Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 3 (2023)

Efficient Method for Early Detection of Brain Tumor

*Dr. Bibin A D[1], Mrs. R Malarvizhi[2], Dr. Ben M. Jebin[3], Dr. Sam Abraham[4]

1 Assistant Professor, Department of Computer Science, Nadar Mahajana Sangam S Vellaichamy Nadar College, Madurai. E-mail: bibin@nmssvnc.edu.in.*Tel.: +91-7598515734*
2 Assistant Professor,Department of Computer Science, Nadar Mahajana Sangam S Vellaichamy Nadar College,Madurai.
E-mail:malarvizhi@nmssvnc.edu.in.
3 Assistant Professor, Department of Computer Science, Malankara Catholic College, Mariagiri, E-mail: benmjebin@gmail.com, Tel.: +91-9443391050.
4 Assistant Professor, Department of Computer Applications, Malankara Catholic College, Mariagiri,
E-mail: samabraham123@gmail.com, Tel.: +91-8848589501.

(Affiliated to Madurai Kamaraj University, Madurai)
**Corresponding Author* E-mail: bibinraj.ad@gmail.com,

Abstract

In this paper, a three-step preprocessing algorithm is proposed to enhance the quality of Magnetic Resonance Imaging (MRI) scans for more accurate detection of various brain diseases. This preprocessing algorithm is combined with a new deep convolutional neural network (DCNN) structure for effective diagnosis of glioma, meningioma, and pituitary. The proposed model is computationally lightweight with a small number of convolutional and max-pooling layers, as well as simple initialization of the layer weights. This allows for faster training with a higher learning rate. To compare the proposed architecture to other models discussed in the paper, a demonstrative contrast was performed. The results of this experiment showed an impressive accuracy of 98.22% for glioma detection, 99.13% for meningioma detection, 97.3% for pituitary detection, and 97.14% for normal images. This was tested on a dataset with 3394 MRI images. The results of this experiment prove the robustness of the proposed architecture, allowing for increased accuracy in the diagnosis of a variety of brain illnesses in a short amount of time.

Keywords: Computer-Aided Diagnosis (CAD), Deep Convolutional Neural Network (DCNN), world health organization (WHO), Magnetic Resonance Imaging (MRI), positron emission to myography (PET), Gray matter (GM), white matter (WM), traverse relaxation (TR).

1. INTRODUCTION

The human brain is the most important part of the body because it controls most of human actions such as memory, speech, thoughts and leg and arms movements. Brain diseases are mostly caused by the abnormal growth of brain cells, which directly damage the brain structure and lead to brain cancer. According to the world health organization (WHO) records, about 9.6 million on every side of the world died from cancer in 2018. Brain cancer is dangerous, rapidly growing and is deadly. Moreover, the complexity of brain construction is a major challenge, so timely and accurate diagnosis is necessary. The MRI images can provide better visualization of contrast and spatial definition. The detection of brain abnormalities process is an important issue to determine whether the abnormalities exist or not in MRI images. Researchers uses deep learning in a wide zone with many medical science fields. Since 2012, researchers have used deep convolutional neural networks (DCNNs) a lot, which achieved great success in the image classification process. Lately, DCNNs also scored promising results in the process of medical images classification.

Brain Tumor

The number of persons infected by brain tumors increases every year. Tumors are caused by abnormal growth of cells. Brain tumors can be benign (noncancerous tumors) or malignant (cancerous). They are also classified as primary and secondary. Primary tumors start in the brain or Central Nervous Systems whereas the secondary tumors spread from other body parts into the brain. Depending on the degree of abnormality of brain tissue, the tumors are typecast into four grading levels. Tumors with 1 and 2 are low grades which are less dangerous. 3 and 4 grade tumors are high-grade tumors that are highly susceptible to cancer. Primary tumors have several types amongst 36.1% all primary tumors are referred to as meningioma that is found near the top and outer curve of the brain. Meningioma is a slowly growing non-cancerous tumor that causes seizures and visual problems.

Glioma is an abnormal growth in glial cells present around the neurons in the brain. Pituitary tumors grow in pituitary glands that affect body functions. Meningioma is iso-dense dural-based masses developed at the meninges of the three layers of protecting tissue of the brain and spinal cord, whose diagnosis depends on its anatomical location, shape, and appearance of cells. Pituitary tumors are abnormal mass growth in cells around the surface of the pituitary gland located at the base of the skull. Early detection of primary brain tumors is highly complex because of their position, shape, and diversity. Non-invasive imaging techniques are based on the absorption properties of tissues. The delineation of absorption rates is very important for the precise imaging of tumors.

The three types of tumors concentrated on this case study are not much discriminative in terms of their absorption levels (Pixel gray level). Hence the shape of the tumors will play a major role in classifying them. Deep learning has evolved in recent years and is very successful in problems that involve pattern recognition or shape detection. Transfer learning made its way into Deep Learning which reduced the hectic work of training the models from scratch. For this reason, we opted for transfer learning with Resnet 50 that is pre-trained with an Image Net database that consists of more than 1000 different target classes. To make it suitable for brain tumor detection we utilized Discriminative Learning rates with Grab Cut and Skull stripping in pre-processing that allows the final layers to be only trained based on the MRI data while the basic pattern recognition is retained from the Resnet50 by using pre-trained weights.

The brain is a vital organ in the human body and responsible for control and decision making. As the managing center of nervous systems, this part is very essential to be protected from any harm and illness. Tumors are the predominant infections caused by abnormal growth of cells that damages the Brain. Meningioma, Glioma, and Pituitary are brain tumors as opposed to the other types. Meningiomas are mostly a non-cancerous class of tumors that often develop in the narrow walls that usually surround the brain. Brain tumors are one of the life-threatening diseases that can directly affect human lives. The correct understanding of brain tumor stages is an important task for the prevention and cure of illness. To do so, Magnetic Resonance Imaging (MRI) is widely used by radiologists to analyze brain tumors. The result of this analysis reveals whether the brain is normal or abnormal. On the other hand, it identifies the type of tumor in the case of abnormality. With the advent of machine learning, the processing of MR images to have a for fast and accurate detection of brain tumors matter.

Convolutional Neural Networks

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet ?? is similar to that of the connectivity pattern of Neurons in the human brain.

