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Brain Tumor Detection Using Deep Learning and Image Processing

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Abstract: **-Brain Tumor Detection is one of the most difficult tasks in medical image processing. The detection task is difficult to perform because there is a lot of diversity in the images as brain tumors come in different shapes and textures. Brain tumors arise from different types of cells and the cells can suggest things like the nature, severity, and rarity of the tumor. Tumors can occur in different locations and the location of tumors can suggest something about the type of cells causing the tumor which can aid further diagnosis. The task of brain tumor detection can become aggravating by the problems which are present in almost all digital images e.g. illumination problems. Tumor and non-tumor images can have overlapping image intensities which makes it difficult for any model to make good predictions from raw images. This paper proposes a novel method to detect brain tumors from various brain images by first carrying out different image preprocessing methods i.e.. Histogram equalization and opening which was followed by a convolutional neural network. The paper also discusses other image preprocessing techniques apart from the ones that are finalized for training and their impact on our dataset. Convolutional Neural Network (CNN) was employed for the task of classification.**

IndexTerms – **Brain Tumor Detection, Computer-aided Diagnosis, Computer Vision, Convolutional Neural Networks, Deep Learning, Image Processing, Transfer Learning etc.**

1. INTRODUCTION

The human body is made up of many organs and brain is the most critical and vital organ of them all. One of the common reasons for dysfunction of brain is brain tumor. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A Brain Cancer is very critical disease which causes deaths of many individuals. The brain tumor detection and classification system is available so that it can be diagnosed at early stages. Cancer classification is the most challenging tasks in clinical diagnosis. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients. Different types of image processing techniques like image segmentation, image enhancement and feature extraction are used for the brain tumor detection in the MRI images of the cancer-affected patients. Detecting Brain tumor using Image Processing techniques its involves the four stages is Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used for improve the performance of detecting and classifying brain tumor in MRI images.

A. Overview of Brain and Brain Tumor

Main part in human nervous system is human brain. It is located in human head and it is covered by the skull. The function of human brain is to control all the parts of human body. It is one kind of organ that allows human to accept and endure all type of environmental condition. The human brain enables humans to do the action and share the thoughts and feeling. In this section we describe the structure of the brain for understanding the basic things.

The brain tumors are classified into mainly two types: Primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor).The benign tumor is one type of cell grows slowly in the brain and type of brain tumor is gliomas. It originates from non neuronal brain cells called astrocytes. Basically primary tumors are less aggressive but these tumors have much pressure on the brain and because of that, brain stops working properly [6]. The secondary tumors are more aggressive and more quick to spread into other tissue. Secondary brain tumor originates through other part of the body. These type of tumor have a cancer cell in the body that is metastatic which spread into different areas of the body like brain, lungs etc. Secondary brain tumor is very malignant. The reason of secondary brain tumor cause is mainly due to lungs cancer, kidney cancer, bladder cancer etc.

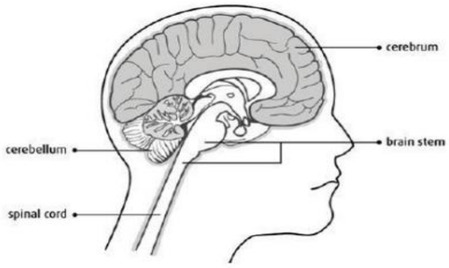

Fig.1: Basic Structure of human brain

B. Magnetic Resonance Imaging (MRI)

Raymond v. Damadian invented the first magnetic image in 1969. In 1977 the first MRI image were invented for human body and the most perfect technique. Because of MRI we are able to visualize the details of internal structure of brain and from that we can observe the different types of tissues of human body. MRI images have a better quality as compared to other medical imaging techniques like X-ray and computer tomography.[8]. MRI is good technique for knowing the brain tumor in human body. There are different images of MRI for mapping tumor induced Change including T1 weighted, T2 weighted and FLAIR (Fluid attenuated inversion recovery) weighted shown in figure 2.

