Classifying & Detecting Brain Tumor Using CNN from MR Images

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This Thesis paper has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering.

DECLARATION

It is officially declared that I completed my thesis named "**Classifying & Detecting Brain Tumor Using a Machine Learning Approach from MR Images"** under the supervision of Dr. Imran Mahmud, Head & Associate Professor, Department of Software Engineering, Daffodil International University's. It is also stated that neither this thesis nor any part of it has been submitted to any other university for the purpose of receiving a degree. Daffodil International University's

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ACKNOWLEDGEMENT

First and foremost, I am grateful to Almighty Allah for allowing me to complete the final thesis.

I'd like to thank my supervisor, Dr. Imran Mahmud, for his consistent assistance with my thesis and research work, which he provided through his understanding, inspiration, energy, and information sharing. His guidance aided me in locating research solutions and arriving at my ultimate theory.

We would like to offer our heartfelt gratitude and appreciation to all of my Software Engineering department teachers for their invaluable assistance, counsel, and support throughout my studies.

I'd want to thank every one of our friends, senior and junior, who have lent a hand in our venture, either directly or indirectly.

Last but not least, we want to express our gratitude to my family for their unwavering physical and spiritual support throughout my life.

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Abstract

The frequency of brain tumors is expanding quickly especially within the youthful era. Tumors can specifically devastate all sound brain cells. Hands on examination could be produce errors. Modified examination methodology is required since it lessens the stack on the human onlooker, exactness isn't influenced due to expansive number of pictures. The discovery of brain tumors in brain (MRI) picture is a critical handle for avoiding prior passing. This article proposes a mechanized computer supported strategy for recognizing and finding the brain tumors in brain MRI pictures utilizing profound learning calculations. Deep learning is perhaps the unexplored frontier of machine learning that has received a lot of attention in recent years. It was broadly connected to a few applications and demonstrated to be a capable machine learning instrument for numerous of the complex issues. In this paper we utilized CNN classifier which is one of the DL structures for classifying a dataset of brain MRIs into two classes e.g. ordinary cell & tumors cell. The classifier was combined with the picture upgrade instrument and picture division Also, coercion scores were very high for all coercion actions. The proposed technique is connected on the brain pictures from open get to dataset. The experimental comes about appeared that the proposed approach able to perform superior compare to existing accessible approaches in terms of precision whereas keeping up the pathology experts' worthy precision rate.

Keywords: CNN, MRI, Brain, Deep Learning, classification, feature extraction

CHAPTER 1: INTRODUCTION

Within the past few a long time since of AI and Profound learning, critical advancement has been made within the restorative science like Restorative Picture preparing strategy which makes a difference specialists to the analyze infection early and effectively, sometime recently that, it was monotonous and time-consuming. So to resolve such kind of impediments computer-aided innovation is much required since Therapeutic Field needs proficient and solid strategies to analyze life-threatening maladies like cancer, which is the driving cause of mortality universally for patients. The quick advancement of wellbeing care innovation within the field of data and communication designing is utilized to deliver the quick recuperating arrangements for numerous wellbeing care issues of the patients around the world. That’s why AI has come to unravel such an issue like this. Brain is the most foremost important organs in our body that workhouse with huge of cells. Brain tumors emerge when there is intemperate cell division shaping an anomalous gather of cells around or interior the brain. That gather of cells can influence the ordinary usefulness of the brain movement and devastate the healthy cells [1]. The rate of brain tumors is expanding quickly especially within the youthful era. Tumors can straightforwardly crush all sound cells. Physical investigation can be human blunder. Automatic classification strategy is required since it diminishes the stack on the human spectator, exactness isn't influenced due to expansive number of pictures. This paper explains endeavor to location & classification of tumor in kind organize. Proposed strategy comprises of two period to be specific picture division and classification. Within the to begin with arrange, gotten the highlights related to MRI pictures utilizing division [2]. For fragmenting we'll utilize binarization technique. Base this methods, we will separate the abnormal section of the images and other stage, the classifier is classified images using Convolutional Neural Network (CNN) classifier. This process is also called pixel-level classification. That is, dividing an image into multiple segments. Concurring to the report gotten from NCE Insights and WHO, each year 12 762 people are influenced by brain tumors [3]. Another estimation appear that 88,970 individuals will get an essential brain tumor determination in 2022 and the middle age at determination for an essential brain tumor is 61 a long time [4]. Later work has appeared that classification of human brain in (MR) pictures is conceivable through directed procedures such as counterfeit neural systems and bolster vector machine (SVM), and unsupervised classification procedures such as self-organization outline (SOM) and fluffy c-means. Other administered classification strategies, such as Convolutional Neural Organize (CNN) can be utilized to classify the normal/pathological MRI pictures.

CHAPTER 2: LITERATURE REVIEW

Author	Year	Paper	Method	Keywords	Findings
Chavan, Nikita V., B. D. Jadhav, and P. M. Patil [1].	2015	Detection and classification of brain tumors.	GLCM	MRI Images, Gaussian filter, Feature Extraction, (GLCM), K-NN	We can use Some Deep learning algorithm to improve accuracy more than 92% to 95%.
Gurunathan A, Krishnan B [2].	2020	Diagnosis of brain tumors using deep learning convolutional neural networks.	LeNET CNN	brain, deep learning, machine learning, segmentation, tumors	So difficult to understand the used architecture.
Das, S., Aranya, O. R. R., & Labiba, N. N [8].	2019	Brain tumor classification using convolutional neural network.	D Probabilistic Deep Learning, V-Net architecture	***Brain Tumor; Convolutional Neural Network; Kernel; Histogram Equalization; Feature Maps; Adam Optimization;***	Image resolution too low and feature are not sufficient

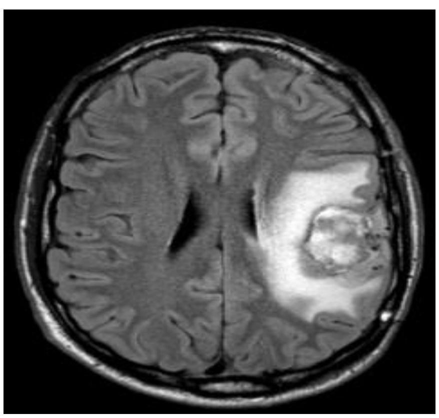
Sazzad, T. S., Ahmmed, K. T., Hoque, M. U., & Rahman, M [7].	2019	Development of automated brain tumor identification using MRI images.	PCA	**Brain Tumor, MRI Images, OTSU's thresholding based Segmentation.**	Accuracy reduced for mot batch of data.
Arif, M., Ajesh, F., Shamsudheen, S., Geman, O., Izdrui, D., & Vicoveanu, D[20].	2022	Brain tumor detection and classification by MRI using biologically inspired orthogonal wavelet transform and deep learning techniques.	BWT algorithm. GLCM, algorithm. SVM Na¨ıve Bayes, BOV-based SVM classifier,	MRI, SVM, CNN, GLCM	This method did not work out nicely.
Mohsen, H., El-Dahshan, E. S. A., El-Horbaty, E. S. M., & Salem [6].	2018	Classification using deep learning neural networks for brain tumors.	DWT, PCA	Deep learning; Discrete wavelet transform; Principle component analysis; Magnetic resonance images	Can increase performance by using CNN.

