RESEARCH ARTICLE

Brain Tumor Classification from Magnetic Resonance Images using Routing Agreement Algorithm

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ABSTRACT: Cancer is the world's most common disease and the second biggest cause of mortality among humans. Brain tumors are protracted forms of cancer due to their aggressive nature, varied features, and dismal relative survival. Pretreatment, segmentation, and detection of infected tumor regions utilizing magnetic resonance (MR) images is a big issue, and radiologists or clinical personnel must complete time-consuming and arduous activities. The brain tumors differ in appearance and resemble normal tissue within the tumor, Convolution Neural Network (CNN) cannot fully exploit spatial correlations. The paper presents an approach to automatically detect brain cancers using deep learning techniques with capsule networks. The proposed strategy allows the capsule network to access the tissue surrounding the tumor without interfering with the tumor's primary function. A modified capsule network design for brain tumor classification has been developed in which a complete tumor boundary is used as an additional input to the pipeline to boost the capsule networks. The proposed method can efficiently classify the brain images with 98.5 percent sensitivity, 97.82 percent specificity, and 98.35 percent accuracy, according to the results of cross-validation.

KEYWORDS: Brain tumor classification, Tumor Boundary, Convolution Neural Network, CapsNet

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1. INTRODUCTION

According to World Health Organization statistics, most cancers is that the other maximum not unusual place disorders with inside the globe, with a predicted the 3.2 million deaths this year (One hundred sixty new most cancers instances and 608,570 deaths in India [1]. After maximum most cancers deaths with inside the 20th century, most cancers prognosis and remedy has been hampered through the 2019 coronavirus pandemic (COVID19). Among the varied kinds of most cancers, mind tumors have low aggressive, heterogeneous (kind), and relative survival rates [2]. This most cancers may have an extreme effect at the first-rate of lifestyles of sufferers and their families. Early prognosis and backbone of the correct kind are vital elements in treating mind tumors and enhancing survival. Brain tumors categorized based totally on their shape, pattern, and region (meningioma, pituitary, glioma, etc.). Determining the correct form of brain tumor is of utmost significance because it has an own large effect on remedy choices and prediction of affected person survival, digital pix with inside the clinical subject used for diagnostics. Early detection of brain tumors is significant for powerful neoplasm remedy. Because of the excessive comparison of smooth tissues and zero publicity to radiation, MRI is that the maximum common approach for diagnosing human brain tumors. However, classifying mind tumors isn't a smooth task. The traditional approach of MRI detection and kind of brain tumors is human examination. This can be predicated closely at the assessment and evaluation of the photograph and, maximum importantly, the radiologist who assists with inside the manufacturing of the photograph. Systems are hardware / pre-processed can assist automate this technique with correct and well-timed effects. Image segmentation, on the choice hand, is that the primary reason for many pc imaginative and prescient and photograph processing implementations. The diagnosing of brain tumors early is significant for higher remedy. Once a neoplasm is clinically detected,

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radiation assessments are come to a decision its location, size, and outcomes on the encircling area. Early detection of a tumor substantially will increase the possibilities of survival for an affected person inflamed with the tumor. The huge quantities of information, the user-assisted type system is impractical and irreproducible. Therefore, automated diagnostic gear is surprisingly suitable to resolve those problems. It additionally aids clinicians of their preceding choice system through facilitating fast, reliable, and proper evaluation. There are varieties of brain tumor categorized based totally on scientific application: (1) Brain pix are categorized as every day or unusual, looking forward to whether the photograph of the mind consists of a tumor. (2) Type inside unusual mind pix, i.e., differentiation among distinctive types of mind tumors [3]. The main contributions of this have a glance at accommodates a full evaluation of Capsule Neural Network (CapsNet) based methodologies, the event of a singular Caps Net topology, testing the proposed topology the utilization of mind scans to categorize the varieties of tumors, and evaluating the results of present methods with inside the literature

There are several studies reported in the literature aimed at improving the diagnosis of central cancer. Various machine learning processes are available for segmenting and classifying brain tumours using MRI. Hasane et al., [4] proposed a system for classifying MRI brain scans with deep handmade image features. Clinical studies have shown that autonomous processing systems have been developed to diagnose brain tumours [5–10]. The standard workflow for developing an automated or semi-automatic system are to first segment the tumour from the MRI image and extract a quantitative feature called "radiomics". Then use Radiomix to train a predictive / survival model for cancer classification. Aerts et al., [11] extracted 400 features from segmented tumours and investigated the relationship between image-based features and clinical outcomes. The relationship between the characteristics and patient survival was analyzed using various statistical models. Nevertheless, it can be concluded that there is a strong correlation between tumour annotations and extracted features. The Radiomix function is very sensitive to discrepancies between observers of tumour segmentation. In other words, hand-designed features appear to be unstable [12], significantly reducing the reliability and applicability of the model. More importantly, this pipeline requires prior knowledge of the functions to extract, but they are not available. The inadequacy of traditional Radiomix workflows tends to use deep learning, especially CNN [13], for cancer diagnosis and classification. Sara Sobour et.al., [14] the classification of brain tumours, 4,444 features were extracted from brain images with six CNN layers. The main objective of the article is to classify brain tumors images and does not require detailed annotations.