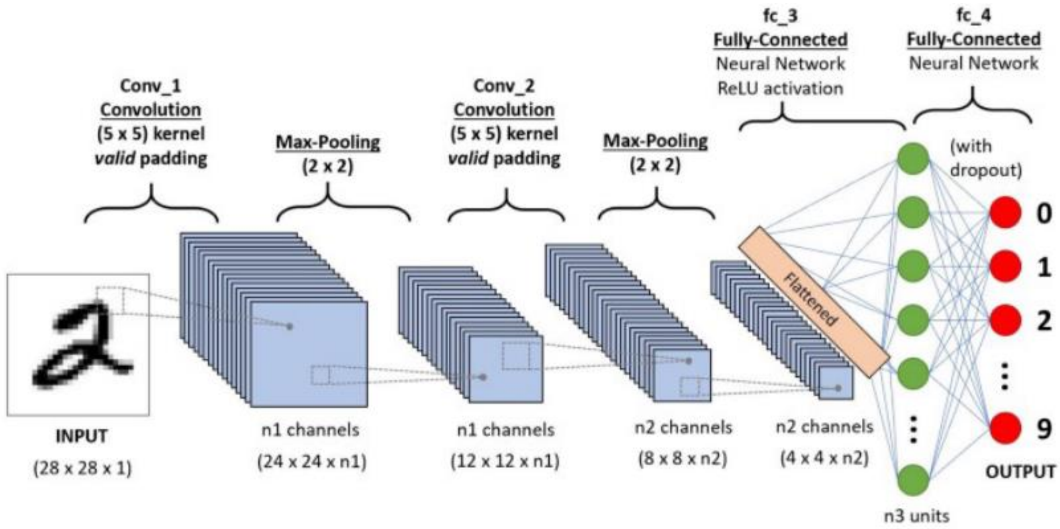

Figure 1.1: Convolutional neural network

A ConvNet is able to capture the spatial and temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and the reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.
The objective of the convolution operation is to extract high-level features such as edges from the input image. ConvNets need not be limited to only one convolutional layer. Conventionally, the first ConvLayer is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the high-level features as well, giving us a network that has a wholesome understanding of images in the dataset, similar to how we would. There are two types of results to the operation — one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding in case of the former, or the Same Padding in the case of the latter.

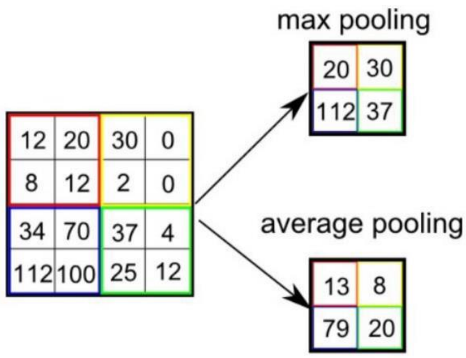

Figure 1.2: Pooling

Similar to the convolutional layer, the pooling layer is responsible for reducing the spatial size of the convolved feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effectively training of the model. There are two types of Pooling: Max Pooling and Average Pooling 1.2. Max Pooling returns the maximum value from the portion of the image covered by the Kernel.

On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling. The Convolutional Layer and the Pooling Layer, together form the i-th layer of a Convolutional Neural Network. Depending on the complexities in the images, the number of such layers may be increased for capturing low-levels details even further, but at the cost of more computational power.

The final output is flattened and feed it to a regular Neural Network for classification purposes. Adding a Fully-Connected layer 1.3 is a usual way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space. Now that we have converted our input image into a suitable form, we shall flatten the image into a column vector. The flattened output is fed to a feed-forward neural network and backpropagation applied to every iteration of training. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the softmax classification technique.

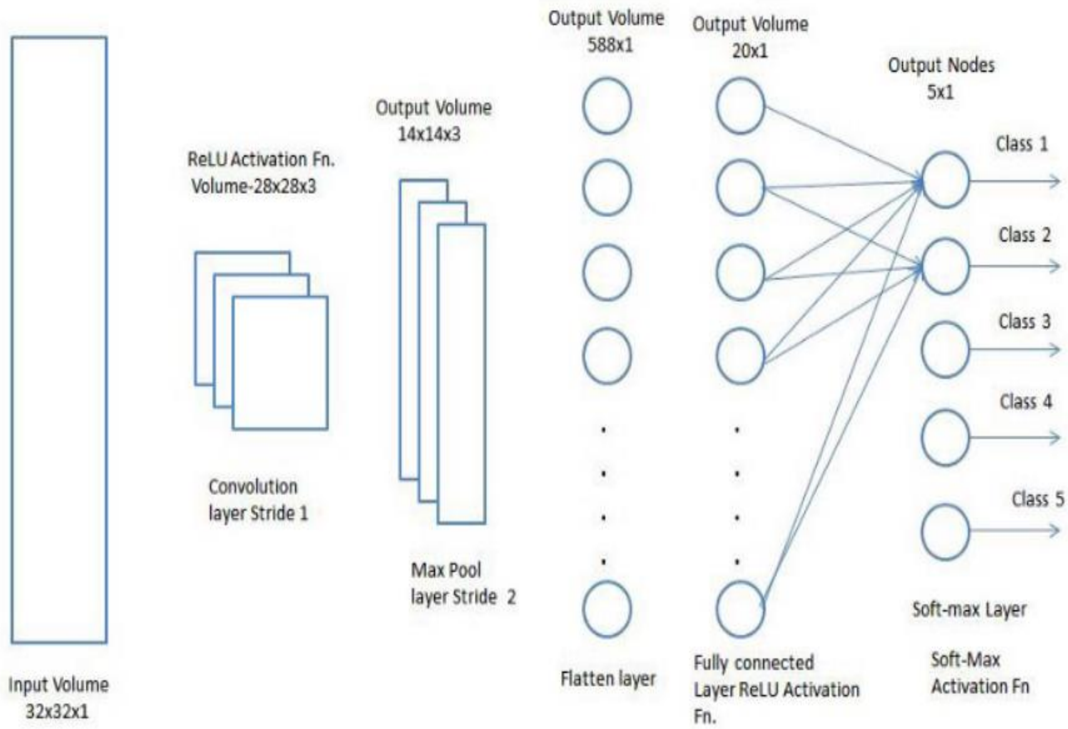

Figure 1.3: CNN classification - fully connected layer

Medical Imaging and Diagnostic Techniques of Brain Tumor

Timely diagnosis helps in treatment procedure. Different techniques are used for the diagnosis tumor and cause and effects of that disease like brain biopsy and brain imaging system.

Biopsy of brain is a procedure in which a hole is grilled in the skull and piece of tissue and tumor is removed to examine the tumor, type of tumor, its composition and cause of tumor under the microscope. FIGURE 1.4 shows the biopsy process. This technique is very risky for human life. Imaging technique is also used in biopsy to locate the tumor and get the part of tissue.

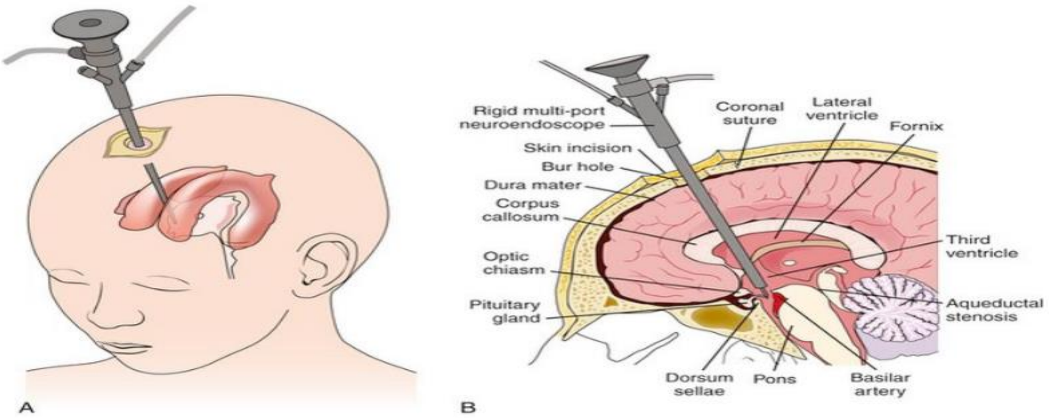

Figure 1.4 Biopsy of brain

Different imaging techniques are used to get the images of brain so that tumor can be diagnosed with its location and size of tumor like x-rays, CT scan and MRI. CT scan is an important imaging technique in the field of medical and provide in formation in seconds and usually the duration minimizes to the fraction of it. It helps in providing more clear information than X-rays but the risk of radiation exposure is very low.

