ORIGINAL ARTICLE

Implementation of a Deep Neural Network for Classifying Images of Brain Tumors

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Abstract

Purpose: Identification and categorization of brain tumors is a cyclical process in which tumor components are assessed and suggestions for therapy are made based on their classifications. Many imaging techniques are used for this work. Because MRI provides better soft tissue than CT, and MRI does not involve radiation. The currently available manual method is inefficient and hence we provide an advanced method by using the deep learning concepts.

Materials and Methods: This MRI creates detailed images of our body's organs and tissues by using a computer's radio wave and an attracting field. Deep Learning (DL), a subset of Machine Learning (ML), is helpful for the categorization and identification of issues. This project uses one dataset consisting of three categories (Meningioma, Glioma, Pituitary.

Results: In this work, the first stage is pre-processing concerning two datasets. Later involves detection by using a Convolution Neural Network algorithm (CNN). The suggested CNN performs admirably, with the greatest overall accuracy for the datasets coming in at 94.3% and 96.1%. The final results demonstrate the model's capability for brain tumor classification and detection problems.

Conclusion: The proposed system helps to automatically differentiate between the types of Tumors from the normal, future it can be improved to analyze the brain tumor and classification, which will be more useful in the treatment. A few more sectors of artificial intelligence can also be incorporated along with the proposed system to increase the standard of the proposed system.

Keywords: Computed Tomography; Magnetic Resonance Imaging; Convolution Neural Network; Deep Learning.

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1. Introduction

A brain tumor results in brain cells developing abnormally and out of control. Any unforeseen development may affect how the body functions if the appropriate brain area is involved since the human skull, is a hard, volume-limited body. It may even extend to other bodily organs and affect how humans perform [1].

Mind tumors are characterized as unnatural and uncontrolled development in the cerebrum cells. Pituitary tumors develop from pituitary organs, which regulate chemicals and direct capacities in the body. It could be kind-hearted, favorable that grows to bones, and dangerous. Pituitary tumors can cause permanent chemical insufficiency and vision problems [2]. WHO has released a study on malignant growth, cerebrum disease represents fewer than 2% of human malignant growth; nonetheless, serious bleakness and difficulties are created. Tumors are in like manner essential and optional.

WHO, for example, on the order of tumors for CNS is a conceptional just as the related outline of an archetype [3]. Further in 2016, CNS and WHO presented a new component like histology just as particles. The CNS governs the majority of the body and mind. It is divided into two sections: the cerebrum and the spinal cord.

The WHO's categorization of malignancies of the Central Nervous System (CNS) was released in its fourth iteration [4]. There are a few new titles and data lists, such as glioma, papillary, and glioneuronal tumor. Histological differences can have different edge distributions, locations, indications, and clinical procedures. Edges are one such element. Edges are critical neighborhood changes in the picture and are significant highlights for investigating pictures.

An edge in a picture is a critical neighborhood change in the picture force, as a rule, related to an intermittence in either the picture power or the primary subsidiary of the picture power [5]. To recognize brain cancers from an MRI image, The Support Vector Machine (SVM) and Fuzzy C-Means (FCM) frameworks were used by the researchers. MRI picture checks are further developed utilizing improvement and center reach expansion. Later, the skull stripe receives twofold edges with morphological activities. Once the disputed zone has been divided and identified, FCM bunching is next used. An immediate model for concerns with order and relapse is SVM.

The organization of the brain MRI images at that time used the SVM technique. Shruthi Santhosh *et al.* [6] used morphological activity and thresholding to detect brain malignancies. The size of a tumor phase is calculated using the data set frameworks method. These photographs contain the MRI image data and the grayscale conversion of the MRI image. High-pass filtration is used to isolate the grayscale image and eliminate extra noise. The articles are removed from the MRI image's base using the thresholding approach; applying later morphological processes like broadening and disintegration. This helps to identify the brain tumor.