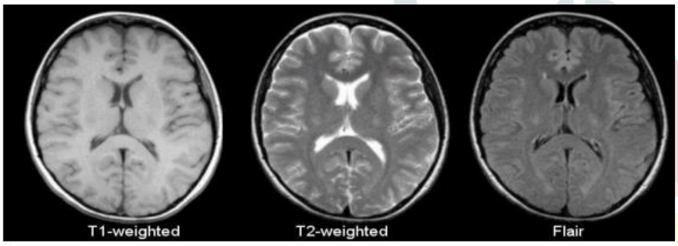

Fig. 2: T1, T2 and Flair image

The most common MRI sequence is T1 weighted and T2 weighted. In T1 weighted only one tissue type is bright FAT and in T2 weighted two tissue types are Bright FAT and Water both. In T1 weighted the repetition time (TR) is short in T2 weighted the TE and TR is long. The TE an TR are the pulse sequence parameter and stand for repetition time and time to echo and it can be measured in millisecond(ms)

C. Motivation

The main motivation behind Brain tumor detection is to not only detect tumor but it can also classify types of tumor. So it can be useful in cases such as we have to sure the tumor is positive or negative, it can detect tumor from image and return the result tumor is positive or not. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients.

The organizational framework of this study divides the research work in the different sections. The Literature survey is presented in section 2. Further, in section 3 shown Scope of the proposed method is discussed and in section 4 shown in proposed system, In section 5 Simulation Results work is shown. Conclusion and future work are presented by last sections 6.

2. LITERATURE SURVEY

Important, because the result is crucial for treatment of patients. There are many popular classification and clustering algorithms used for prediction. The goal of clustering a medical image is to simplify the representation of an image into a meaningful image and make it easier to analyze. Several Clustering and Classification algorithms are aimed at enhancing the prediction accuracy of diagnosis process in detecting abnormalities.

A. Sivaramakrishnan et al. (2013) [1] projected an efficient and innovative discovery of the brain tumor vicinity from an image that turned into finished using the Fuzzy Capproach grouping algorithm and histogram equalization. The disintegration of images is achieved by the usage of principal factor evaluation is done to reduce the extent of the wavelet coefficient. The outcomes of the anticipated FCM clustering algorithm accurately withdrawn tumor area from the MR images.

M. M. Sufyan et al. [2] has presented a detection using enhanced edge technique for brain-tumor segmentation that mainly relied on Sobel feature detection. Their presented work associates the binary thresholding operation with the Sobel approach and excavates diverse extents using a secure contour process. After the completion of that process, cancer cells are extracted from the obtained picture using intensity values.

Sathya et al. (2011) [3], provided a different clustering algorithm such as K-means, Improvised K-means, C-means, and improvised C-means algorithms. Their paper presented an experimental analysis for massive dat=asets consisting of unique photographs. They analyzed the discovered consequences using numerous parametric tests.

B. Devkota et al. [4] have proposed that a computer-aided detection (CAD) approach is used to spot abnormal tissues via Morphological operations. Amongst all different segmentation approaches existing, the morphological opening and closing operations are preferred since it takes less processing time with the utmost efficiency in withdrawing tumor areas with the least faults.

K. Sudharani et al. [5] presented a K- nearest neighbor algorithm to the MR images to identify and confine the hysterically full-fledged part within the abnormal tissues. The proposed work is a sluggish methodology but produces exquisite effects. The accuracy relies upon the sample training phase.

Jaskirat Kaur et al. (2012) [6] defined a few clustering procedures for the segmentation process and executed an assessment on distinctive styles for those techniques. Kaur represented a scheme to measure selected clustering techniques based on their steadiness in exceptional tenders. They also defined the diverse performance metric tests, such as sensitivity, specificity, and accuracy.

J.T. Kwok et al. [7] delivered wavelet-based photograph fusion to easily cognizance at the object with all focal lengths as several vision-related processing tasks can be carried out more effortlessly when wholly substances within the images are bright. In their work Kwok et al. investigated with different datasets, and results show that presented work is extra correct as it does not get suffering from evenness at different activity stages computations.

Kumar and Mehta [8] proposed the texture-based technique in this paper. They highlighted the effects of segmentation if the tumor tissue edges aren't shrill. The performance of the proposed technology may get unwilling results due to those edges. The texture evaluation and seeded region approach turned into executed inside the MATLAB environment.

Dalia Mahmoud et al. [9] presented a model using Artificial Neural Networks for tumor detection in brain images. They implemented a computerized recognition system for MR imaging the use of Artificial Neural Networks. That was observed that after the Elman community was used during the recognition system, the period time and theaccuracy level were high, in comparison with other ANNs systems. This neural community has a sigmoid characteristic which elevated the extent of accuracy of the tumor segmentation.