Saranya, N., & Renuka, D. K [9].	2021	Brain Tumor Classification Using Convolution Neural Network.	VGG)	inception; resnet brain tumor; VGG deep learning	Can be improve this model further re-architecture design.
Tonmoy Hossain; Fairuz Shadmani Shishir; Mohsena Ashraf; MD Abdullah Al Nasim; Faisal Muhammad Shah[21].	2019	Brain Tumor Detection Using Convolutional Neural Network	SVM,KNN,CNN	Tumors , Image segmentation , Magnetic resonance imaging , Feature extraction , Brain modeling , Convolutional neural networks , Task analysis	The suggested system's observed accuracy can be enhanced.

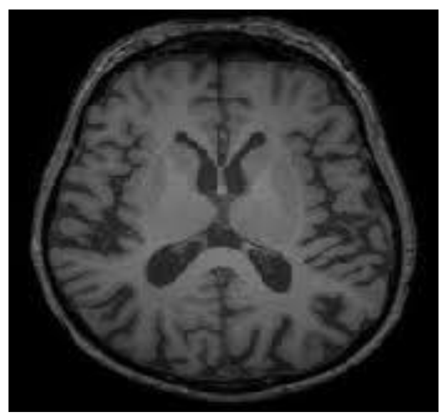
CHAPTER 3: METHODOLOGY

3.1 MR Image Dataset

This article uses brain MRI images from the Harvard Medical School open access dataset. This dataset consists of brain images annotated by his two independent experts in the field. The image has mixed pixel resolutions. In this article, a sample of 253 brain MRI images (155 positive, 98 negative) was acquired resulting in 253 sample images. Height or width with a resolution of 250 x 250.



a) Tumor positive



b) Tumor negative

Figure 1: MR image dataset sample

3.2 Methodology Structure

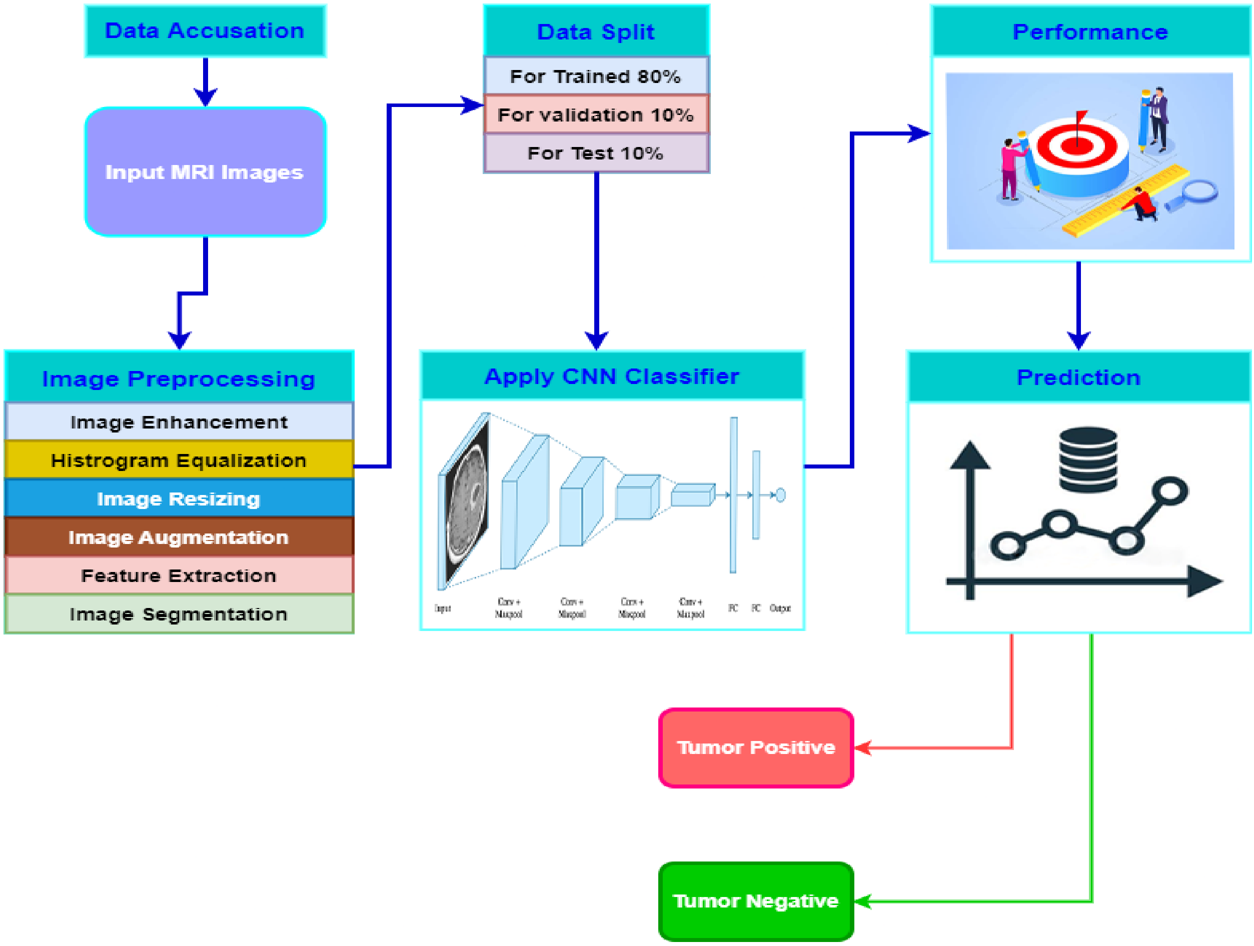


Figure 2: Research Methodology

3.3 Image Pre-Processing

Therapeutic picture investigation run into the pre-processing, since of the commotion might be included to the MR pictures due to imaging gadgets. This study is utilized picture enhancement, picture resizing, Picture augmentation, picture segmentation,

3.3.1 Image Enhancement

Picture enhancement is a picture preparing strategy to extend worldwide differentiate of a picture utilizing the picture escalated histogram. This strategy needs no parameter, but it some of the time comes about in an unnatural looking image. The major issue within prepare of discovery of border of tumor is that the tumor shows up exceptionally dim on the picture that is exceptionally confounding or hazy. To fathom that issue, Histogram Equalization has used on picture, which progress differentiate of MRI picture to make strides attribute [5].