PET is a positron emission tomography in which a radioactive material is injected in the blood and a scanner detects this material to get the image. This technique gives an idea of brain's activity and function. This method is cost effective harmful material is used.

X-rays is an imaging technique which does not give the detailed information about the organ. X-rays may cause skin cancer if it used multiple times on the same body and place. But this technique is less expensive and easy to use.

MRI is another technique which uses the radio frequency signals to get the image of brain. This imaging technique is our focusing technique.

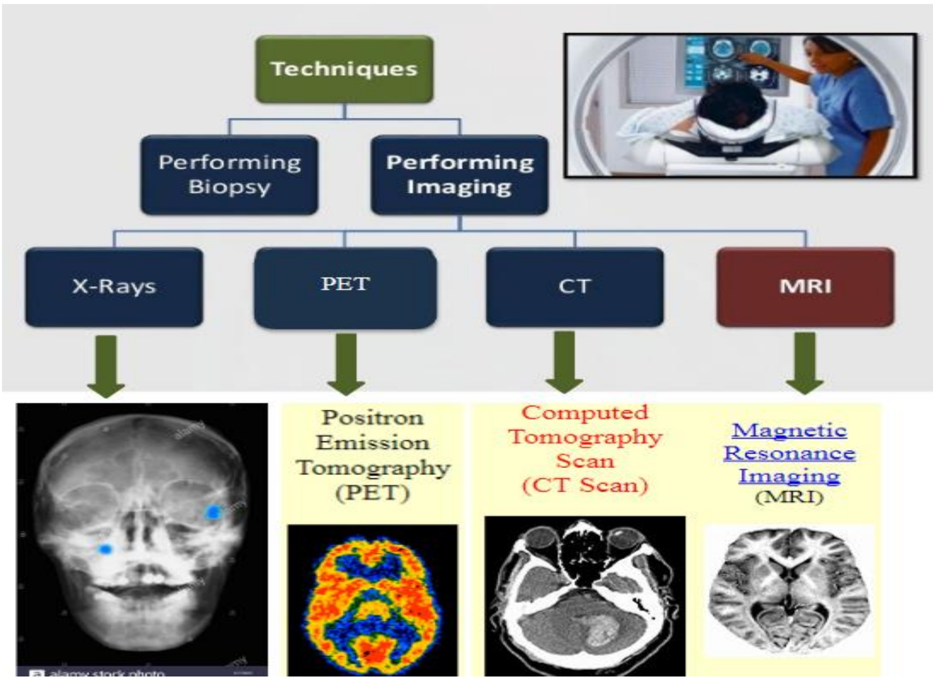

Figure 1.5 Different technique of Brain tumor imaging.

MR Image Characteristics of Brain Tumor

MRI is an imaging technique which is more useful than then X-ray. MR images do not used harmful radiations and provide the enough information for disease diagnosis and decision making for the doctors. MR Images are used in pre-processing of brain tumor detection and diagnosis. Different types of MRI are used in this procedure according to the requirement. Type of sequences used in MRI provided as an input in the preprocessing step like T1, T2 and FLAIR.

To understand the concept of different types of MRI images, it is necessary to clear the concept of the TE and TR. TE is the (time of echo) time difference between the delivery of RF pulse and the receiving of echo signal. TR is (repetition time) the reception time between two continuous pulses applied in a same sequence.

T1-weighted images: contain dark appearance of CSF and fluid. Gray matter (GM) is darker than white matter (WM). T1 gives better result in the case of brain structure images and fat appears brighter in this type. TE and TR time (TRà500msec, TEà14msec) is short to produce the images (uses longitudinal relaxation).

T2-weighted images: which contain higher signal intensity of CSF and fluid as compare to tissue and for that reason it appear bright. T2 used long time (TRà4000msec, TEà19msec) for TE and TR to produce images (traverse relaxation). T2 is brighter for water and fluid, ideal for the oedema tissue.

FLAIR is just like to T2 but it has attenuated CSF fluid but abnormalities remain bright. It is good for imaging the cerebral oedema. It uses very long TE and TR time (TRà9000msec, TEà114msec) for producing images. FIGURE1.6 represents the difference between these types of sequence in MRI image.

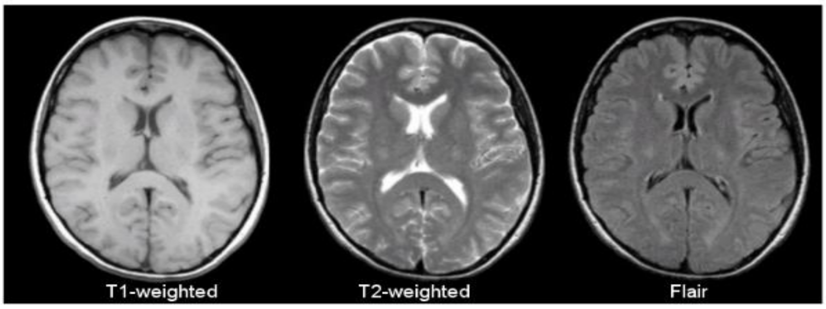

Figure 1.6 Type of MRI imaging technique

Tissues	T1-weighted	T2-weighted	FLAIR
CSF	Dark	Bright	Dark
White matter	Light	Dark grey	Dark grey
cortex	Grey	Light grey	Light grey
Fat(within bone marrow)	Bright	Light	Light
Inflammation (impurity)	Dark	Bright	Bright

Table 1.1 Represent the differences on the basis of different types of issues

Marks Of Brain Structure

Three-dimensional biological structure of the brain is used so that any point inside or on brain can be localized on three "axes" or "planes" - the x, y and z axes or planes. The brain is often imaged on two-dimensional images (slices). These slices are usually made in one of three orthogonal planes: coronal, horizontal (axial) and sagittal.