2. MATERIALS AND METHOD

This method is separated into three steps: (1) Image pre-processing (2) Image Segmentation and (3) classification by CapsNet model. The current study has been conducted for the classification of oral biopsy images into benign or malignant. Figure.1 represents the diagrammatic illustration of the suggested method carried out in five stages:

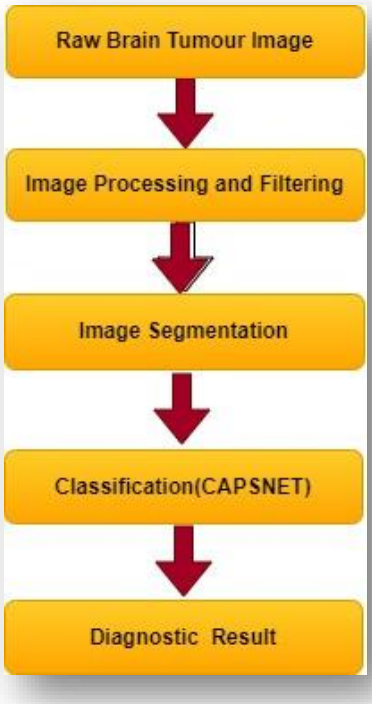


Figure 1: Proposed method for Image classification

2.1 PRE-PROCESSING AND FILTERING

Clinical brain tumors images are filtered through multiple stages to reduce noise. Each noise source is in a characteristic frequency band. Low conductivity between the skin and the electrodes creates a slowly changing

potential that manifests itself as image baseline movement. The output function of this WT is a The parameters of this filtering are the attenuation factor β , and the basic frequency f .

$$\Psi\left(t\right) = \exp\left(\frac{t^2}{\beta^2}\right)\cos\left(2\Pi ft\right) - \lambda \quad (1)$$

β - Attenuation factor, f - base frequency, $\Psi\left(t\right)$ -Wavelet Transform, λ - DC factor eliminator

Our goal is to find these parameter values and make the greatest contribution to a comprehensive demonstration of excellent datasets, preprocessing steps, and CapsNet. The fact that the values of all these parameters are selected is an additional calculation of the signal attenuation ratio that guarantees a significant percentage of the total defined in equation (1). The capsule network allows taking full advantages of unique spatial association and simulating the ability to perceive visual changes. filtered signal. $\Psi\left(t\right)$ given in the equation (1).

Others have a clustered background, while others have an untouched, immutable background. Images should be preprocessed to remove contaminants and prepare them for subsequent processing such as segmentation and feature extraction. The Gaussian blur is used in the image preprocessor to remove the noises and smooth the edges before converting the image to grayscale. In automated diagnostic systems, accurate segmentation sends the actual data that leads to the correct classification of histological images. The proposed automatic segmentation of research typically involves the separation of homogeneous objects. To train a deep learning model, to provide enough training data and over fitting can occur if only a modest amount of training data is used. These data extension is to avoid missing data and over fitting of various class categories.