Springer, Berlin, Heidelberg. L. Marroquin et al. [10] presented the automated 3d segmentation for brain MRI scans. Using a separate parametric model in preference to a single multiplicative magnificence will lessen the impact on the intensities of a grandeur. Brain atlas is hired to find nonrigid conversion to map the usual brain. This transformation is further used to segment the brain from nonbrain tissues, computing prior probabilities and finding automatic initialization and finally applying the MPM-MAP algorithm to find out optimal segmentation. Major findings from the study show that the MPM-MAP algorithm is comparatively robust than EM in terms of errors while estimating the posterior marginal. For optimal segmentation, the MPM-MAP algorithm involves only the solution of linear systems and is therefore computationally efficient.

3. SCOPE OF THE PROJECT

Our aim is to develop an automated system for enhancement, segmentation and classification of brain tumors. The system can be used by neurosurgeons and healthcare specialists. The system incorporates image processing, pattern analysis, and computer vision techniques and is expected to improve the sensitivity, specificity, and efficiency of brain tumor screening. The primary goal of medical imaging projects is to extract meaningful and accurate information from these images with the least error possible. The proper combination and parameterization of the phases enables the development of adjunct tools that can help on the early diagnosis or the monitoring of the tumor identification and locations.

3. PROPOSED APPROACHED

Here we proposing a novel technique for brain tumor detection using image processing techniques. For getting accurate output for detecting brain tumor, we have collected images of brain tumor images of different patients. By using image processing detecting brain tumor. Firstly, we take the image dataset of different patients and brain tumor detection using image processing. Here we investigate a better and accurate method for brain tumor detection using Deep learning and image processing techniques.

In our proposed method we are using the ResNet101v2 network of the deep learning which is a Convolutional Neural Network (CNN). These algorithms are been used to train the brain images which considered in the three classes as the Normal which is not affected with any disease and the other classes which were affected with brain tumor. From which we can also find out the ages from the classified images.

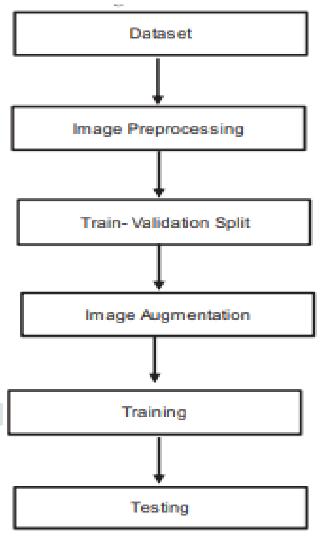

Fig.3 Block Diagram of Proposed Method

We used a convolutional neural network as our model as CNNs are the neural networks that are best suited for images. The Convolutional Neural Network (CNN or ConvNet) is a subtype of Neural Networks that is mainly used for applications in image and speech recognition. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. That is why CNNs are especially suited for this use case.

Transfer learning has been applied which means the training our neural network will do will be based on a pretrained network. We have used a pre-trained model that has already learned a lot of complex features. The pre-trained model used is ResNet101v2 which will become our base model on top of which we will fine-tune our task to classify tumor and non-tumor images.

ResNet, which was proposed in 2015 by researchers at Microsoft Research introduced a new architecture called Residual Network. Residual Network: In order to solve the problem of the vanishing/exploding gradient, this architecture introduced the concept called Residual Blocks.

Magnetic Resonance Imaging is a standard modality used in medicine for brain diagnosis and treatment. It offers the advantage to be a noninvasive technique that enables the analysis of brain tissues. The early detection of tumor in the brain leads on saving the patients' life through proper care. Due to the increasing of medical data flow, the accurate detection of tumors in the MRI slices becomes a fastidious task to perform.