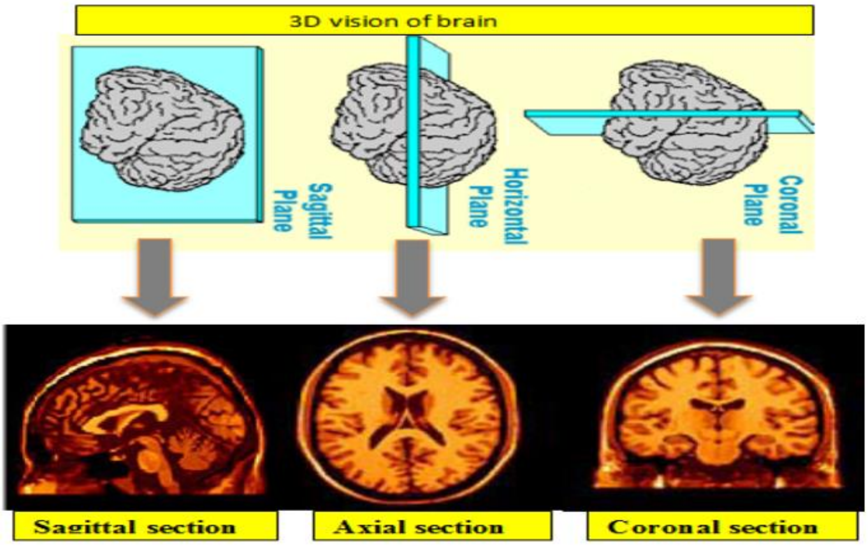

Figure 1.7 3D and 2D vision Brain

Objectives of the project

The objectives of the project is:

- A three-step pre-processing method is proposed as an initial step. The pre-processing method enhances the quality of the MRI images, stretches their histogram and improves their contrast.
- Measuring the quality of the output image with blind referenceless image spatial quality evaluator (BRISQUE) is used as an assessment on the pre-processing phase.
- A diagnosis architecture that uses DCNN to classify MRI images as glioma, meningioma, pituitary, and normal.
- The Batch normalization technique is applied to train the model faster, get a higher learning rate and enable initializing layer weights easier.
- An analytical detailed comparison of Glioma, Meningioma and Pituitary detection is conducted between the proposed architecture and well-known approaches including and the recent approaches like CNN-SVM

II) Related Work

To introduce the fundamentals of deep learning methods and review their successes in image registration, detection of anatomical and cellular structures, tissue segmentation, computer-aided disease diagnosis and prognosis, and so on[10] s typical multilayer neural networks that take vector-format (i.e., nonstructured) values as input and convolutional networks that take 2D or 3D (i.e., structured) values as input. Because of the structural characteristics of images (the structural or configural information contained in neighboring pixels or voxels is another important source of information), convolutional neural networks (CNNs) have attracted great interest in the field of medical image analysis.

The segmentation, detection, and extraction of infected tumor area from magnetic resonance (MR) images are a primary concern but a tedious and time taking task performed by radiologists or clinical experts, and their accuracy depends on their experience only. So, the use of computer aided technology becomes very necessary to overcome these limitations. In this study, to improve the performance and reduce the complexity involves in the medical image segmentation process, we have investigated Berkeley wavelet transformation (BWT) based brain tumor segmentation.[1] Furthermore, to improve the accuracy and quality rate of the support vector machine (SVM) based classifier, relevant features are extracted from each segmented tissue.

The experimental results of proposed technique have been evaluated and validated for performance and quality analysis on magnetic resonance brain images, based on accuracy, sensitivity, specificity, and dice similarity index coefficient. The experimental results achieved 96.51% accuracy, 94.2% specificity, and 97.72% sensitivity, demonstrating the effectiveness of the proposed technique for identifying normal and abnormal tissues from brain MR images. [12] propose a new measure, the method noise, to evaluate and compare the performance of digital image denoising methods. We first compute and analyze this method noise for a wide class of denoising algorithms, namely the local smoothing filters. Second, we propose a new algorithm, the nonlocal means (NL-means), based on a nonlocal averaging of all pixels in the image. Finally, we present some experiments comparing the NL-means algorithm and the local smoothing filters.[2] an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3 ×3 kernels.

The use of small kernels allows designing a deeper architecture, besides having a positive effect against overfitting, given the fewer number of weights in the network. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Our proposal was validated in the Brain Tumor Segmentation Challenge 2013 database (BRATS 2013), obtaining simultaneously the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric (0.88, 0.83, 0.77) for the Challenge data set. Also, it obtained the overall first position by the online evaluation platform.

We also participated in the on-site BRATS 2015 Challenge using the same model, obtaining the second place, with Dice Similarity Coefficient metric of 0.78, 0.65, and 0.75 for the complete, core, and enhancing regions, respectively.[13] The use of Gaussian filter as preprocessing for edge detection will also give rise to edge position displacement, edges vanishing, and phantom edges. In this paper, we first review various techniques for these problems. We then propose an adaptive Gaussian filtering algorithm in which the filter variance is adapted to both the noise characteristics and the local variance of the signal. [3] The proposed technique is based on the following computational methods, the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal.

The experiments were carried out on 101 images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The classification accuracy on both training and test images is 96% which was significantly good.[14] The reason for its success is its good performance and computational simplicity. The theoretical analysis of its deterministic and statistical properties has started at the end of the seventies. [5] n categorical object recognition, provide a detailed analysis of the current state of the field of large-scale image classification and object detection, and compare the state-ofthe-art computer vision accuracy with human accuracy. We conclude with lessons learned in the 5 years of the challenge, and propose future directions and improvements.[15] the full-reference peak signal-to-noise ratio and the structural similarity index, and is highly competitive with respect to all present-day distortion-generic NR IQA algorithms. BRISQUE has very low computational complexity, making it well suited for real time applications. BRISQUE features may be used for distortion-identification as well.

To illustrate a new practical application of BRISQUE, we describe how a nonblind image denoising algorithm can be augmented with BRISQUE in order to perform blind image denoising. [6] In this paper, we discuss some widely-used deep learning architectures and their practical applications. An up-to-date overview is provided on four deep learning architectures, namely, autoencoder, convolutional neural network, deep belief network, and restricted Boltzmann machine. Different types of deep neural networks are surveyed and recent progresses are summarized. [16] proposing a system performing detection and classification by using Deep Learning Algorithms using ConvolutionNeural Network (CNN), Artificial Neural Network (ANN), and TransferLearning (TL) would be helpful to doctors all around the world.[7] Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. This paper reviews the major deep learning concepts pertinent to medical image analysis and summarizes over 300 contributions to the field, most of which appeared in the last year.

We survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. [18] MRI has an advantage over CT in being able to detect flowing blood and cryptic vascular malformations. It can also detect demyelinating disease, and has no beam-hardening artifacts such as can be seen with CT. Thus, the posterior fossa is more easily visualized on MRI than CT. Imaging is also performed without any ionizing radiation.[20]T he results illustrate that the full-training of convnets using five spectral bands outperforms the other strategies for all convnets. InceptionResNetV2, ResNet50, and Xception are distinguished as the top three convnets, providing state-of-the-art classification accuracies of 96.17%, 94.81%, and 93.57%, respectively.

The classification accuracies obtained using Support Vector Machine (SVM) and Random Forest (RF) are 74.89% and 76.08%, respectively, considerably inferior relative to CNNs. Importantly, InceptionResNetV2 is consistently found to be superior compared to all other convnets, suggesting the integration of Inception and ResNet modules is an efficient architecture for classifying complex remote sensing scenes such as wetlands.