[7] explained recognition of mind tumors in attractive reverberation pictures utilizing covered-up Markov arbitrary field and limitation. The pictures from MRI checks are changed over into 2D pictures. The segmentation of photos into groups based on names makes it easier to identify an object's borders and gauge the tumor's development. In this instance, a pixel limit value has been defined, and the pixels in the photographs whose values are lower than the edge will be black while the remaining pixels, whose values are more noticeable, will have a different tone for the indicated edge value. This aids in identifying the brain tumor. The dark Level Run Length Matrix (GLRLM) is used to retain details in the brain image.

In [8], the suggestion was to remove edges from MRI images of the cerebrum to extract the tumor region. This method uses the very accurate edge localization approach to identify brain tumors in MRI images. If the image is a shading image, it is converted to a dim image for X-ray. To remove the noise from the image, preprocessing is carried out using the middle channel. After the middle channel, the produced image successfully identifies the tumor, and at that moment, the image's standard deviation is recorded.

[9] One of the common illnesses of the sensory system, brain tumors can seriously harm a person's health and even cause death. Gliomas are among the brain tumors with the greatest rates of death and morbidity. It is frequently separated into Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) (LGG), and patients who have progressed into HGG typically have a life expectancy of two years or less. Numerous imaging methods, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), positron emission tomography (PET), and Single-Photon discharge Positron Emission Tomography, have been utilized to investigate brain

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malignancies (SPECT). Ideal models that are administered and unsupported span two broad areas of AI [10, 17].

The solo worldview is considerably less investigated. The method of the future managed learning, which is also one of the most fascinating areas of open research worldview of controlled learning is the dominant one in AI, and a significant number of publications have been written about it. We discuss division, relapse, order, and numerous methods for controlled learning. Between the two, a few strategies do both, directed and unaided. They combine controlled learning with a solo learning component under the names of semi-managed or self-administered [11, 14].

It was suggested to use a different technique to separate images for Positron Emission Tomography (PET) filter images by [12, 13]. The Spatial Fuzzy C-Means (FCM) bunching computation is used in this approach. This technique combines geographical neighborhood data with the FCM and then updates the target capacity for each group. In light of the insights given by the goal work, the gauging capacity is determined which is then applied to the participation work [15, 16].

2. Materials and Methods

The main objective of the work is the multi-classification of images of brain tumors using deep neural networks. The first step in this research's three goals is preprocessing the dataset, followed by brain tumor identification and segmentation using the CNN method, and finally computing the dataset's performance metrics. In this work, a CNN architecture is suggested. The research is organized as follows: The recommended method is thoroughly covered in Section 2 starting with the dataset, followed by Section 3's discussion of the findings and Section 4's discussion of the conclusion and potential applications.

2.1. Datasets

This work incorporates the two online datasets. The dataset is a set of pictures; it is a genuine informational collection used to prepare the model for performing different activities. Datasets can hold data, for example, clinical records or protection records, to be utilized by a program running on the framework. Datasets are likewise used to store data required by applications or the working framework itself. In this work, we use two different online datasets. The database contains Dataset I, which consists of meningiomas, gliomas, and pituitary tumors, three different forms of brain cancers [19, 20].

a. Meningioma:

It is an essential focal anxious system (CNS)tumor. This implies it starts in the mind or spinal cord. Overall, meningiomas are the most well-known sort of essential cerebrum tumor.

b. Glioma:

It is a sort of tumor that happens in the mind and spinal line. Gliomas start in the gluey strong cells and help them work. Three kinds of glial cells can deliver tumors.

c. Pituitary:

A pea-sized organ connected to the piece of the mind is called the hypothalamus. It lies at the nose. The nerve center conveys messages to the pituitary organ, which then, at that point makes chemicals that control different organs and a large number of the body's capacities, including development and richness.