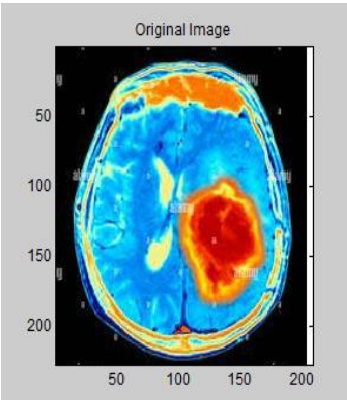


Fig (2.a): Original Image

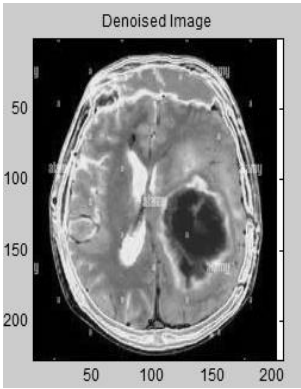


Fig (2.b): Denoised Image

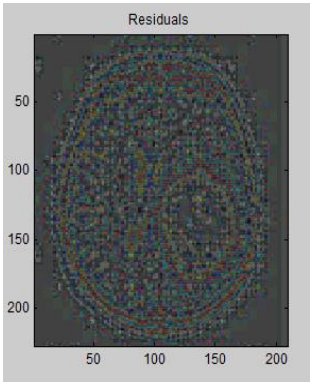


Fig (2.c): Residue Image

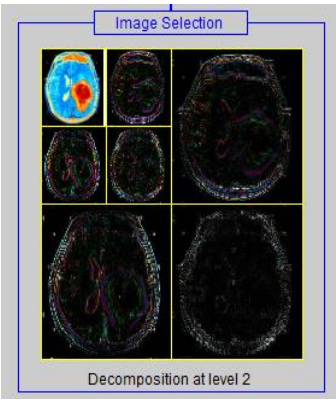


Fig (2.d): Decomposition at level 2

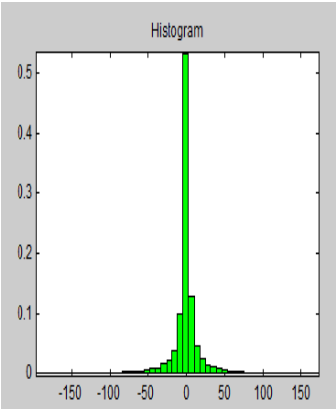


Fig (2.e): Histogram

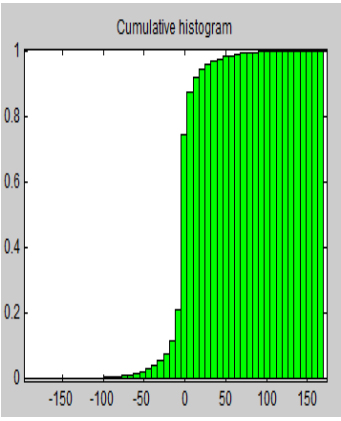


Fig (2.f): Cumulative Histogram

Figure (2.a) Image of the brain obtained by MRI. Figure (2.b) images converted to a gray color image. H-2D image, Gray color images consist of an intensity of 50,200 pixels. 50 stand for black and 200 stands for white. The histogram is a graph between the number of

pixels and the number of pixels. The bar chart to display a histogram diagram (2.e). The histogram code works by first reading the grayscale value. The first entry is between pixel intensities 50 and 200. If increased the total number of pixels by then, proceed to the next row or column entry. Finally, the two histogram of tumors (Figs. 2.e and 2.f), and comparison for tumor identification were presented. Figure 3 and Figure 4 shows Tumor segmentation is a basic step in Radiomix analysis because it transforms the original medical image into an extractable images.

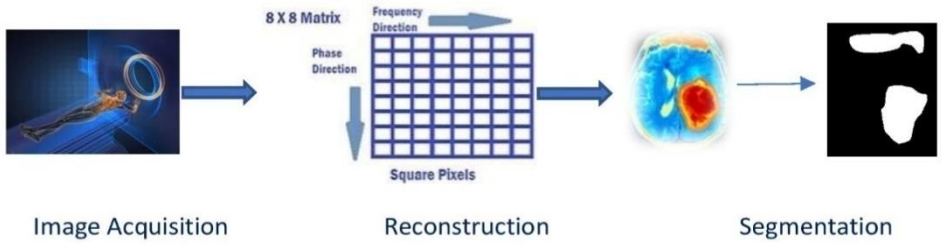


Figure 3: Brain Tumor Image Segmentation

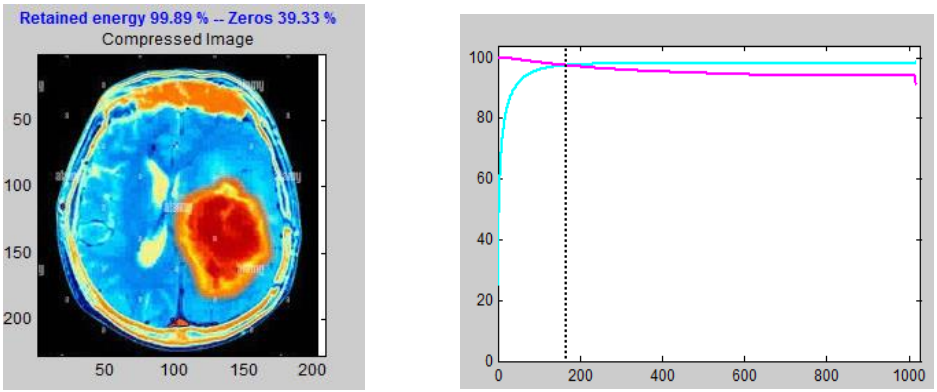


Figure 4: Compressed Image

Table 1: Dataset of Brain tumor considered for the study [26]