III) Objectives of the project

The objectives of the project is:

- A three-step pre-processing method is proposed as an initial step. The pre-processing method enhances the quality of the MRI images, stretches their histogram and improves their contrast.
- Measuring the quality of the output image with blind referenceless image spatial quality evaluator (BRISQUE) is used as an assessment on the pre-processing phase.
- A diagnosis architecture that uses DCNN to classify MRI images as glioma, meningioma, pituitary, and normal.
- The Batch normalization technique is applied to train the model faster, get a higher learning rate and enable initializing layer weights easier.
- An analytical detailed comparison of Glioma, Meningioma and Pituitary detection is conducted between the proposed architecture and well-known approaches including and the recent approaches like CNN-SVM

IV)PROJECT DESCRIPTION

4.1 About Project

THE PROPOSED PRE-PROCESSING APPROACH

In the classification challenge for detecting the brain tumor in MRI images, the identification of a correct pattern is the main key in the classification process. Many issues in the MRI images face the classification models, which mislearning can happen and leads award downgrading the classification accuracy. So, we proposed a three-step pre-processing approach.

A) Removing the Confusing Objects

Confusing objects such as texts and black areas on the right and left corners have been removed by cropping 100 pixels from each side of the image to get the exact brain object as shown in figure 4.1

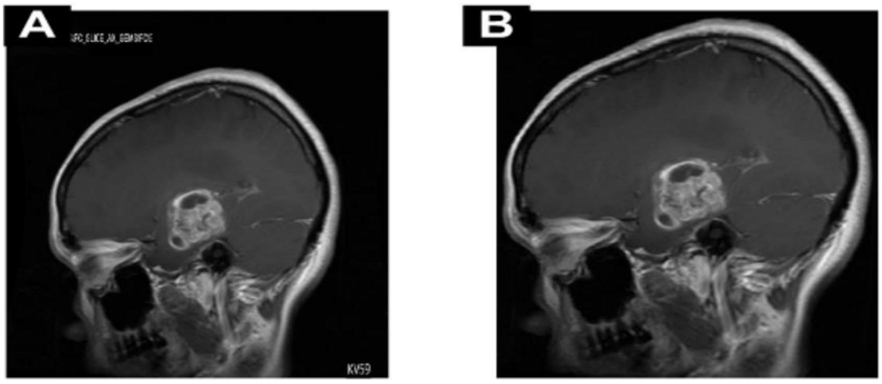

FIGURE 4.1. Removing the Confusing Objects

FIGURE 4.1. Figure A shows An example of MRI images before the cropping process. Figure B shows the same image after the cropping process.

B) Enoising The Mri Images

Non-local mean algorithm (NLM) deal with noise efficiently in MRI images. The noise in these images lead to learning undesirable patterns consequently, downgrading the classification accuracy. The NLM algorithm greatly enhances the quality of the MRI images as compared with Gaussian and Median algorithms according to the blind reference less image spatial evaluator (BRISQUE).

C) Histogram Equalization

Histogram Equalization extremely enhances the contrast in the MRI images. Moreover, it allows the detecting small details by setting regions lower contrast with appropriate contrast. It accomplishes this process by performing a separation to the most frequent intensity values. It also clears up the interference of the most frequent patterns in the MRI images as showed in figure 2.2-E.

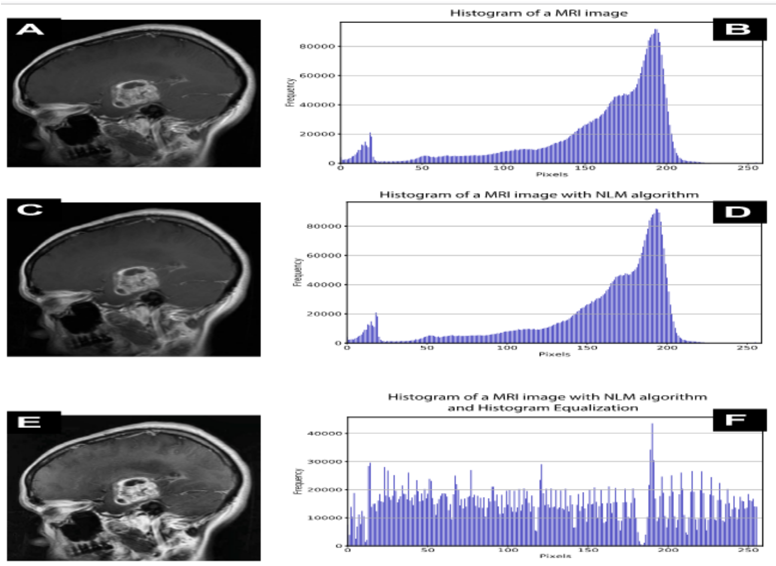

FIGURE 4.2. Histogram Equalization

FIGURE 4.2. Figure A shows a sample of MRI images after the cropping process. Figure B shows the histogram of Figure A. Figure C shows the same image after applying the NLM algorithm. Figure D shows the histogram of Figure C. Figure E shows the Figure D image after applying Histogram Equalization. Figure F shows the histogram of Figure E.

DATASET

The dataset that has been used in the experiments and test formed based on Sartaj brain MRI images dataset and the Navoneel brain tumor dataset. The used dataset contains two types of MRI images: T1-weighted and T2-weighted. T1-weighted images are produced using short time to echo (TE) and repetition time (RT) constraints, which are 14 and 500 milliseconds, respectively. T2-weighted images are produced using longer TE and RT constraints, which are 90 and 4000 milliseconds, respectively. The dataset has been divided into three folders (Training, Testing and Validating), with sub-folders for each class (GLIOMA, MENINGIOMA, NO-TUMOR and PILUITARY). There're 3394 MRI images organized into four classes of GLIOMA (934), MENINGIOMA (945), NO-TUMOR (606) and PILUITARY (909). The training folder contains 826 images for GLIOMA, 822 images for MENINGIOMA, 827 images for PILUITARY and 493 images for NO-TUMOR. The testing folder contains 100 images for GLIOMA, 115 images for MENINGIOMA, 105 images for PILUITARY and 74 images for NO-TUMOR. The validating folder contains 8 images for GLIOMA, 8 images for MENINGIOMA, 8 images for PILUITARY and 8 images for NO-TUMOR.