As seen in Figure 1, Dataset II comprises several glioma grades (Grade II, Grade III, and Grade IV). Additional information regarding the two datasets is shown in Table 1, respectively.

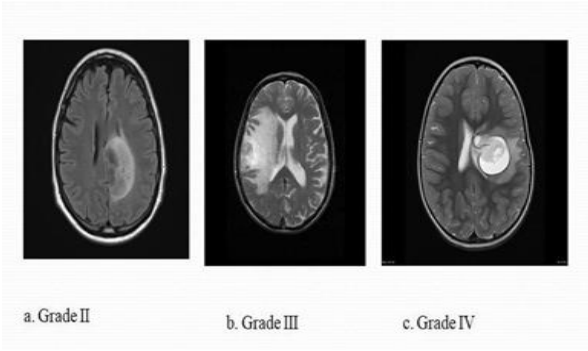

Figure 1. Dataset II a. Grade II, b. Grade III, c. Grade IV

The grade of a glioma brain tumor indicates the predicted course of the tumor's growth.

Grade II glioma (low-grade glioma): Although grade II gliomas can affect kids and teens, they are more prevalent in adults. Although they start as a slow-growing (low-grade) type of brain tumor, they

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frequently advance over time— typically years—to a higher grade. These tumors have lower growth and dissemination risk but are more likely to return following therapy.

Grade III glioma (anaplastic glioma): The term "anaplastic" refers to the fast division of glioma brain tumor cells. Grade III gliomas, also known as anaplastic gliomas, are considered to be malignant types of brain cancer. They are more difficult to cure than low-grade gliomas and frequently spread to other areas of the brain. These tumors are more likely to have living cells that are dividing quickly than dead ones. They can expand rapidly.

Grade IV glioma (glioblastoma multiforme): The name of a Glioblastoma Multiforme (GBM) brain tumor changes after it is determined to be a high-grade glioma, even if it may have originated from a lower-grade glioma. This is done to represent the reality that a grade IV glioma typically contains a variety of cancer cells. primarily astrocytoma and oligodendroglioma cells. In a grade IV tumor, cells in the tumor are actively dividing. In addition, the tumor has both abnormal blood vessel growth and areas of dead tissue. These tumors can grow and spread quickly (Table 1).

Table 1. The number of photos in dataset II for various glioma grades

Tumor Category	Number of Images
Meningioma	115
Glioma	100
Pituitary tumor	74
Tumor Category	Number of Images
Grade II	10
Grade III	10
Grade IV	10

2.2. Input MRI Image

The pre-processing phase comes next. The next step is to segment the input MRI image using the CNN (Convolution Neural Network) approach to locate the tumor region. The computations for network training and performance are provided last. An MRI scan produces precise pictures of the body's organs and structures without causing any discomfort and is both painless and safe. A wide variety of disorders, including those affecting the brain, spinal cord, bones, hands, and feet, are diagnosed using MRI. While an X-ray cannot always produce clear pictures of human components, in rare circumstances it can. This study employs the dataset.

The first steps in this pre-processing are the input of an MR image and subsequent grayscale processing. It is the only one in which salt and pepper noise and various hues of grey serve as the sole colors. Finally, it will use the median filter to decrease the noise. The most widely used technique for noise disposal is this filter. It is a "non-direct" way of filtering. With this, the "Salt and Pepper" noise in the input MRI image is eliminated.

2.3 Detection

This recognition (detection) of a tumor includes the accompanying six stages specifically Filtered picture, bounding box, Tumor alone, Tumor framework, and afterward detected tumor part. The initial step is to give the information MRI picture of either dataset-I or dataset-II. This input picture is sent through the filtered image, it performs preprocessing and eliminates the clamor, and afterward goes through the bounding box. Tumors are confined in a rectangular shape, then, at that point, it shows just the tumor alone part and the tumor layout.

a. Input Image

The initial step is to give the information MRI picture of either dataset-I (Glioma, meningioma, pituitary) or dataset-II (Grade II, Grade III, Grade IV).