Algorithms	Classes	Precision	Recall	Accuracy
Convolution 3X3	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Densenet_Block Features A	meningiomas, pituitary glands gliomas	98.00 96.00 95.00	97.00 96.00 94.00	99.00 97.00 96.00
Concatenated	meningiomas, pituitary glands gliomas	95.00 95.00 95.00	96.00 97.00 99.00	98.00 98.00 96.00
Densenet_BlockFeatures B	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Concatenated	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Inception Features A	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Inception Features B	meningiomas,	99.00	98.00	99.00

	pituitary glands gliomas	95.00 95.00	97.00 99.00	98.00 96.00
Inception Features C	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Combined Inception	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00
Combined Densenet	meningiomas, pituitary glands gliomas	99.00 95.00 95.00	98.00 97.00 99.00	99.00 98.00 96.00

2.2 CAPSULE NETWORK

Capsule Network is an advanced machine learning architecture introduced to better model the hierarchical pose relationships. These capsules are "routed" to of the next capsule layer and a dynamic routing algorithm is used to determine the correspondence between these capsule vectors. This creates a partial traction connection that does not exist on traditional CNNs. According to the summary of current research, CapsNet is a network that can capture spatial information and more important features to overcome the loss of information due to the bundle process. "Dynamic routing between capsules" for training capsule networks. Convolution neural networks have made remarkable achievements in the field of computer vision. Capsule networks are coming to overcome all the shortcomings of CNN. After training, the primary capsules recognize different types of individual shapes show in Figure 5 (squares, circles, vernier), and the secondary capsules group these shapes into groups 1, 3, or 5. The square will be the main square. The capsule recognizes three squares. In consensus routing, the second square capsule recognizes this group of three squares. For 5 circles during the presentation, the capsule of the main circle will recognize the 5 circles. When routed, the square circular capsule represents a group of five circles, and when a vernier is presented, it is recognized and sent to the second vernier capsule.

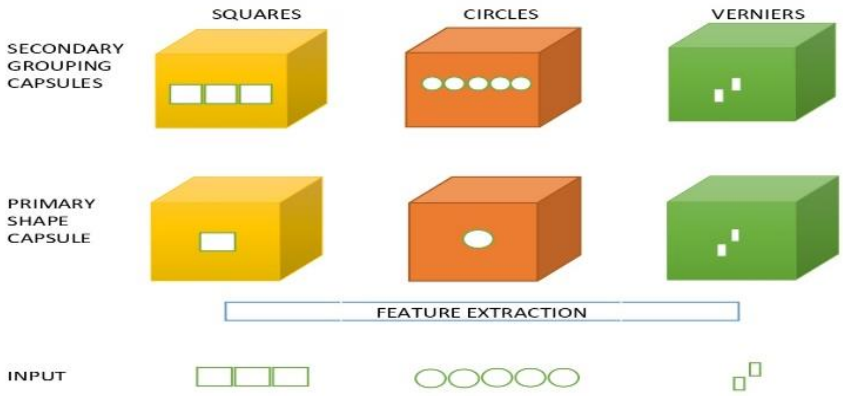


Figure 5: Grouping of Tumors in Primary capsule as Input

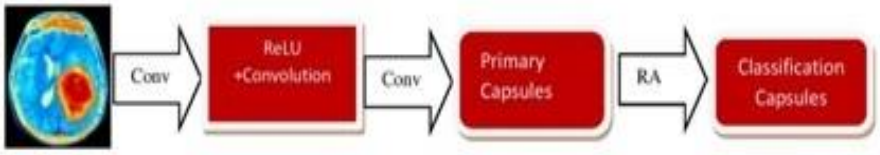
Capsule network makes to understands spatial information and more important features and can overcome the loss of information due to the aggregation process. In this process, low-level capsules predict the outcome of the mother capsule. This activates Mother Capsule only if the predictions match. Recent studies [16] have shown that CapsNets is superior to CNN in terms of classification of brain tumors. However, because CapsNet is very sensitive to the background of the image, segmented tumor classification is compared to the scenario where the image of the entire brain is the input. A human expert manually performs tumor segmentation is a very time-consuming and difficult task, usually requires many steps, and the results are highly dependent on human expertise. Segmentation algorithms studied for a long time, but there is a need to improve fully automated segmentation algorithms, especially

in the field of medical image analysis. However, there are two main problems with the need for segmented tumors.

(i) First, tumor segmentation is a time-consuming task that can only be performed by specialists.

(ii) Second, the tissue surrounding the tumor contains valuable information that would not be accessible if only segmented areas were delivered to the network.

Since the post specifically deals with the above topics, the capsule network shows a very different way to solve the problems of image recognition and access to tissue around the tumor. In addition, neural networks have come a long way in recognizing images. Improving the robustness of CNNs requires large amounts of data that are not always available, especially when classifying brain tumors without diverting the need for detailed annotations of the tumor. This is the main motivation for this research's contribution.