TRAINING STRATEGY

In our training strategy, we trained our model from scratch, so our model can be considered problem-based. We used the image data generator to generate a sufficient number of MRI images for the training process. The generation process produced data from the same domain as the used dataset, so the models learned only the desirable features. The training process has 60 epochs with 385 stepper epoch and batch size 16. Using a batch size of 16, means that 16 samples are passed at a time to the trained model until all training data is passed to complete one single epoch. This value is suitable for Google Colaboratory since we have a limited RAM size of 13 GB. Therefore, increasing batch size in our case causes out of memory crashes during the training process. We saved the weights of each model after the training process. So, we don't need to repeat the training process to detect the abnormalities in a specified MRI Image. The average training time in seconds per one epoch is 253, 268, 233, and 196 for VGG16, VGG19, CNN-SVM, and the proposed model, respectively. We implemented the training process using 13 GB of RAM and the Tesla P100 GPU provided by Google Colaboratory Notebooks. We applied our training strategy to all of the explored models. See figure4.3

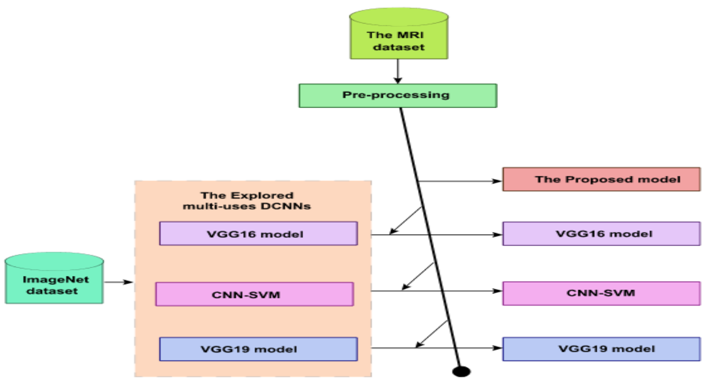

FIGURE 4.3 training strategy workflow

FIGURE 4.3. VGG16, VGG19 and CNN-SVM model were pre-trained with ImageNet dataset before the training process with the used MRI dataset, however, the proposed model were trained only with the used MRI images dataset.

THE PROPOSED MODEL

This paper proposes a Deep convolutional neural network (DCNN) model. The proposed model resolves many issues such as decreasing the overfitting, slow learning rates and lack of training accuracy due to the batch normalization operation. The proposed model consists of a convolutional part and a classifier part. The convolutional part has ten convolutional layers, five batch normalization layers and four max-pooling layers. The classifier part has three dense layers and two dropout layers as showed in figure 4.4

A) The Convolutional Operation

The convolutional operation is an important part of the proposed model because it's responsible for gathering features from the MRI image. The expected features are good enough to perform a reliable training process. In case of the first convolution layer, the input vector consists of the input image and in case of the other convolution layers, the input vector consists of the previous layer feature maps. We perform the convolutional operation using equations 1 and 2

$$RELU(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

where RELU is rectified linear unit activation function; x is the input to RELU

$$C_r^T = RELU\left(\sum_{y=1}^{N} \sum_{u=-x}^{X} \sum_{v=-x}^{X} P_y^{T-1}(i-u, j-v) \cdot K_{y,r}^T(u,v) + B_r^T\right)$$

where N represents number of feature maps in the input vector; r,y are feature map indices of the current layer and the previous layer respectively; T is the layer index; Initially p_y^0 represents the input image vector and PT −1 y represents the feature maps vector of the previous layer of T layer; K is the kernel matrix; u,v are the indices of the kernel values; X,B are the size and bias of the filter respectively.

The convolutional operation results in a distortion in the output values. This distortions causes Overfitting, which reduces the learning rates. Overfitting issue has been processed using the batch normalization operation.

B) The Key Role Of Batch Normalization Operation

During the training process of a DCNN model, the distribution of input values for a specific layer depends on the previous layers of that model. This variability causes over fitting and reduces the learning rates. In this paper, batch normalization is hired to speed up the training process and decrease the Overfitting issue by standardizing the input vector in a way that eliminates the noisy features, which stabilizes the training process, see Figure 2.4. The normalization allows to use lower dropouts rates because it acts as a regularizer and the input to this process is an vector. Batch normalization process has been performed through equations.

$$M_{BN}(X) = \frac{1}{N} \sum_{i=1}^{N} X_i$$

where M_{BN} is the mean for the input X ; N is the number of elements in the input vector X .

$$\sigma_{BN}^2(X) = \frac{1}{N} \sum_{i=1}^{N} (X_i - M_{BN}(X))^2$$

where σ_{BN}^2 is the variance for the input X .

$$Y_i = \frac{X_i - M_{BN}(X)}{\sqrt{\sigma_{BN}^2(X)}}$$

where Y_i is the output of the batch normalization operation.

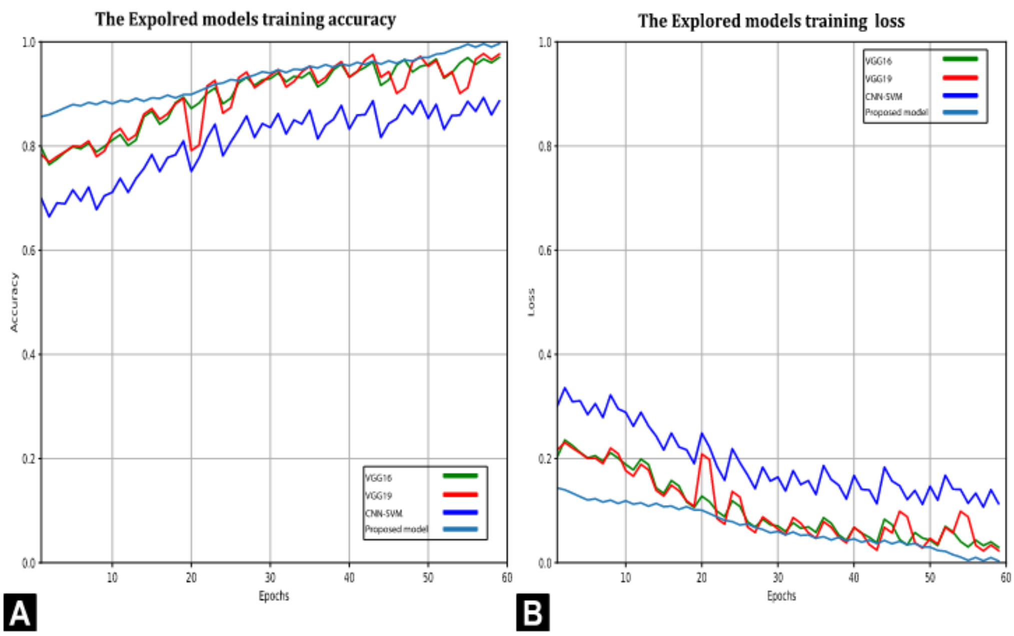

FIGURE 4.4.output of the batch normalization

FIGURE 4.4. A shows the proposed model and the other explored models (VGG16, VGG19, and CNN-SVM) training accuracies, and B shows the proposed model and the other explored models (VGG16, VGG19, and CNN-SVM) training losses through the training process.

V.EXISTING SYSTEM

This study addresses the problems of segmentation of abnormal brain tissues and normal tissues such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) from magnetic resonance (MR) images using feature extraction technique and support vector machine (SVM) classifier. The tumor is basically an uncontrolled growth of cancerous cells in any part of the body, whereas a brain tumor is an uncontrolled growth of cancerous cells in the brain. A brain tumor can be benign or malignant. The benign brain tumor has a uniformity in structure and does not contain active (cancer) cells, whereas malignant brain tumors have a nonuniformity (heterogeneous) in structure and contain active cells.

VI.PROPOSED SYSTEM

This Project proposes a deep convolutional neural network (DCNN) model. The proposed model resolves many issues such as decreasing the overfitting, slow learning rates and lack of training accuracy due to the batch normalization operation. The proposed model consists of a convolutional part and a classifier part. The convolutional part has ten convolutional layers, five batch normalization layers and four max-pooling layers. The classifier part has three dense layers and two dropout layers.