b. Filtered Image

First taking the MRI has the information then, at that point plays out the activity of sifting. There are countless channels in picture handling. This stage utilizes a middle channel. The sifting is utilized to eliminate the commotion from the mind tumor picture. This middle channel lessens the salt and pepper commotion.

c. Bounding box

Overall, the bounding box is a square shape that fills in as a point reference for object location and makes a crash box for that item. Information annotators draw these square shapes over pictures, illustrating the object of interest inside each picture by characterizing its X and Y arranges. In this stage, it can without much

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of a stretch recognize the tumor part in a rectangular shape (Bounding box).

d. Tumor alone

In this recognition, subsequent stage is to show the solitary tumor part for the information MR (Magnetic Resonance) picture. It will show the tumor part in white (light) shading with a black (dark) foundation.

e. Tumor outline

The following stage is the tumor diagram, it traces the tumor part in white (Light) shading in the black (dark) foundation. It assists with distinguishing the tumor part for the information MRI picture.

f. Detected Tumor

At last, the tumor part will be recognized. Continuously the tumor part shows a red tone. In this recognition, subsequent stage is to show the solitary tumor part for the information MR. Continuously the tumor part shows a red tone.

The Discrete Wavelet Transform (DWT) is employed to convert the picture's pixels into wavelets once the MRI image is initially entered. A rapid wavelet change of a sign can be processed automatically using discrete wavelet change. Similar to other wavelet changes, it has the benefit of getting both repetition and area information, which gives it a significant edge over Fourier changes. According to the input photos, the Convolution Neural Network (CNN) method is utilized to identify the type of tumor. The DWT process, CNN process, and detection and region of detection are the three phases that make up this process. Figure 2 illustrates the segmentation and classification stage for Grade IV.

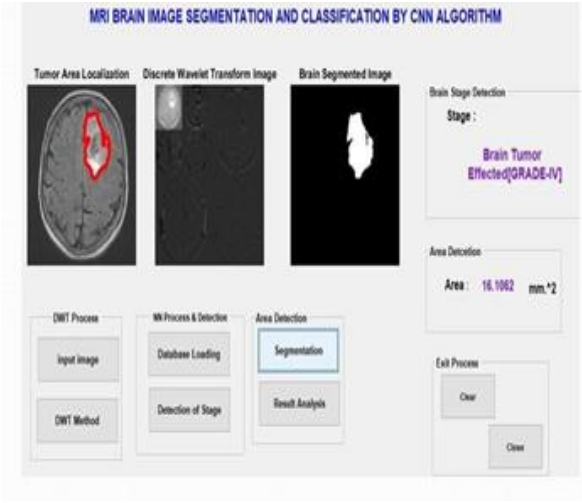

Figure 2. Segmentation and classification stage for Grade IV

3. Results and Discussion

Finally, the performance metrics for the two datasets were calculated separately. This calculation involves the four parameters of Accuracy, Precision, Sensitivity, and Specificity with the help of four values, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

The percentage of real positives among anticipated positive instances (TP).

The number of expected negative situations that are also negative is known as True Negative (TN).

False-positive (FP), also known as Type 1 error, is the proportion of positive projected cases that turn out to be negative.

False Negative (FN), also known as Type 2 error, is the proportion of anticipated negative situations that turn out to be positive.

Figure 3 illustrates the Performance graph for meningioma. Figure 4 represents the Performance graph for Glioma. Figure 5 illustrates the Performance graph for pituitary. Table 2 demonstrates the Performance metrics for Brain Tumor Detection.