* PA - Primary Capsules, RA - Routing by Agreement, CA - Classification Capsules

Figure 6: Routing by Agreement

CapsNet focus on important areas while providing information from the surrounding tissue shown in Figure 6. This information is sent to CapsNet at the final level before going through the final set of fully connected levels and the final SoftMax level that makes the decision.

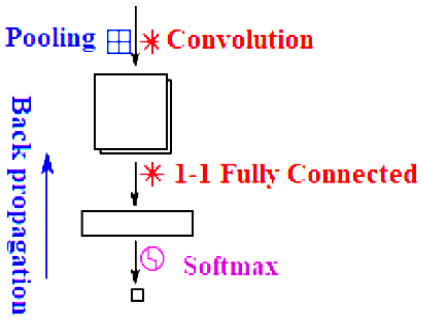


Figure 7: SoftMax for CAPSNET

SoftMax prevents the capsule layer from forming optimal bonds between low- and high-level capsules. SoftMax shown in Figure 7 limits the dynamic range of the routing factor, leading to the probability that it will remain about the same after several routing iterations. It is time efficient and is done by specialists and radiologists. The proposed method has been superior to CapsNet, which only supplies brain or segmented tumor images.

2.3. CLASSIFICATION OF CAPSULE NETWORK

CNN [15] is basically a stack of convolution layers, pooling layers, and in some cases fully connected layers, benefiting from the fact that the weights are distributed across the input. This significantly reduces computational costs and allows the network to extract basic elements. These networks have become popular architectures in medical imaging since they do not require prior knowledge of the types of features.

Figure 8 is c layer of convolution process. It is the input neuron data extracting function. The size of the input feature map is n x n and is represented by X. The size of a matrix with a convolution kernel is k × k, and the size of a matrix labeled Y on the output is m × m. The three-dimensional relationships are as follows

$$m = n - k + 1 \qquad (2)$$

The specific formula for the calculation is:

$$Y_{ij} = f_s\,(\sum i = 1k \sum j = 1k\,(X_{ij}C) + a) \qquad (3)$$

where X_{ij} and Y_{ij} are the elements corresponding to the convolution kernel of the input and

output layers, a is the offset and f_s is the sigmoid. It is a function.

The sub sampling or pooling layer is integrated into the CNN to not only reduce the number of parameters, but also to make the network transformation immutable. However, these layers lose information about the exact location of the feature detector. This issue remains unresolved unless all possible situations are included in the training data. The following CapsNets have features to help you solve this problem.

$$S_{ij}=1c2(\sum i=1c\sum j=1cF_{ij}) +b \quad (4)$$

$$maxi=1,j=1c(F_{ij})+b \quad (5)$$

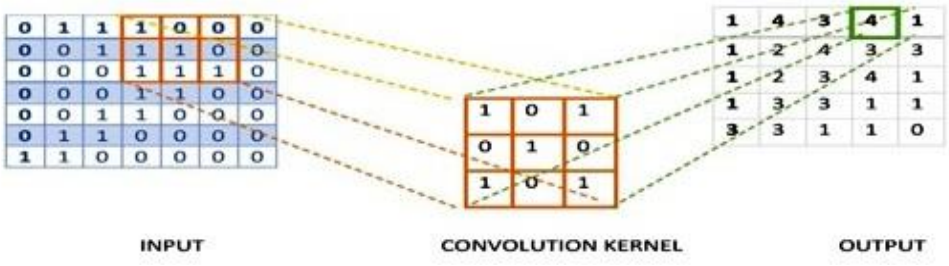


Figure 8: Principle diagram of convolution process.

2.4. CAPSULE NETWORKS (CAPSNETS)

Each CapsNet pill is used to understand the possibility of numerous instantiation parameters consisting of rotation and length for the underlying item. It is made from neurons. Shredder features are usually used to hold vector lengths much less than one. To clear up issues associated with CNN pooling ranges, those ranges had been changed through a technique called "contractual routing". This technique relies upon on how the pill contribution relies upon, in place of by chance under sampling the characteristic map.

More specifically, u_i is described because the output of a low degree pill

i,u^j|i is defined as the prediction of the high-level capsule.

j, W_{ij} is defined as, and the weights connecting them are back propagation.

Learn through gating. Using this notation, u_{jj} can be calculated as follows:

$$u^{}_{j|i} = W_{ij}u_i \quad (6)$$

The strength of the connection between the capsule and its parent depends on how well it matches the actual output of the parent. In other words, this correspondence between u^j|i and the actual output of the mother capsule j labeled sj determines the coupling coefficient c_{ij}. Capsule i then sends its output to capsule j as follows:

$$s_j = \sum c_{ij}u^{}_{j|i} \quad (7)$$

The strength of the connection between the capsule and its parent depends on how closely it matches the performance of the actual parent

The log probability of whether capsule i needs to be bound to capsule j is expressed in bij. This should be learned in the "Routing by Agreement" and is set to 0 in the initialization step.