Advantages

- Accurate detection
- Higher learning rate
- Train the model faster

VII. SYSTEM DESIGN

7.1 INTRODUCTION

Design is the first step into the development phase for any engineered product or system. Design is a creative process. A good design is the key to effective system. The term “design” is defined as “the process of applying various techniques and principles for the purpose of defining a process or a system in sufficient detail to permit its physical realization”. It may be defined as a process of applying various techniques and principles for the purpose of defining a device, a process or a system in sufficient detail to permit its physical realization. Software design sits at the technical kernel of the software engineering process and is applied regardless of the development paradigm that is used. The system design develops the architectural detail required to build a system or product. As in the case of any systematic approach, this software too has undergone the best possible design phase fine tuning all efficiency, performance and accuracy levels. The design phase is a transition from a user oriented document to a document to the programmers or database personnel. System design goes through two phases of development: Logical and Physical Design.

Logical Design

The logical flow of a system and define the boundaries of a system. It includes the following steps:

- Reviews the current physical system – its data flows, file content, volumes, frequencies etc.
- Prepares output specifications – that is, determines the format, content and frequency of reports.
- Prepares input specifications – format, content and most of the input functions.
- Prepares edit, security and control specifications.
- Specifies the implementation plan.
- Prepares a logical design walk through of the information flow, output, input, controls and implementation plan.
- Reviews benefits, costs, target dates and system constraints.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 3 (2023)

Physical Design

Physical system produces the working systems by define the design specifications that tell the programmers exactly what the candidate system must do. It includes the following steps.

- Design the physical system.
- Specify input and output media.
- Design the database and specify backup procedures.
- Design physical information flow through the system and a physical design Walk through.
- Plan system implementation.
- Devise a test and implementation plan and specify any new hardware/software.

Design/Specification activities

- Concept formulation.
- Problem understanding.
- High level requirements proposals.
- Feasibility study.
- Requirements engineering.
- Architectural design.

7.2 INPUT DESIGN

The input design is the process of entering data to the system. The input design goal is to enter to the computer as accurate as possible. Here inputs are designed effectively so that errors made by the operations are minimized. The inputs to the system have been designed in such a way that manual forms and the inputs are coordinated where the data elements are common to the source document and to the input. The input is acceptable and understandable by the users who are using it. The quality of the system input determines the quality for system output. Input specification describes the manner in which data entered the system processing. Input design is the process of converting user-originated inputs to a computer-based format input data are collected and organized into group of similar data. Once identified, appropriate input media are selected for processing. The input design also determines the user to interact efficiently with the system. Input design is a part of overall system design that requires special attention because it is the common source for data processing error. The goal of designing input data is to make entry easy and free from errors. Five objectives of the input design are:

- Effectiveness
- Accuracy
- Ease to use
- Consistency
- Attractiveness

The main objectives that are done during the input design are:

- Data are collected from the source
- Transfer of data to an input form is done

- Data is converted to a computer acceptable form
- The converted data are verified.
- Data are checked for its accuracy.
- Validation of input data are done
- Data collections are done to eliminate the error

7.3 OUTPUT DESIGN

The output design was done so that results of processing could be communicated to the users. The various outputs have been designed in such a way that they represent the same format that the office and management used to. Computer output is the most important and direct source of information to the user. Efficient, intelligible output design should improve the systems relationships with the user and help in decision making. A major form of output is the hardcopy from the printer. Output requirements are designed during system analysis. A good starting point for the output design is the Data Flow Diagram (DFD). Human factors educe issues for design involves addressing internal controls to ensure readability. Design is concerned with identifying software components specifying Relationships among components. Specifying software structure and providing blue print for the document phase. Modularity is one the desirable properties of large systems. It implies that the system is divided into several parts. In such a manner, the interaction between parts is minimal clearly specified. Design will explain software components in detail. This will help the implementation of the system. Moreover, this will guide the further changes in the system to satisfy the future requirements

System design is described as a process of planning a new business system or more to replace or to complement an existing system. The system design states how a system will meet the requirements identified during the system analysis. It describes a solution of approaching to the creation of new system. System design is a transmission from a user-oriented document to a document oriented to programmers. It goes through a logical and physical design. The key points followed at the times of designing are:

- Preparing input and output specification
- Data flows and stores
- Preparing security and control specification
- Temporary and permanent collection of data
- A walk through before implementation

Reviewing the study phase activities and making decisions about which functions are to be performed by the hardware, software, and human ware started in the design phase. The output, input and file design for each of the programs was done. Finally, the generalized systems were explained to the management for approval

The steps involved in designing phase were:

a) The function to be performed is identified

b) The input, output and file design is performed

c) The system and component cost requirements is specified

d) The design phase report is generated

7.4 Architecture Diagram

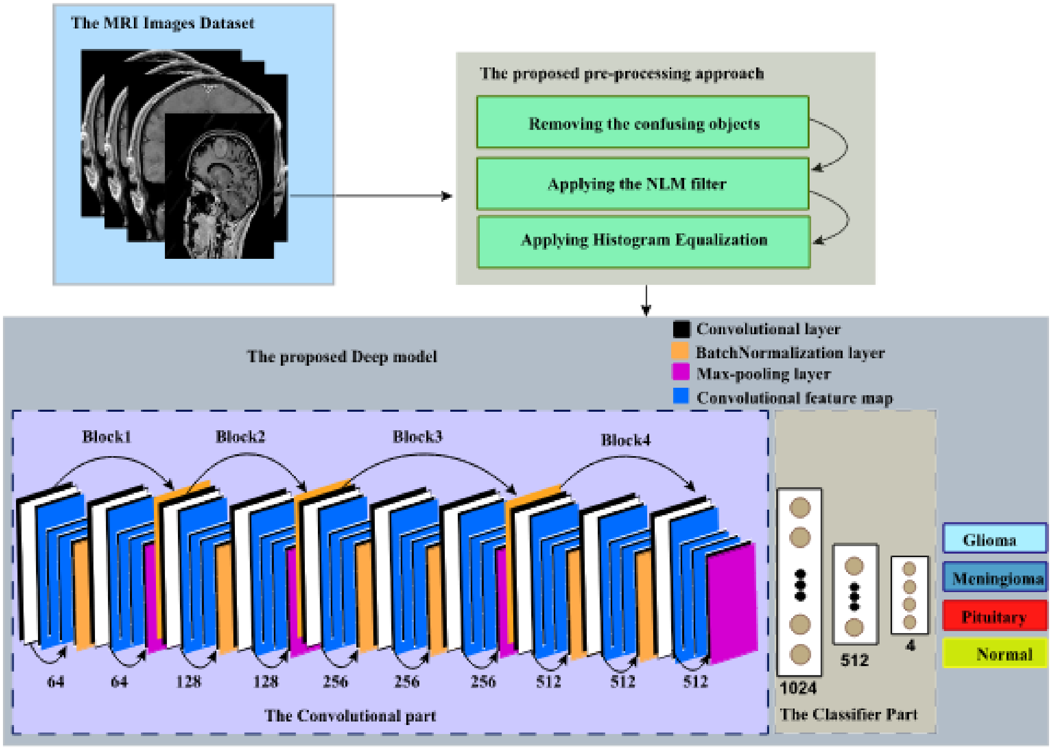

Fig. 7.1 System Architecture

In the classification challenge for detecting the brain tumor in MRI images, the identification of a correct pattern is the main key in the classification process. Many issues in the MRI images face the classification models, which mislearning can happen and leads award downgrading the classification accuracy. So, we proposed a three-step pre-processing approach.