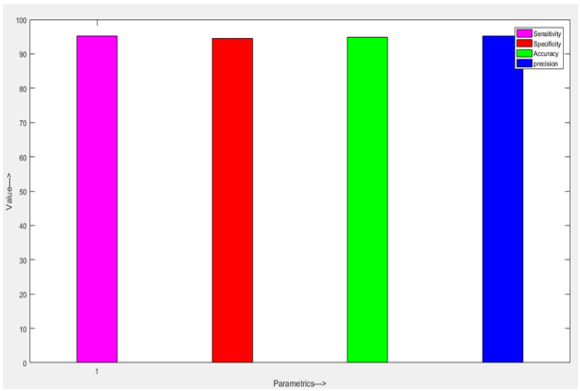

Figure 3. Performance graph for meningioma

4. Conclusion

In Dataset I and Dataset II, this study categorizes brain tumor MR images into three kinds. Pre-processing activity has been performed by utilizing the dataset in MATLAB 2018b version. By using this

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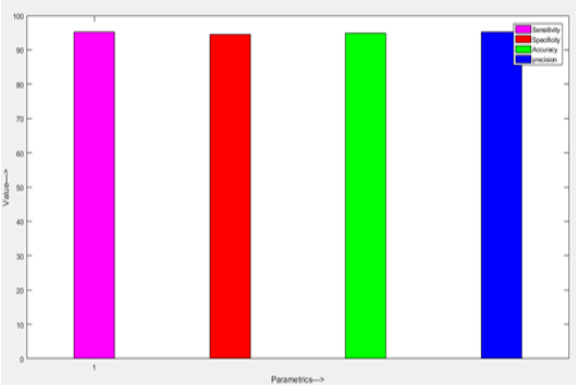

Figure 4. Performance graph for Glioma

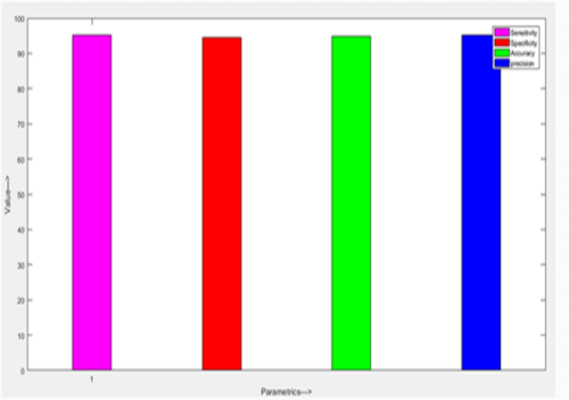

Figure 5. Performance graph for pituitary

Table 2. Performance Metrics for Brain Tumor Detection

	Classes	Sensitivity	Specificity	Accuracy
Proposed	meningioma	0.945	0.951	94.93
Sultan [1]	meningioma	0.955	0.987	97.54
Proposed	Glioma	0.921	0.942	93.15
Sultan [1]	Glioma	0.944	0.951	96.89
Proposed	Pituitary	0.942	0.945	94.11
Sultan [1]	Pituitary	0.934	0.97	96.89

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methodology, it can easily locate the affected part and it can reduce the death rate. Training is done for the two datasets and performance metrics are measured for the two datasets. The proposed method helps even the junior doctors to treat the patient in the absence of the senior doctor since everything is generated automatically. Only few are fully automatic among the methods that are proposed, the manual dependent of X-ray results could lead to time delay, which can be avoided if the following is incorporated. The proposed system helps to automatically differentiate between the types of Tumor from the normal, future it can be improved to analyze the brain tumor and classification, which will be more useful in the treatment. Few more sectors of artificial intelligence can also be incorporated along with the proposed system to increase the standard of the proposed system. Observed the accuracy for the dataset-I is 94.3% and dataset-II is 96.4%. Finally, it concludes that almost the same accuracy was found for both the datasets in the existing and proposed methods. This approach results in little improvements in accuracy. The proposed strategy outperforms the old one. It will shorten the segmentation and classification stages. In the future, this procedure can be applied to 3D images, to distinguish the grade and phase of the tumor, and attempt to know the area of the tumor from 3D pictures.

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