Algorithm 1: The routing-by-agreement algorithm (CapsNet)

1: xi: inputs
2: $W_{ij:}$ weights
3: $u_{ij} = W_{ij}x_i$
4: $b_{ij} \leftarrow 0$
5: for r iterations do:
6: $c_{ij} \leftarrow$ P exp (b_{ij}) k exp (b_{ik})
7: $s_j \leftarrow$ P k $c_{kj}u_{kj}$
8: $y_j \leftarrow k_{sj}k_{sj}1+2\ k_{sj}$
9: $b_{ij} \leftarrow b_{ij}+ u_{ij} \cdot y_j$
10: return y_j

During routing in the consent process, this probability is updated based on the similarity between s_j and u^j | i. The basic approach to calculating this similarity is to take the inner product of the two underlying vectors. Each capsule j in the last layer (classification part) is

connected to the loss function l_j. This is intended to encapsulate capsules with large instantiation vectors (in the sense of standard values). The loss function lj is calculated as

$l_j = T_j \max(0, m + -|| s_j ||) 2 + \lambda (1-T_j) \max(0, || s_j || m) 2$ (8)

The terms m+ and m– are hyper parameters that must be specified before the learning process. Total loss is the sum of the losses from all output capsules. The original capsule network also has a set of fully connected layers called the decoder part. The decoder part takes the final instantiation parameters of the true class as input and attempts to reconstruct the original image with the goal of having the network capture the actual representative features shown in Figure 9. Decoder loss is defined as a simple squared error and contributes to the final error compared to the loss of lightweight capsules. This is done so that it does not get in the way of the network from the main purpose of the network, the classification of objects. This concludes our brief introduction to CNN and CapsNet.

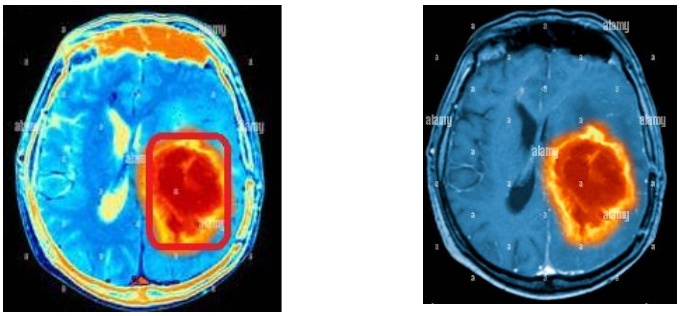


Figure 9: Original image Grey scale Defining the tumor boundary box

3. PROPOSED FRAMEWORK

The proposed method is to detect brain disease, meningioma, pituitary gland, and glioma using the most used MRI images. It can be divided into three categories of tumors. The CNN has one major drawback that limits its application to real-world problems. They do not fully consider the exact spatial relationships between objects caused by the loss of information in the pooling layer. Pooling layers, on the other hand, cannot be deleted because networks without these layers are very sensitive to slight shifts in the image. The spatial information lost on the CNN is very important for the classification of brain tumors. This is because the relationship between the location of the tumor and the surrounding tissue can have a strong effect. Figure 10 shows the tumor classification method from brain image

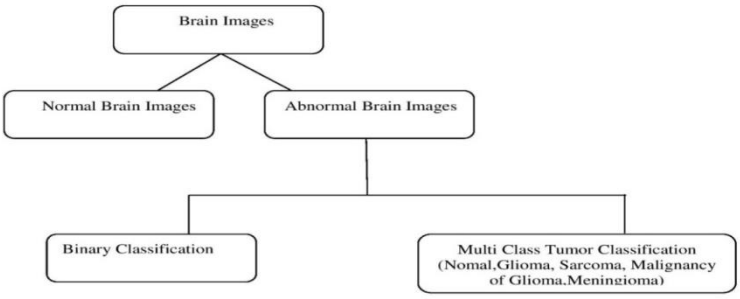


Figure 10:Tumor classification method from brain image

Previous studies [16] have shown that CapsNet out performs CNN on this issue. However, these networks are sensitive to the background of the image. With 4,444 detailed MRI images of the brain, this property can adversely affect network performance. Previous results show that CapsNet is more accurate than whole-brain images of segmented tumors. In addition, annotating brain images is time consuming and not always possible. Consistent with the above issues, the CapsNet architecture was developed in this article. It leaves the capsule layer and passes through a series of fully