VIII.IMPLEMENTATION

Preprocessing

- The pre-processing method enhances the quality of the MRI images, stretches their histogram and improves their contrast.

Removing the confusing object

- Confusing objects such as texts and black areas on the right and left corners have been removed by cropping 100 pixels from each side of the image to get the exact brain object.

NLM filter

- The NLM algorithm greatly enhances the quality of the MRI images as compared with Gaussian and Median algorithms according to the blind reference less image spatial evaluator.

Histogram Equalization

- Histogram Equalization extremely enhances the contrast in the MRI images.

- Moreover, it allows the detecting small details by setting regions lower contrast with appropriate contrast.
- It accomplishes this process by performing a separation to the most frequent intensity values.

Deep CNN

- This paper proposes a Deep convolutional neural network (DCNN) model.
- The proposed model resolves many issues such as decreasing the overfitting, slow learning rates and lack of training accuracy due to the batch normalization operation.

Classifier

- A diagnosis architecture that uses DCNN to classify MRI images as glioma, meningioma, pituitary, and normal.
- The NoTumor, GLIOMA, MENINGIOMA and PILUITARY classes are renowned as negative, positive, double-positive and triple-positive respectively.

IX. CONCLUSION

A deep convolution neural network architecture is proposed for glioma, meningioma and pituitary brain diseases detection with an objective of high classification accuracy within a short time. First, a proper brain tumor dataset for efficiently performing the training and testing process. Second, a three-step pre-processing approach was removing the confusing variables, denoising the MRI images and enhancing the contrast of these images. This approach positively and directly reflected on all of the explored models.Third,atrainingstrategy includes training our model on the desirable patterns from scratch. Fourth, we hired our model to extract the MRI images features and efficiently classify them. We evaluate the pro-posed model on a dataset with 394 MRI images. The proposed model accomplished an accuracy of 97.72% overall, 99% in detecting glioma, 98.26% in detecting meningioma, 95.95%in detecting pituitary and 97.14% in detecting normal images. In real practice, the proposed model can be considered as an automated computer-aided detector tool to timely detect brain abnormalities in MRI images with high accuracy.

X. FUTURE ENHANCEMENT

In the future, we are going to increase MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, Applying the proposed approach to other types ofmedical images such as x-ray, computed tomography (CT), and ultrasound may constitute a principle of future studies.

References

[1] N. B. Bahadure, A. K. Ray, and H. P. Thethi, ‘‘Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM,’’ Int. J. Biomed. Imag., vol. 2017, pp. 1–12, Mar. 2017, doi: 10.1155/2017/9749108.

[2] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, ‘‘Brain tumor seg-mentation using convolutional neural networks in MRI images,’’ IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1240–1251, May 2016, doi: 10.1109/TMI.2016.2538465.

---

[3] World Health Organization. Accessed: Jun. 10, 2021. [Online]. Available:https://www.who.int E. El-Dahshan, H. Mohsen, K. Revett, and A. Salem, ''Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm,'' Expert Syst. Appl., vol. 41, no. 11, pp. 5526–5545, 2014, doi: 10.1016/j.eswa.2014.01.021.

[4] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, ''ImageNet large scale visual recognition challenge,'' Int. J. Comput. Vis., vol. 115, no. 3, pp. 211–252, Dec. 2015, doi: 10.1007/s11263-015-0816-y.

[5] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, ''A survey of deep neural network architectures and their applications,'' Neurocomputing, vol. 234, pp. 11–26, Apr. 2017, doi: 10.1016/j.neucom.2016.12.038.

[6] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, ''A survey on deep learning in medical image analysis,'' Med. Image Anal., vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media. 2017.07.005.

[7] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, M. P. Lungren, and A. Y. Ng, ''CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning,'' 2017, arXiv:1711.05225.

[8] D. Shen, G. Wu, and H.-I. Suk, ''Deep learning in medical image analysis,'' Annu. Rev. Biomed. Eng., vol. 19, pp. 221–248, Jun. 2017, doi: 10.1146/annurev-bioeng-071516-044442.

[9] J. H. Chen and S. M. Asch, ''Machine learning and prediction in medicine—Beyond the peak of inflated expectations,'' New England J. Med., vol. 376, no. 26, pp. 2507–2509, Jun. 2017, doi: 10.1056/NEJMp1702071.

[10] B. Remeseiro and V. Bolon-Canedo, ''A review of feature selection methods in medical applications,'' Comput. Biol. Med., vol. 112, Sep. 2019, Art. no. 103375, doi: 10.1016/j.compbiomed.2019.103375.

[11] Buades, B. Coll, and J.-M. Morel, ''A non-local algorithm for image denoising,'' in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2005, pp. 60–65, doi: 10.1109/CVPR.2005.38.

[12] G. Deng and L. W. Cahill, ''An adaptive Gaussian filter for noise reduction and edge detection,'' in Proc. IEEE Conf. Rec. Nucl. Sci. Symp. Med. Imag. Conf., vol. 3, Nov. 1993, pp. 1615–1619, doi: 10.1109/NSS-

MIC.1993.373563.

[13] Pitas and A. N. Venetsanopoulos, ''Median filters,'' in Nonlinear Digital Filters: Principles and Applications. Boston, MA, USA: Springer, 1990, pp. 63–116, doi: 10.1007/978-1-4757-6017-0_4

[14] Mittal, A. K. Moorthy, and A. C. Bovik, ''No-reference image quality assessment in the spatial domain,'' IEEE Trans. Image Process., vol. 21, no. 12, pp. 4695–4708, Dec. 2012, doi: 10.1109/TIP.2012.2214050.

[15] Sartaj. Brain Tumor Classification (MRI) Dataset. Accessed: Jun. 10, 2021. [Online]. Available: https://www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri

[16] N. Chakrabarty. Brain MRI Images for Brain Tumor Detection Dataset. Accessed: Jun. 10, 2021. [Online]. Available: https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection

[17] D. C. Preston. Magnetic Resonance Imaging (MRI) of the Brain and Spine: Basics. Accessed: Dec. 31, 2021. [Online]. Available: https://case.edu/med/neurology/NR/MRI%20Basics.htm

[18] Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' 2014, arXiv:1409.1556.

[19] M. Mahdianpari, B. Salehi, M. Rezaee, F. Mohammadimanesh, and Y. Zhang, ''Very deep convolutional neural networks for complex land cover mapping using multispectral remote sensing imagery,'' Remote Sens., vol. 10, no. 7, p. 1119, Jul. 2018, doi: 10.3390/rs10071119