3.3.1.1 Histogram Equalization

To begin with normalize the escalated values between 0 to 1. Map the concentrated values employing a monotonically expanding work S given by,

Sk = T (rk) = (L - 1) Pkj=0r (r j)

= (L-1) nkj=0j / MN ……k= 0, 1,.. .L-1

= (L-1)/MN nkj=0j…………………… …… (2)

Where, sk= output image, rk =Input image with intensity &T (rk) = Transformation function.

Using the Histogram equalization, transform the original image to a histogram equalized image using the intensity rk into a corresponding pixel with level sk in the output image [6].

3.3.2 Image Resizing

Image resizing is an important preprocessing step in computer vision. Our machine learning models typically train faster on smaller images. Additionally, many deep learning model designs require that the photos be the same size, even if the raw images collected are of different sizes. All photos must be scaled to 250x250 before feeding to the CNN, as the neural network requires the same input size. The less shrinkage required, the larger the fixed size. Less shrinkage means less distortion of image features and patterns.

3.3.3 Image Augmentation

Image augmentation may be a strategy of altering existing pictures in arrange to create extra information for the demonstrate preparing handle. In other words, it is the method of misleadingly expanding the dataset accessible for profound learning demonstrate preparing. Image augmentation is a technique for expanding a data collection artificially. This is useful when dealing with a data collection that has only a few data samples. This is a terrible circumstance in Deep Learning since the model tends to over-fit when we train it on a small number of data samples. We generated positive 1085 and 980 negative images by augmentation from 155 positive and 98 negative images.

3.3.4 Image Segmentation

One of the most important operations in computer vision is division. Image segmentation is the allocation of parts of an image that are clustered together and located in the same object class. This preparation is also called pixel-level classification. In other words, the image (or video frame) must be split into multiple fragments or objects. For sectioning we are going utilize binarization technique. Image binarization is utilized as pre-processor which changes over gray scale picture in to a twofold picture (either dark or white) base on a few edge esteem. The only thresholding strategies supplant each pixel in an picture with a dark pixel in the event that the picture concentrated $I_{i,j}$ is less than a few settled steady T (that's $I_{i,j} < T$), or a white pixel in the event that the picture concentrated is more prominent than that consistent. There was a swell utilized for segmentation because it is most reasonable for the show application in arrange to discover a binarized picture with gray level 1 speaking to the tumor locale and gray level 0 speaking to the rear [7].

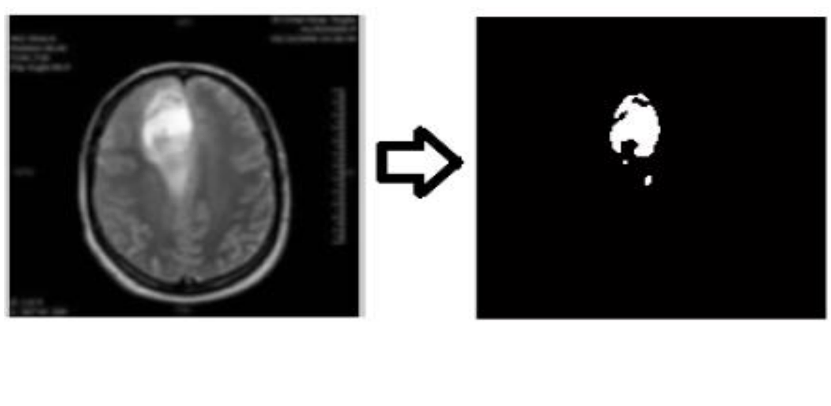


Figure 3: Brain tumor Segmented Image

3.3.5 Feature Extraction

Working with expansive sums of information in machine learning can be a dull assignment. It takes a pointless sum of time and capacity and a part of the input information is frequently repetitive. Usually where feature extraction comes in. Include extraction may be a procedure utilized to diminish a large input information set into pertinent highlights. Typically done with dimensionality diminishment to convert expansive input information into littler, significant bunches for handling.

Benefits

Feature extraction can demonstrate supportive when preparing a machine learning demonstrate. It leads to:

A Boost in training speed

- An improvement in model accuracy
- Overfitting risk reduction.
- Improved Data Visualization.
- Increase in explain ability of our model.

GLCM matrix highlights are used to distinguish between typical and abnormal brain tumors. GLCM is Gray Level Co-occurrence Grid (GLCM), also known as Gray Level Spatial Matrix. A GLCM is a matrix whose number of rows and columns equals the number of gray levels in the image [8].

Gray level co-occurrence matrix (GLCM):

A grayscale co-occurrence matrix (GLCM) is essentially a two-dimensional histogram. The GLCM strategy takes into account spatial relationships between pixels of different gray levels. This strategy computes GLCM by calculating how regularly a pixel with a given concentration i occurs relative to another pixel j at a given discrete d and introduction ϴ. Co-occurrence networks can be recognized by their relative frequencies P (i, j, d, ϴ). The co-occurrence network is therefore the task of removing d, the point ϴ, and the dimensional scales i and j. [9].

Texture Features: Surface highlights utilized within the investigation and elucidation of pictures. Whereas the gray-level co-occurrence framework (GLCM) is generated, contained textures can be properly computed from a grayscale co-occurrence network (GLCM). GLCM is extracted from each image. Co-occurrence networks are computed in four directions: 0, 45, 90, and 135 degrees. The following measurable surface highlights are computed:

1] Entropy - measures the arbitrariness that can be used to characterize the surface of the input image. Entropy is when all Pij are 0. Entropy = $-\ pi, * \log 2(\ pi, j)$..(3)

2] Relationship - The degree to which a pixel is related to its neighbors across the image, run [-1 1]. The correlation is 1 or -1 for perfectly enhanced or unfavorably connected images. Relation = $\boldsymbol{i}-\boldsymbol{i}\ \boldsymbol{j}-\square\boldsymbol{j}\ \boldsymbol{p}\ (\boldsymbol{i},)\boldsymbol{i}\ \boldsymbol{\sigma j i,j}$ ..(4)

3] Energy – Returns the sum of the squared components in the GLCM, Run[0 1]. For a consistent image, the energy is 1. Vitality = pi, (i , j)2… (5)

4] Homogeneity - distribution of components within the GLCM and spatial proximity across the GLCM to measure Range [0 1] for edge-to-edge GLCM, uniformity is 1. Uniformity = (i,j)1+ $i-j$ i,j. ... (6)

5] Differential - The degree of centralized differentiation between the pixel and its neighbors across the image. Differentiation is for a consistent image. Differential = $i-j$ i,2 p (i, j).. (7)

3.4 Data Split:

By the way, the data was part of the intake: 80% of the information for training. 10% of the information for approval. 10% of the information for testing.

