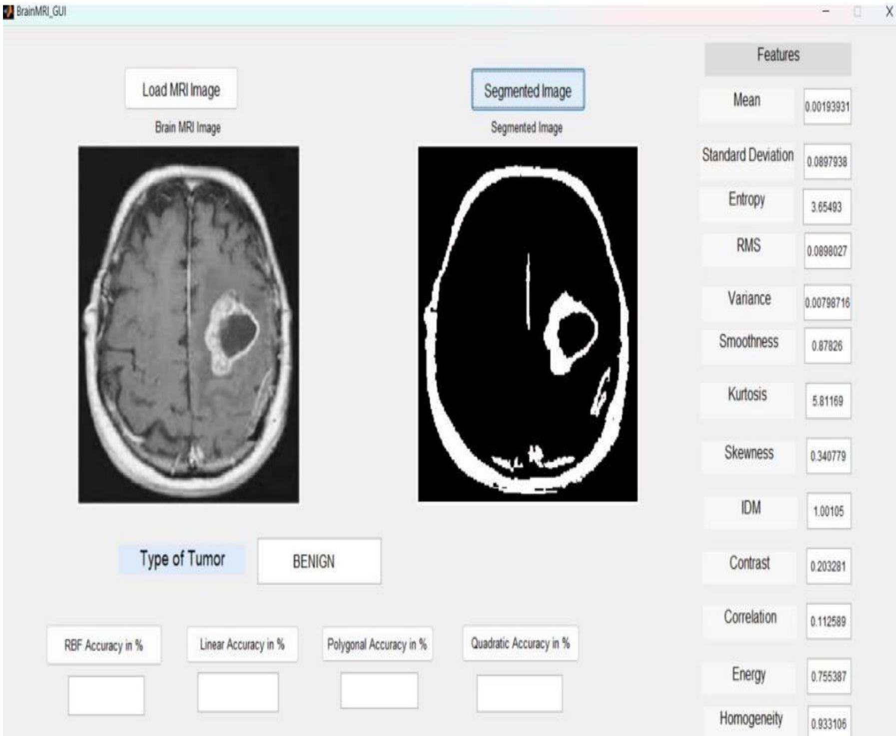

Figure.6. Linear SVM

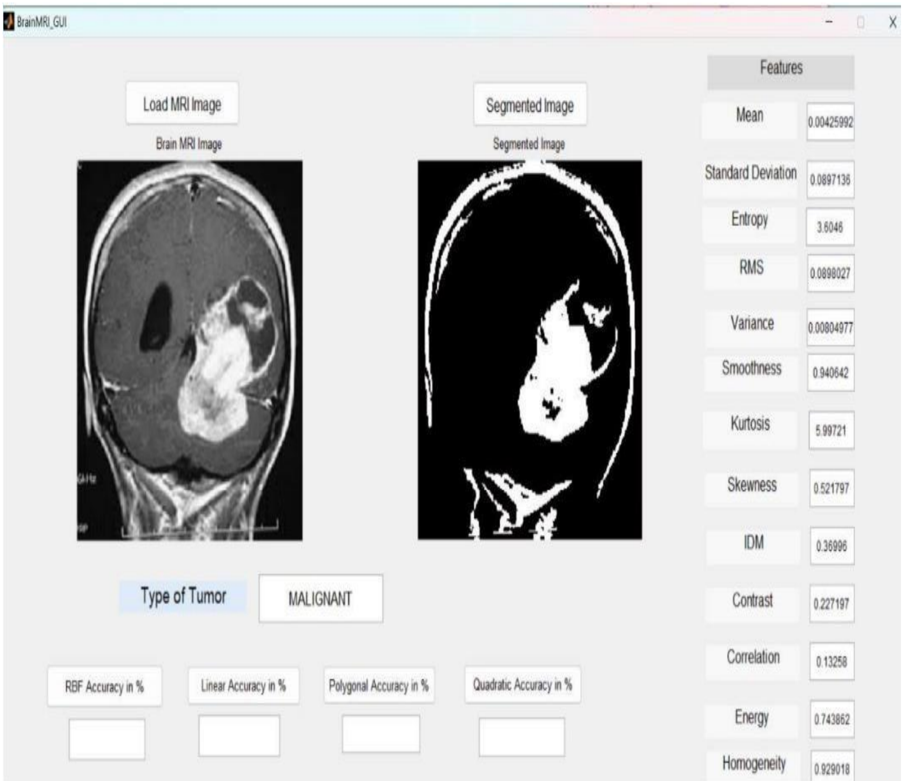

Figure.7. Non-Linear SVM.

The above data represent the results of this study, which aims to determine if a given tumour image is benign or malignant.

5. CONCLUSION:

In conclusion, it can be inferred that the detection of brain tumours involves an initial preprocessing stage, which includes the use of a median filter. Additionally, segmented images are pre-processed utilising diagonal as well as antidiagonal masks, and skull masking is performed as part of this procedure. After applying skull masking techniques, fatty tissues and other undesirable characteristics are effectively smoothed out. The pre-processed image undergoes segmentation using the K-Mean algorithm, followed by object labelling using the Histogram of Oriented Gradients (HOG) method. HOG is a suitable technique for feature extraction in this context. In this system, Colour and texture features are retrieved to locate the area of interest. SVM, or the Support Vector Machine, is used for this pattern mapping and pattern matching. Additionally, it can be utilised for the purpose of acquiring knowledge in the field of Neural Network. The field of image processing has assumed significant importance in contemporary society. Currently, image processing finds applications in various fields such as medicine, remote sensing, and electronics, among others. In the context of medical applications, picture segmentation is extensively employed for the aim of diagnosis. This work presents a proposed approach for detection & identification of brain cancers using segmentation of magnetic resonance images of the brain. The tumour's location and grade are identified. Possible future directions for cancer localization and classification in the brain & in the acquisition of three-dimensional brain images, which would enable the determination of tumour size, evaluation of tumour type, and assessment of tumour stage.

6. REFERENCES:

[1] Shaoguo Cui,Lei Mao,Jingfeng Jiang,Chang Liu,1and Shuyu Xiong "Automatic Semantic Segmentation of Brain Gliomas from MRIImages Using a Deep Cascaded Neural Network", Journal of Healthcare Engineering,2018.

[2] Chakrabarty, Navoneel, "Brain MRI Images for BrainTumorDetection", https://www.kaggle.com/navoneel/brainmri-images-for-brain-tumor-detection, 2019. Authorized licensed use limited to: Cornell Un

[3] P.N.Gopal and R.Sukanesh," wavelet statistical feature based segmentation and classification of brain computed tomography images" IET Image Prosess Vol.7 pp 25 -32 2013

[4] Laxmi and P.Samata, "Optimization of visual presentation of MRI image for accurate detection of tumor in human brain using virtual instrument" in The Biomedical Engineering International Conference 2012.

[5] B.C.Patel and G.R.Sinha, "An adaptive K-Means Clustering algorithm for breast image segmentation" International Journal of Computer Applications, vol. 7, no. 4, pp. 35-38, 2010.

[6] T.Kalaiselvi and K.Somasundaram, "Fuzzy c-means technique with histogram based centroid initialization for brain tissue segmentation in MRI of head scans" in Proceedings in IEEE-international Symposium on Humanities, Science and Engineering Research, pp. 149- 154, 2011.

[7] M.Shasidhar, Y.S.Raja and B.Y.Kumar, "MRI brain image segmentation using modified fuzzy c-means clustering algorithm," in Proceedings in IEEEInternational Conference on Communication Systems and Network Technologies, pp. 473-478, 2011.