connected layers to make the final decision on the type of tumor. The result of this work is a feature map tensor 20x20x256, which is fed to core 256, 9x9, second stage, and second convolution layer (Primary Caps) using ReLU activation. This creates a 6x6x256 feature map tensor that represents the low-level capsules of the web. A set of eight scalar neurons in a 6x6x256 tensor are grouped by channel to form a low-level capsule i, a total of 6x6x (256/8) = 1152 low level capsules. The Primary Caps output is provided by the dynamic routing algorithm and becomes the DigitCaps output matrix. The partition function used to calculate v_j. Each row of the DigitCaps matrix represents a single instantiation parameter of the 16D class, and the vector length 16 Drepresents the probability that a particular class exists. During training, the non-basic truth lines were masked with zeros, and the Matrix was fully connected with two fully connected layers in dimensions 512 and 1024 with ReLU activated, and the last fully connected in dimension 784.The output uses the longest row of the DigitCaps matrix as the predicted feature class. The input data to the routing algorithm is the prediction vector u_j. These prediction vectors are computed using the trained transform weight matrix and the capsule output of the Primary Caps layer. The prediction vector remains fixed within the algorithm while the bootstrap of the routing procedure uses the prediction vector to compute the DigitCaps capsule vj. There is no gradient flow in the routing layer, but both the inputs and outputs of the routing layer are exposed to normal gradient flows during training. DigitCaps capsules are passed to sub networks that learn to reconstruct the original input image. The prediction vector and the parent-level capsule tend to evolve, and the scaled sum of the prediction vector is like the parent-level capsule. In other words, in the forward path, the network calculates a high-level set of capsules used to restore the original image. Reconstruction network errors propagate to the prediction vector and the previous plane. During the next direct path, the prediction vector is extended by the transformation matrix to match the previously calculated high-level capsule. The routing procedure using Max-Min regularization is similar except that the Max-Min function replaces the Softmax function. Where p / q is the lower / upper bound of regularization. The first iteration initializes the routing arguments outside of the routing loop [14].

LOSS FUNCTION:

Loss of output of the capsule layer, as in (9),

$$\text{Loss} = \sum_{1}^{K} [y \log p(y)) + (1-y)\log(1-p(y))] \quad (9)$$

Item p (y) is probability of, and there are class determined by the network. K is the number of output classes (tumor type). This loss is fed back to the entire network, including the layer fully connected to the capsule layer. This concludes the description of the proposed CapsNet architecture for the brain tumor classification problem.

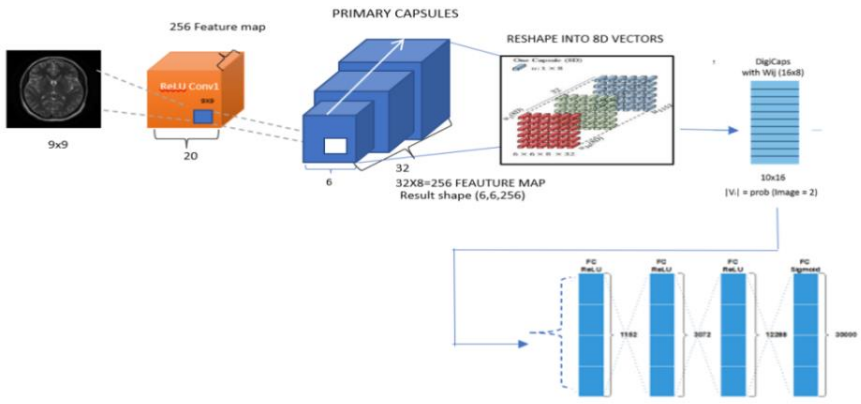


Figure 11: CapsNet architecture proposed for classifying brain tumors

4. RESULTS AND DISCUSSION

The scale on the right has various colors that represent the range of energy available for that waveform sector after removing the baseline. Sensitivity indicates the percentage of beats correctly recognized by the algorithm.

$$\text{Sensitivity}\ (\%) = \frac{TP}{TP+FN} \quad (10)$$

TP is true positive (correctly recognized)
FN is false negative (unrecognized number)
Positive Prediction shows the percentage of hit detection that was a real hit.

$$\text{Positive "Prediction"}(\%)" = TP/(TP+FP) \quad (11)$$

False positive FP (number of additional entries) in QRS complex

The FN and FP values tend to drop sharply to the lower values of the record corresponding to (104, 203, 207). The ECG curve in the above record is characterized by a high level of complexity, which makes it internally difficult to recognize the QRS complex. This section briefly describes CNNs, and then intuitively explains why CNNs are transformation-invariant. H. It is not possible to locate another object from one object. Figure 12 and 13 shows the Tumor classification method from brain image and training and validation Accuracy across the Epoch.