3.5 Classification

In this study we proposed a CNN learning design for classification, and the classifier distinguishes brain tumors on brain MRI. Techniques that have been proposed to classify brain tumors on brain takes after:

Step 1: Data acquisition

Step 2: Picture segment

Step 3: Extracting feature from images

Step 4: Classification using CNN

Classification is the method of assigning courses to specific tests based on information gathered by classifiers during preparation. Its job is to point the input design addressed by the vector to one of a number of predefined classes. In this article, we use a CNN classifier to classify MRI images of the brain between healthy or tumor brain. In this article we will use mainly CNN Algorithm.

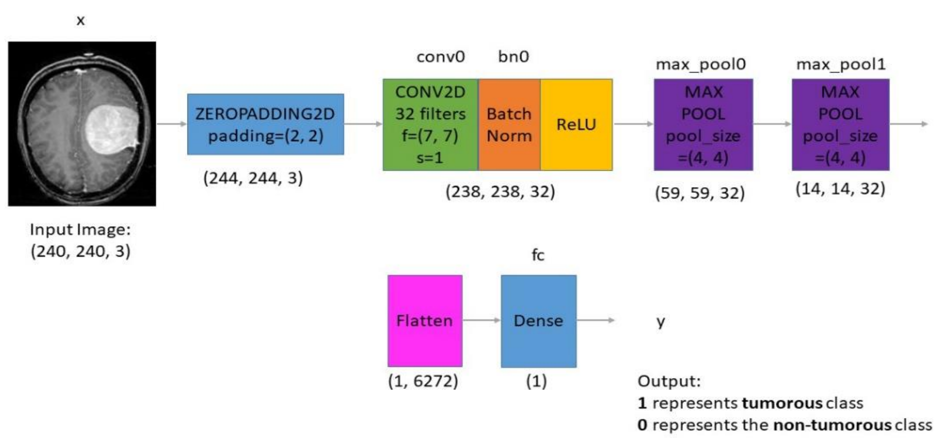


Figure 4: CNN Architecture

3.5.1 Architecture Overview:

Each input x(image) contains the form (240, 240, 3) and is inserted into the neural array. And then go through the next layer.

Zero-loss layer with pool estimates of (2, 2).

32-channel convolutional layer. The channel estimate is (7, 7) and the walk break even is to 1.

A group normalization layer that normalizes pixel values to speed up computation.

ReLU translation layer.

max pooling layer with f=4 and s=4. Max pooling layer with f=4 and s=4 as before.

Linearization plane for linearizing a 3D grid into a 1D vector. A thick (yield unit) layer perfectly associated with neurons with sigmoidal runs.

3.5.2 Why this architecture?

In general, CNNs tend to be more powerful and accurate methods for solving classification problems. We initially combined exchange learning with ResNet50 and vgg-16, but these models were too complex to measure information and overfit. Of course, applying exchange learning to these models using information augmentation yields excellent results. However, I use the preparation on computers with limited hardware resources. Therefore, computational complexity and memory limitations had to be considered.

CHAPTER 4: ANALYSIS & PERFORMANCE

4.1 Validation: Model validation is a method of evaluating a prepared demonstration using a set of test information. The test data set could be split packets of the same set of information from which the preparation set is persuaded. The most reason of utilizing the testing information set is to test the generalization capacity of a prepared show. Demonstrate approval is carried out after demonstrate preparing.

Figure 5: Training and validation loss

This plot x-axis is for epoch and y-axis for performance rate at every epoch. Yellow color shows validation loss and greenish color shows training loss.

This plot illustrates some performance measure validation for the model. It shows that loss and validation are used to evaluate the model. The model achieved the precision of 94%, 98% for Class negative and positive respectively that show in the next chapter. The model was trained for 24 epochs and these are the loss plots. We can see that more epoch produce more less validation loss.

Our method is very data intensive algorithm. That's why its produce less loss with more annotation data with more epoch.

4.2 Accuracy: Accuracy is one metric for assessing classification models. Casually, exactness is the division of forecasts our show got right. Formally, exactness has the taking after definition: Exactness = Number of adjust expectations Add up to number of predictions.

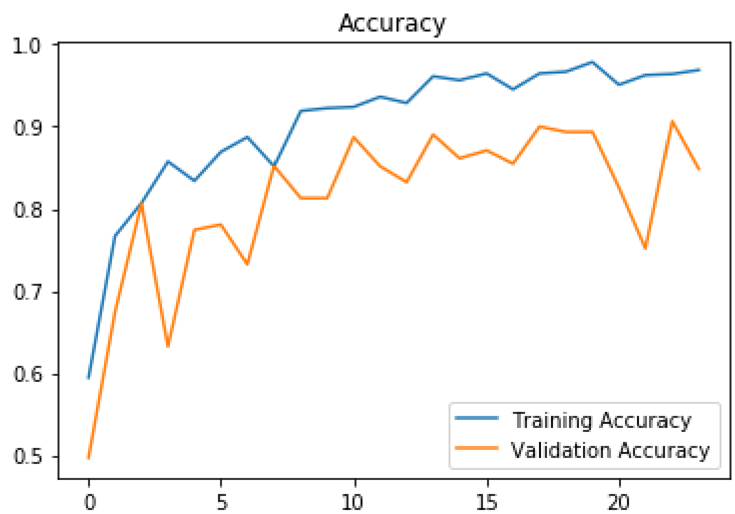


Figure 6: Training and validation accuracy

This plot x-axis is for epoch and y-axis for performance rate at every epoch. Yellow color shows validation accuracy and greenish color shows training accuracy.

The most excellent validation precision was accomplished on the 23rd iteration. The designed architecture or framework is also analyzed with respect to simulation environment parameters and metrics. Sensitivity and specificity define the number of correctly correlated tumor area pixels, and precision defines the total number of tumor and non-tumor pixels accurately detected in the final segmented brain image of the tumor area. To do. Accuracy defines well-detected non-tumor pixels and disc similarity index indicates the total number of similar tumor-detected pixels including the ground truth image. All these parameters are measured in percent and vary from 0.1 to 1.0.