Performance Metrics Performance metrics measure the performance of a model based on the predictions made v/s the true labels. The 3 metrics were accuracy, precision, and recall. F1 score is another metric that makes use of precision and recall. Accuracy is the percentage of correctly classified data points. Accuracy is not a good metric as it fails to suggest anything in the case of imbalanced classes. Consider 10 images out of which 9 are tumor images and 1 is a non-tumor image. If the model learns badly and predicts every image as tumor images, then also the accuracy would be 90% in this

model was bad. Precision is a metric that says out of all the images which the metric classified as tumor images, how many of those were tumors. Suppose the model identifies an image to be a tumor image, the person can consult a doctor to check if there's a tumor. In this case, there is no health risk ie in case of a false positive, the person will only have to spend that extra money and time for consulting a doctor. Recall says that of all tumor images, how many of those did the model predict that there is a tumor. This is an extremely important metric and the one we will focus on in this task. Suppose if a person had a tumor, and the model classifies it as non-tumor. The person would not consult a doctor and could die due to the lack of attention given to that case. Health risk increases if the model predicts a false negative. F1 score is a metric that conveys the balance between precision and recall. It is the harmonic mean of precision and recall and penalizes the model a lot even when only one of them is low.

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FN} \\ F1 &= \frac{2 \times precision \times recall}{precision + recall} \\ accuracy &= \frac{TP+TN}{TP+FN+TN+FP} \end{aligned}$$

In the above
TP - True Positive
FP - False Positive
TN - True Negative
FN - False Negative

5. SIMULATION RESULTS

The input image is the initial image that is being processed for brain tumor detection Shown in fig.4.

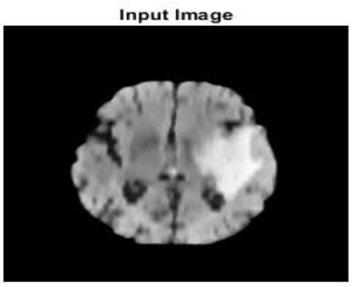

Fig.4: Input Image

The next step is histogram equalization, which is a technique used to enhance the contrast of an image by adjusting the intensity values of the pixels in the image. This helps to improve the visual quality of the image, making it easier to detect any abnormalities or tumors shown in fig.5.

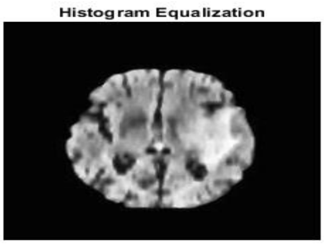

Fig.5: Histogram Equalization

After histogram equalization, the image undergoes erosion and dilation operations. Erosion is a morphological operation that removes small or thin structures from an image, while dilation is an operation that enlarges the boundaries of objects in an image. These operations help to further enhance the features in the image, making it easier to distinguish between normal and abnormal tissues. Shown in fig.6 and 7.

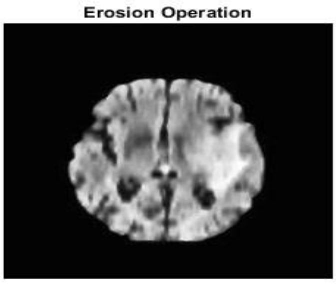

Fig.6: Erosion Operation

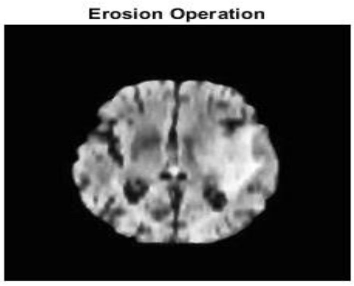

Fig. 7: Dilation Operation

The output of these image processing techniques is then fed into a Convolutional Neural Network (CNN) classifier Shown in fig.8.. A CNN is a deep learning model that is commonly used for image classification tasks. It works by extracting features from the input image using convolutional layers, and then classifying the image based on those features using fully connected layers.

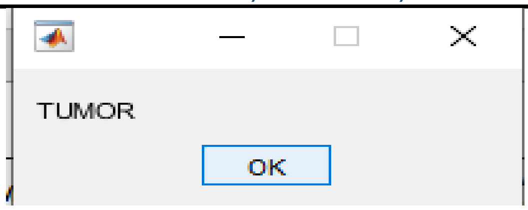

Fig.8: Classification Output through message box

The performance of the CNN classifier is evaluated using performance metrics such as accuracy, precision, recall, and F1 score. Accuracy is a measure of how well the classifier correctly identifies both positive and negative samples. Precision measures the proportion of true positives among the samples that the classifier predicted as positive, while recall measures the proportion of true positives that were correctly identified by the classifier. The F1 score is a weighted average of precision and recall, and is used to balance the trade-off between these two metrics. All performance metrics values displayed in command wind shown in below Fig.9.