Table 1: Cross - validation accuracy using Confusion Matrix

True Vs Predicted	Benign	Malignant	Pitutary gland
CNN	86.56	84.19	91.90
CAPSNET	99.34	99.51	98.69

Table 2.Performance Measurement for proposed System

MODEL	Sensitivity	Specificity	Accuracy	Precision
LONG BASED SOFTMAX	86.56	88.34	98.60	97.90
CNN	84.19	85.50	90.02	93.30
CAPSNET	91.90	99.51	99.62	98.53
COMBINED FEATURES	93.68	99.00	98.23	98.30

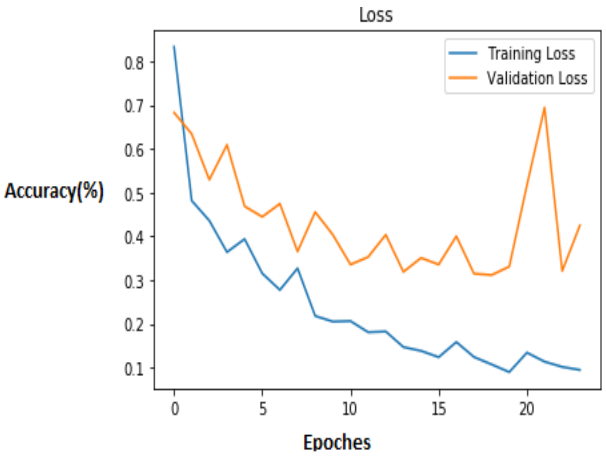


Figure 12: Tumor classification method from Brain Image

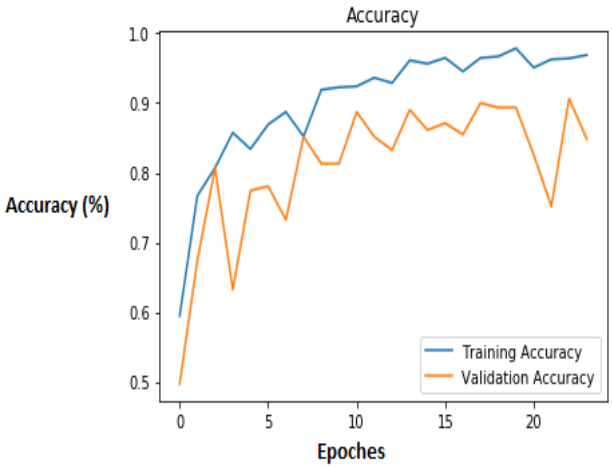


Figure 13: The Training and validation Accuracy across the Epoch

Below are the experimental results used to evaluate the effectiveness of the proposed architecture. The CNN proposed for tumor classification of the same mental disorders. The CapsNet architecture presented in this post outperforms CNN in all situations and performs best when given the boundary between the brain image and the macroscopic tumor.

Table 3: Hyper parameter training for classification of brain tumors via optimizer

Hyper-parameter	Optimized Value
Number of images	100

Number of Epochs	500
Batch size	4
Non-Augmented	128
Augment Routing iteration	3
Learning rate	0.0001
Learning rate decay	0.9
Loss	0.20
m+ (in Eq. (7))	0.8
m− (in Eq. (7))	0.2

Table 4: Comparison of the proposed approach with previous results

S.No	Approach	Accuracy
1.	Input of brain image in CapsNets	70%
2.	Segmented Tumor in CapsNets as input	86.56%
3.	CapsNet Architecture	91.43%
4.	Input of Brain Image in CNN	74.36%
5.	Segmented Tumor in CNN as input	78.44%
6.	Softmax normalization and routing coefficients	99.30%

5. CONCLUSION

A complete study of CapsNets is presented in this paper, and a new CapsNet topology for tumour classification is constructed and validated using brain MR images. Feature detection (if the feature exists in the image) is provided by the pooling function in CNNs, but the relationship between features is lost (i.e. spatial information of these features). CNNs, as a result, result in poor categorization results. CapsNet is a promising new method for resolving this issue. The dynamic routing technique in CapsNets saves all relevant detail information and improves learning. Existing brain classification methods use CNNs to classify images as abnormal or normal. However, a CapsNet model was used to classify photos into three tumour kinds in this study (pituitarie, glioma and meningioma). The proposed topology's efficiency has been demonstrated by the use of information about tumours. According to the findings of the experiments, the proposed method can assist doctors in classifying pituitary, glioma, and meningioma from MR images. Experiments with enhanced CapsNet topologies may yield better results in the future. Comparative assessments revealed that the suggested method outperforms a CapsNet with a segmented tumour image or a complete brain image as the input image. Furthermore, the suggested technology eliminates the need for radiologists to perform any manual operations in order to receive findings.

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