CHAPTER 5: RESULT & DISCUSSION

5.1 Result

Now, the best performing model is which perform best on test set. Our model detects brain tumor with:

97.3% accuracy on the test set.

0.96 f1 score on the test set.

Above results are impressive that the data is not so rich.

Result are given below:

	Validation set	Test set
Accuracy	98.6%	89%
F1 score	0.98	0.88

The method proposed in this article is simulated using a notebook with python environment with a 16GB memory and a 3.6GHz CPU. This developed framework is evaluated in terms of classification rate, which is the ratio between correctly recognized images and the total images considered in this work. The proposed system classifies 155 brain MRI images as normal, achieving a classification rate of 97.3%. This framework also classified 105 brain MRI images as abnormal against 102, receiving a classification rate of 98% for the abnormal category. Therefore, this framework based on the CNN approach achieves an average detecting rate of 97.3%.

5.2 Comparing Result with other algorithm:

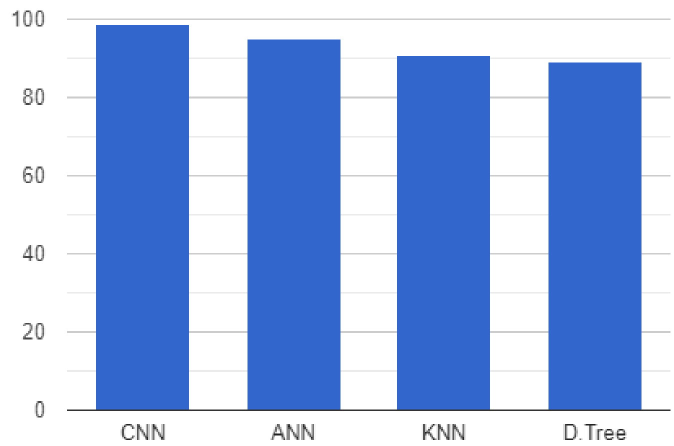


Figure 7: Different algorithm performance

We can see that CNN perform superior over ANN, KNN, and Decision Tree. CNN perform better when we have big dataset to find tumor cell. Our model produce The F1 score is defined as the harmonic mean of precision and recall 0.98 that is very good perform comparing to other others model. Overall accuracy is more than 97% for positive and 97.3% for negative tumor cell detection.

5.3 Discussion

A CNN is proposed in this framework to identify tumor-affected images. CNN architecture is designed with convolutional layers and pooling layers by NN. Neural network algorithms generate output patterns for either tumor-affected or non-tumor-affected brain images. Morphological segmentation methods, including dilation followed by erosion in neoplastic brain images, are then used to identify neoplastic pixels. The proposed method is tested on brain MRI images acquired from open-access datasets. The performance of this proposed method is analyzed in terms of classification rate, sensitivity, specificity and accuracy. The proposed brain tumor detection achieves an average classification accuracy of 98% His, with a sensitivity of 97.2%, a specificity of 98.9% and a tumor segmentation result of 98.5%. Additionally, diagnostics are performed using the CNN architecture. The average diagnosis rate using the proposed CNN framework is about 97.7%. Tumor regions in thermally scanned brain images are identified as promising regions.

CHAPTER 6: CONCLUSION

Physically location of brain tumor isn't as it were a long prepare but moreover the victory rate depends on the individual who is doing it adjacent to, programmed approaches takes less time but comprises of numerous complex approaches. This inquire about not as it were contracts down the approaches which diminish the time but moreover gives the higher precision comparing to others. As early location of tumor is exceptionally imperative for a brain tumor understanding, this investigate will help the pathologists to distinguish brain tumor more rapidly with higher precision. But it is still conceivable to extend the exactness rate and subsequently there's still scope to work with brain tumor MRI gray-scale pictures. On the off chance that picture quality remains comparative for diverse research facilities and specialists intra and inters observation inconstancy issues can be minimized at that point in future it'll be possible to extend the precision rate. In this circumstance the as it were parameter will need to be calibrated is the tumor locale region in pixels which falls in between (200-20000). The proposed brain tumor detection achieves an average classification accuracy of 97.3% with a sensitivity of 97.2%, a specificity of 98% and a tumor segmentation result of 98.5%. Additionally, diagnostics are performed using the CNN architecture. LBP features along with GLCM are used in this framework for tumor diagnosis. The average diagnosis rate using the proposed CNN framework is about 97.3%. Tumor regions in thermally scanned brain images are identified as promising regions.

CHAPTER 7: FUTURE WORK

In this paper we proposed an effective technique which combines the Histogram equalization to classify the brain MRIs into Normal and dangerous brain tumors. The new methodology design take after Neural Network with more layer architecture but requires more hardware specifications and takes a helpful time of handling for huge estimate pictures .The great comes about accomplished utilizing the DWT seem be employed with the CNN within the future and compare the results.