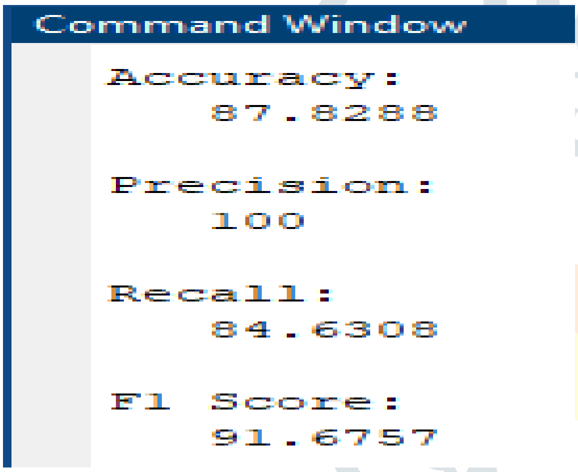

Fig.9: Performance metrics values displayed in command wind

Table I: Performance Metrics

Algorithm	**Performance Metrics**			
	Accuracy	***Precision***	***Recall***	***F1 Score***
CNN	87.8288	100	84.63	91.67

In summary Shown in above Table I, the simulation process involves enhancing the input image using histogram equalization, erosion, and dilation operations, and then classifying the image using a CNN classifier. The performance of the classifier is evaluated using metrics such as accuracy, precision, recall, and F1 score.

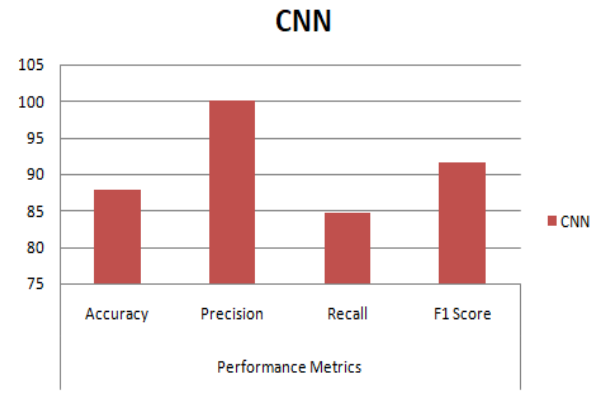

Fig.10. Evaluation graph based on performance metrics

The performance metrics for the CNN algorithm are as follows:

- Accuracy: 87.8288%
- Precision: 100%
- Recall: 84.63%
- F1 Score: 91.67%

These metrics indicate that the CNN algorithm has a high accuracy in detecting brain tumors, with an overall accuracy of 87.8288%. The precision of 100% indicates that all the positive predictions made by the model were correct, while the recall of 84.63% indicates that the model correctly identified 84.63% of the total positive cases.

The F1 score of 91.67% is a weighted average of the precision and recall, and provides an overall measure of the model's performance. This score indicates that the model has a good balance between precision and recall, which is desirable in medical applications where false positives or false negatives can have serious consequences.

Overall, these performance metrics suggest that the CNN algorithm is effective in detecting brain tumors with high accuracy and reliability.

6. CONCLUSION & FUTURE SCOPE

This paper presents a novel method involving image processing techniques for image manipulation which would aid our CNN model to classify tumor and non-tumor images better. Image Processing techniques helped us solve the illumination issues and brought the tumor into focus. Data augmentation was used to reduce the chances of overfitting, as it artificially expands the size of a training dataset, thus bringing out an improvement in the performance and the ability of the model to generalize. Transfer learning is also used as a pre-trained model, ResNet101v2 was used as the base model, upon which further training was applied to tune our task. CNN combined with transfer learning proved to be an effective training model which can be seen in the extremely good values of the performance metrics.

Future Scope

In future, Deep neural networks have the ability to learn and improve over time. With more data and better algorithms, the accuracy of brain tumor detection using deep neural networks can be improved. This will lead to better diagnosis and treatment planning for patients. And Real-time detection of brain tumors using deep neural networks can be extremely helpful in emergency situations. Future research can focus on developing algorithms that can quickly and accurately detect brain tumors in real-time.

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