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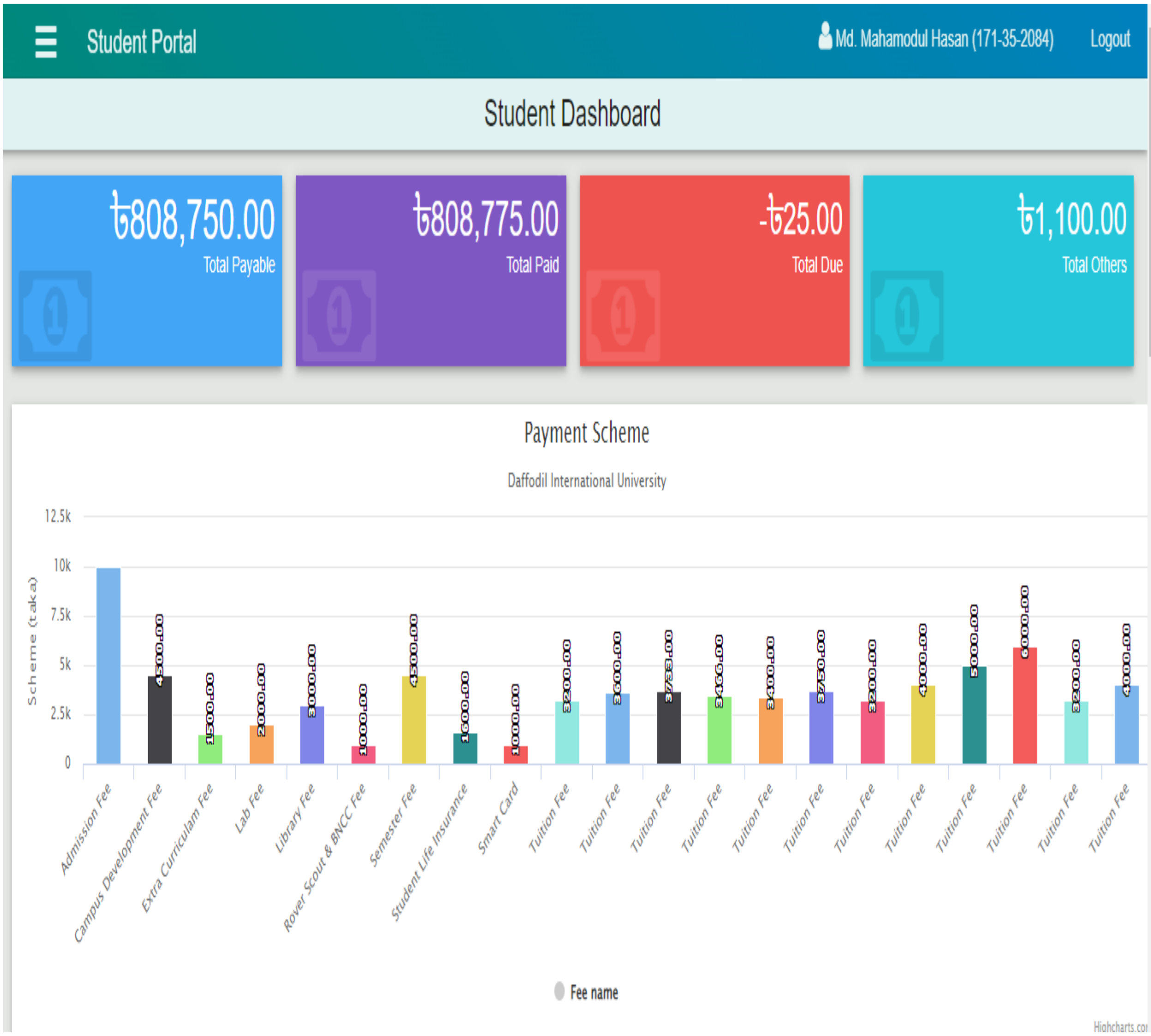
Classifying & Detecting Brain Tumor Using CNN from MR Images Submitted by Md. Mahamodul Hasan ID: 171-35-2084 Department of Software Engineering Daffodil International University Supervised by Dr. Imran Mahmud Head & Associate Professor Department of Software Engineering Daffodil International University This Thesis paper has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering. © All right Reserved by Daffodil International University Abstract The frequency of brain tumors is expanding quickly especially within the youthful era. Tumors can specifically devastate all sound brain cells. Hands on examination could be produce errors. Modified examination methodology is required since it lessens the stack on the human onlooker, exactness isn't influenced due to expansive number of pictures. The discovery of brain tumors in brain (MRI) picture is a critical handle for avoiding prior passing. This article proposes a mechanized computer supported strategy for recognizing and finding the brain tumors in brain MRI pictures utilizing profound learning calculations. Deep learning is perhaps the unexplored frontier of machine learning that has received a lot of attention in recent years. It was broadly connected to a few applications and demonstrated to be a capable machine learning instrument for numerous of the complex issues. In this paper we utilized CNN classifier which is one of the DL structures for classifying a dataset of brain MRIs into two classes e.g. ordinary cell & tumors cell. The classifier was combined with the picture upgrade instrument and picture division Also, coercion scores were very high for all coercion actions. The proposed technique is connected on the brain pictures from open get to dataset. The experimental comes about appeared that the proposed approach able to perform superior compare to existing accessible approaches in terms of precision whereas keeping up the pathology experts' worthy precision rate. Keywords: CNN, MRI, Brain, Deep Learning, classification, feature extraction CHAPTER 1: INTRODUCTION Within the past few a long time since of AI and Profound learning, critical advancement has been made within the restorative science like Restorative Picture preparing strategy which makes a difference specialists to the analyze infection early and effectively, sometime recently that, it was monotonous and time-consuming. So to resolve such kind of impediments computer-aided innovation is much required since Therapeutic Field needs proficient and solid strategies to analyze life-threatening maladies like cancer, which is the driving cause of mortality universally for patients. The quick advancement of wellbeing care innovation within the field of data and communication designing is utilized to deliver the quick recuperating arrangements for numerous wellbeing care issues of the patients around the world. That's why AI has come to unravel such an issue like this. Brain is the most foremost important organs in our body that workhouse with huge of cells. Brain tumors emerge when there is intemperate cell division shaping an anomalous gather of cells around or interior the brain. That gather of cells can influence the ordinary usefulness of the brain movement and devastate the healthy cells [1]. The rate of brain tumors is expanding quickly especially within the youthful era. Tumors can straightforwardly crush all sound cells. Physical investigation can be human blunder. Automatic classification strategy is required since it diminishes the stack on the human spectator, exactness isn't influenced due to expansive number of pictures. This paper explains endeavor to location &classification of tumor in kind organize. Proposed strategy comprises of two period to be specific picture division and classification. Within the to begin with arrange, gotten the highlights related to MRI pictures utilizing division [2]. For fragmenting we'll utilize binarization technique. Base this methods, we will separate the abnormal section of the images and other stage, the classifier is classified images using Convolutional Neural Network (CNN) classifier. This process is also called pixel-level classification. That is, dividing an image into multiple segments. Concurring to the report gotten from NCE Insights and WHO, each year 12 762 people are influenced by brain tumors [3]. Another estimation appear that 88,970 individuals will get an essential brain tumor determination in 2022 and the middle age at determination for an essential brain tumor is 61 a long time [4]. Later work has appeared that classification of human brain in (MR) pictures is conceivable through directed procedures such as counterfeit neural systems and bolster vector machine (SVM), and unsupervised classification procedures such as self-organization outline (SOM) and fluffy c-means. Other administered classification strategies, such as Convolutional

Neural Organize (CNN) can be utilized to classify the normal/pathological MRI pictures. CHAPTER 3: METHODOLOGY 3.1 MR Image Dataset This article uses brain MRI images from the Harvard Medical School open access dataset. This dataset consists of brain images annotated by his two independent experts in the field. The image has mixed pixel resolutions. In this article, a sample of 253 brain MRI images (155 positive, 98 negative) was acquired resulting in 253 sample images. Height or width with a resolution of 250 x 250. a) Tumor positive b) Tumor negative Figure 1: MR image dataset sample 3.2 Methodology Structure Figure 2: Research Methodology 3.3 Image Pre-Processing Therapeutic picture investigation run into the pre-processing, since of the commotion might be included to the MR pictures due to imaging gadgets. This study is utilized picture enhancement, picture resizing, Picture augmentation, picture segmentation, 3.3.1 Image Enhancement Picture enhancement is a picture preparing strategy to extend worldwide differentiate of a picture utilizing the picture escalated histogram. This strategy needs no parameter, but it some of the time comes about in an unnatural looking image. The major issue within prepare of discovery of border of tumor is that the tumor shows up exceptionally dim on the picture that is exceptionally confounding or hazy. To fathom that issue, Histogram Equalization has used on picture, which progress differentiate of MRI picture to make strides attribute [5]. 3.3.1.1 Histogram Equalization To begin with normalize the escalated values between 0 to 1. Map the concentrated values employing a monotonically expanding work S given by, Sk = T (rk) = (L - 1) Pii=0r (r i) = (L-1) nii=0j / MN .....k= 0, 1,... .L-1 = (L-1)/MN nii=0j...................... ...... (2) Where, sk= output image, rk =Input image with intensity &T (rk) = Transformation function. Using the Histogram equalization, transform the original image to a histogram equalized image using the intensity rk into a corresponding pixel with level sk in the output image [6]. 3.3.2 Image Resizing Image resizing is an important preprocessing step in computer vision. Our machine learning models typically train faster on smaller images. Additionally, many deep learning model designs require that the photos be the same size, even if the raw images collected are of different sizes. All photos must be scaled to 250x250 before feeding to the CNN, as the neural network requires the same input size. The less shrinkage required, the larger the fixed size. Less shrinkage means less distortion of image features and patterns. 3.3.3 Image Augmentation Image augmentation may be a strategy of altering existing pictures in arrange to create extra information for the demonstrate preparing handle. In other words, it is the method of misleadingly expanding the dataset accessible for profound learning demonstrate preparing. Image augmentation is a technique for expanding a data collection artificially. This is useful when dealing with a data collection that has only a few data samples. This is a terrible circumstance in Deep Learning since the model tends to over-fit when we train it on a small number of data samples. We generated positive 1085 and 980 negative images by augmentation from 155 positive and 98 negative images. 3.3.4 Image Segmentation One of the most important operations in computer vision is division. Image segmentation is the allocation of parts of an image that are clustered together and located in the same object class. This preparation is also called pixel-level classification. In other words, the image (or video frame) must be split into multiple fragments or objects. For sectioning we are going utilize binarization technique. Image binarization is utilized as pre-processor which changes over gray scale picture in to a twofold picture (either dark or white) base on a few edge esteem. The only thresholding strategies supplant each pixel in an picture with a dark pixel in the event that the picture concentrated Ii,j is less than a few settled steady T (that's Ii,j < T), or a white pixel in the event that the picture concentrated is more prominent than that consistent. There was a swell utilized for segmentation because it is most reasonable for the show application in arrange to discover a binarized picture with gray level 1 speaking to the tumor locale and gray level 0 speaking to the rear [7]. Figure 3: Brain tumor Segmented Image 3.3.5 Feature Extraction Working with expansive sums of information in machine learning can be a dull assignment. It takes a pointless sum of time and capacity and a part of the input information is frequently repetitive. Usually where feature extraction comes in. Include extraction may be a procedure utilized to diminish a large input information set into pertinent highlights. Typically done with dimensionality diminishment to convert expansive input information into littler, significant bunches for handling. Benefits Feature extraction can demonstrate supportive when preparing a machine learning demonstrate. It leads to: A Boost in training speed ? An improvement in model accuracy ? Overfitting risk reduction. ? Improved Data Visualization. ? Increase in explain ability of our model. GLCM matrix highlights are used to distinguish between typical and abnormal brain tumors. GLCM is Gray Level Co-occurrence Grid (GLCM), also known as Gray Level Spatial Matrix. A GLCM is a matrix whose number of rows and columns equals the number of gray levels in the image [8]. Gray level co-occurrence matrix (GLCM): A grayscale co-occurrence matrix (GLCM) is essentially a two-dimensional histogram. The GLCM strategy takes into account spatial relationships between pixels of different gray levels. This strategy computes GLCM by calculating how regularly a pixel with a given concentration i occurs relative to another pixel j at a given discrete d and introduction θ. Co-occurrence networks can be recognized by their relative frequencies P (i, j, d, θ). The co-occurrence network is therefore the task of removing d, the point θ, and the dimensional scales i and j. [9]. Texture Features: Surface highlights utilized within the investigation and elucidation of pictures. Whereas the gray-level co-occurrence framework (GLCM) is generated, contained textures can be properly computed from a grayscale co-occurrence network (GLCM). GLCM is extracted from each image. Co-occurrence networks are computed in four directions: 0, 45, 90, and 135 degrees. The following measurable surface highlights are computed: 1] Entropy - measures the arbitrariness that can be used to characterize the surface of the input image. Entropy is when all Pij are 0. Entropy = − pi, • log2(pi, i)..(3) 2] Relationship - The degree to which a pixel is related to its neighbors across the image, run [-1 1]. The correlation is 1 or -1 for perfectly enhanced or unfavorably connected images. Relation = i=i i= i p (i,)i σii,i ..(4) 3] Energy – Returns the sum of the squared components in the GLCM, Run[0 1]. For a consistent image, the energy is 1. Vitality = pi, (i , j)2... (5) 4] Homogeneity - distribution of components within the GLCM and spatial proximity across the GLCM to measure Range [0 1] for edge-to-edge GLCM, uniformity is 1. Uniformity = (i,i)1+ i=i i,i. ... (6) 5] Differential - The degree of centralized differentiation between the pixel and its neighbors across the image. Differentiation is for a consistent image. Differential = i=i i,2 p (i, j).. (7) 3.4 Data Split: By the way, the data was part of the intake: 80% of the information for training. 10% of the information for approval. 10% of the information for testing. 3.5 Classification In this study we proposed a CNN learning design for classification, and the classifier distinguishes brain tumors on brain MRI. Techniques that have been proposed to classify brain tumors on brain takes after: Step 1: Data acquisition Step 2: Picture segment Step 3: Extracting feature from images Step 4: Classification using CNN Classification is the method of assigning courses to specific tests based on information gathered by classifiers during preparation. Its job is to point the input design addressed by the vector to one of a number of predefined classes. In this article, we use a CNN classifier to classify MRI images of the brain between healthy or tumor brain. In this article we will use mainly CNN Algorithm. Figure 4: CNN Architecture 3.5.1 Architecture Overview: Each input x(image) contains the form (240, 240, 3) and is inserted into the neural array. And then go through the next layer. Zero-loss layer with pool estimates of (2, 2). 32-channel convolutional layer. The channel estimate is (7, 7) and the walk break even is to 1. A group normalization layer that normalizes pixel values to speed up computation. ReLU translation layer. max pooling layer with f=4 and s=4. Max pooling layer with f=4 and s=4 as before. Linearization plane for linearizing a 3D grid into a 1D vector. A thick (yield unit) layer perfectly associated with neurons with sigmoidal runs. 3.5.2 Why this architecture? In general, CNNs tend to be more powerful and accurate methods for solving classification problems. We initially combined exchange learning with ResNet50 and vgg-16, but these models were too complex to measure information and overfit. Of course, applying exchange learning to these models using information augmentation yields excellent results. However, I use the preparation on computers with limited hardware resources. Therefore, computational complexity and memory limitations had to be considered. CHAPTER 4: ANALYSIS & PERFORMANCE 4.1 Validation: Model validation is a method of evaluating a prepared demonstration using a set of test information. The test data set could be split packets of the same set of information from which the preparation set is persuaded. The most reason of utilizing the testing information set is to test the generalization capacity of a prepared show. Demonstrate approval is carried out after demonstrate preparing. Figure 5: Training and validation loss This plot x-axis is for epoch and y-axis for performance rate at every epoch. Yellow color shows validation loss and greenish color shows training loss. This plot illustrates some performance measure validation for the model. It shows that loss and validation are used to evaluate the model. The model achieved the precision of 94%, 98% for Class negative and positive respectively that show in the next chapter. The model was trained for 24 epochs and these are the loss plots. We can see that more epoch produce more less validation loss. Our method is very data intensive algorithm. That's why its produce less loss with more annotation data with more epoch. 4.2 Accuracy: Accuracy is one metric for assessing classification models. Casually, exactness is the division of forecasts our show got right. Formally, exactness has the taking after definition: Exactness = Number of adjust expectations Add up to number of predictions. Figure 6: Training and validation accuracy This plot x-axis is for epoch and y-axis for performance rate at every epoch. Yellow color shows validation accuracy and greenish color shows training accuracy. The most excellent validation precision was accomplished on the 23rd iteration. The designed architecture or framework is also analyzed with respect to simulation environment parameters and metrics. Sensitivity and specificity define the number of correctly correlated tumor area pixels, and precision defines the total number of tumor and non-tumor pixels accurately detected in the final segmented brain image of the tumor area. To do. Accuracy defines well-detected non-tumor pixels and disc similarity index indicates the total number of similar tumor-detected pixels including the ground truth image. All these parameters are measured in percent and vary from 0.1 to 1.0. CHAPTER 5: RESULT & DISCUSSION 5.1 Result Now, the best performing model is which perform best on test set. Our model detects brain tumor with: 97.3% accuracy on the test set. 0.96 f1 score on the test set. Above results are impressive that the data is not so rich. Result are given below: Validation set Test set Accuracy 89.6% 97.3% F1 score 0.88 0.96 The method proposed in this article is simulated using a notebook with python environment with a 16GB memory and a 3.6GHz CPU. This developed framework is evaluated in terms of classification rate, which is the ratio between correctly recognized images and the total images considered in this work. The proposed system classifies 155 brain MRI images as normal, achieving a classification rate of 97.3%. This framework also classified 105 brain MRI images as abnormal against 102, receiving a classification rate of 98% for the abnormal category. Therefore, this framework based on the CNN approach achieves an average detecting rate of 97.3%. 5.2 Comparing Result with other algorithm: Figure 7: Different algorithm performance We can see that CNN perform superior over ANN, KNN, and Decision Tree. CNN perform better when we have big dataset to find tumor cell. Our model produce The F1 score is defined as the harmonic mean of precision and recall 0.98 that is very good perform comparing to other others model. Overall accuracy is more than 97% for positive and 97.3% for negative tumor cell detection. 5.3 Discussion A CNN is proposed in this framework to identify tumor-affected images. CNN architecture is designed with convolutional layers and pooling layers by NN. Neural network algorithms generate output patterns for either tumor-affected or non-tumor-affected brain images. Morphological segmentation methods, including dilation followed by erosion in neoplastic brain images, are then used to identify neoplastic pixels. The proposed method is tested on brain MRI images acquired from open-access datasets. The performance of this proposed method is analyzed in terms of classification rate, sensitivity, specificity and accuracy. The proposed brain tumor detection achieves an average classification accuracy of 98% His, with a sensitivity of 97.2%, a specificity of 98.9% and a tumor segmentation result of 98.5%. Additionally, diagnostics are performed using the CNN architecture. The average diagnosis rate using the proposed CNN framework is about 97.7%. Tumor regions in thermally scanned brain images are identified as promising regions. CHAPTER 6: CONCLUSION Physically location of brain tumor isn't as it were a long prepare but moreover the victory rate depends on the individual who is doing it adjacent to, programmed approaches takes less time but comprises of numerous complex approaches. This inquire about not as it were contracts down the approaches which diminish the time but moreover gives the higher precision comparing to others. As early location of tumor is exceptionally imperative for a brain tumor understanding, this investigate will help the pathologists to distinguish brain tumor more rapidly with higher precision. But it is still conceivable to extend the exactness rate and subsequently there's still scope to work with brain tumor MRI gray-scale pictures. On the off chance that picture quality remains comparative for diverse research facilities and specialists intra and inters observation inconstancy issues can be minimized at that point in future it'll be possible to extend the precision rate. In this circumstance the as it were parameter will need to be calibrated is the tumor locale region in pixels which falls in between (200-20000). Paraphrased Text The proposed brain tumor detection achieves an average classification accuracy of 97.3% with a sensitivity of 97.2%, a specificity of 98% and a tumor segmentation result of 98.5%. Additionally, diagnostics are performed using the CNN architecture. LBP features along with GLCM are used in this framework for tumor diagnosis. The average diagnosis rate using the proposed CNN framework is about 97.3%. Tumor regions in thermally scanned brain images are identified as promising regions. CHAPTER 7: FUTURE WORK In this paper we proposed an effective technique which combines the Histogram equalization to classify the brain MRIs into Normal and dangerous brain tumors. The new methodology design take after Neural Network with more layer architecture but requires more hardware specifications and takes a helpful time of handling for huge estimate pictures .The great comes about accomplished utilizing the DWT seem be employed with the CNN within the future and compare the results. 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22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