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DEEP LEARNING BASED EARLY PREDICTION OF BRAIN TUMOR USING PRE-TRAINED FAST MASK RCNN

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ABSTRACT

It is important to observe and diagnose individuals' health issues carefully and at an early stage, as well as to treat them with appropriate medication. It is possible to detect many health disorders at an early stage and therefore reduce their impact before they become severe. Medical professionals have been concerned about brain tumors. A medical expert's manual segmentation of brain tumors is time-consuming and should be automated. Computer-aided diagnosis (CAD) reduces the overall time it takes to diagnose the tumor and improves diagnosis accuracy. Surgical planning and surgical intervention can be more effective when brain tumors are segmented precisely. As the patient's survival depends upon well-timed treatment, physical detection of MRI images can be Computationally complex,, and the performance is dependent upon domain expertise. In this paper, we suggest Deep learning based Early Prediciton of Brain tumor using Pre-Trained Fast Mask RCNN for precise classification and segmentation. A comparison is made between the simulation results of the neural network and those of any other neural network.

Keywords: Brain Tumor, Prediction, Classification, Pre-Trained Fast Mask RCNN, Segmentation.

1 INTRODUCTION

In the human body, the brain contributes significantly in controlling the action of other organs and in helping make decisions. The brain is primarily responsible for controlling the functions of the nerves system; all voluntary and involuntary functions are under direction. Tumors are fibrous meshes of uncontrolled growth inside the brain that proliferate uncontrollably. There are about 3,450 children's identified with brain tumors at age 15 this year [1]. To prevent and cure the illness, one must understand brain tumors and their stages [2]. A widely used imaging technique by radiologists for the diagnosis of tumors is MRI. In this paper, deep learning techniques are applied to determine the normality or disease of a brain.

It is believed that brain tumors are caused by abnormal cell division and growth [4]. Diagnostic medical imaging techniques depict it as a solid mass. Brain tumors fall into two categories: primary and metastatic [5]. Metastatic brain tumors are those that arise elsewhere in the body and spread through the brain while primary brain tumors occur in the brain and tend to remain there. A brain tumor's symptoms are determined by its location, size, and type. The tumor causes pressure on the surrounding cells when it compresses them [7]. The tumor can also cause headaches, nausea and vomiting, and difficulty walking or balancing due to the blockage of the fluid flow [8].

CT scans and MRIs can be used for the diagnosis of brain tumors. It depends on the type of location and the purpose of the examination whether either of these methods is more effective at detecting cancer. CT images are preferred in this paper since they are easy to examine and give accurate information on calcification and foreign mass locations. Human skulls are very rigid, which enclose the brain [9]. Growing within such a limited area can present a number of difficulties. A brain tumor can be either malignant (cancerous) or benign (benign).

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The growth of benign or malignant tumors can result in an increase in the pressure within the skull. There is a possibility that this can result in brain damage, which is potentially fatalPrimary brain tumors originate from the brain. There are many benign primary brain tumors [10]. Metastatic brain cancer, also called secondary brain cancer, is caused by cancer cells spreading from another organ to the brain. Brain tumor symptoms vary depending on their position and size. There are tumors that cause damage directly to brain tissue by invading it while there are others that exert pressure on the surroundings of the brain tissue.

2 RELATED WORKS

MRI scans are no longer required to determine whether a patient has a tumour due to advancements in medical imaging technology for autodetecting equipment. Because of this [11], it has been highly helpful for individuals who are unable to see a physician right away. Researchers in the field of ML have been exploring the segmentation of diseases in recent years. It is imperative that brain tumors be segmented accurately for a successful surgical procedure [12]. When laryngeal cancer is advanced, treatment is more complicated. The head and neck region of the patient suffers from this type of cancer.

Medical imaging techniques [14] are designed to extract as much accurate and meaningful information as possible from images with a minimum amount of error. The contouring manually of these brain tumors, however, is extremely time consuming, costly, and subject to interobserver variability. In this work [15], it is proposed that the detection and segmentation of neoplasms are crucial to radiotherapy treatment planning, checking of disease progression, and forecasting treatment outcomes.

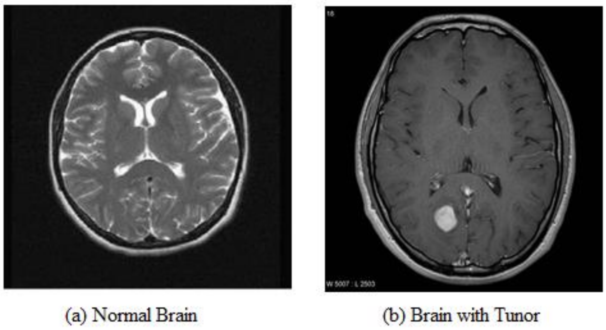
Modern applications increasingly rely on machine intelligence-driven automation, and vision-based analysis is a key component of this [16]. By partitioning regions of interest for additional processing, segmentation plays a critical role in the goal of vision-based understanding of images. In order to avoid future complications, Brain tumors must be diagnosed in order to be treated as early as possible and as accurately as possible [17]. By segmenting brain tumors precisely, doctors are able to plan surgery and administer treatment more effectively.

Recently, deep learning algorithms have become increasingly popular for the detection of skin cancer [18]. A novel method of multiclassifying skin cancer types such as melanoma is proposed in this study, which is based on deep learning. Millions of people around the world suffer from brain tumors. The survival rate of patients with this disease is very low if it is not diagnosed at an early stage [19]. This necessitates a rapid and accurate diagnosis of brain tumors.

A common problem that arises when medical research is applied to the situations is the high incidence of false positives. Due to this circumstance, experts receive unnecessary alarms, which increase their workload. Based on this study [20], we propose an approach for reducing bias-based errors in the detection of articles in the brain that can be detected using MRI.

3 PROPOSED METHODOLOGY

MRI images of brain tumors are included in kaggle dataset. A normal brain image is in one folder and a tumor image is in the other folder. Both folders contain a total of 2065 images. An image of a normal brain and a brain tumor is shown in Figure 1. A total of 1076 tumorous images and 978 non-tumorous images were taken. A variety of shapes and sizes are represented in the images. There are 1562 images for training, 186 images for validation, and 207 images for testing. The total number of 1672 training images is composed of 877 tumor images and 795 non-tumor images. A total of 186 validation images were selected, of which 92 showed tumors and 94 showed non-tumors. There were 208 testing images, 114 images depicting tumors and 91 images depicting non-tumors.



(a) Normal Brain (b) Brain with Tunor

Figure 1. Comparison of Normal Brain and Tumor Brain

As shown in Figure 2, we have proposed a model for classifying lung MRI images in order to detect diseases based on Pre-Trained Fast mask RCNN in Deep Learning. The proposed work for tumor detection of MRI brain images includes Image Preprocessing, segmentation, feature extraction, and classification with the addition of pre-trained models.

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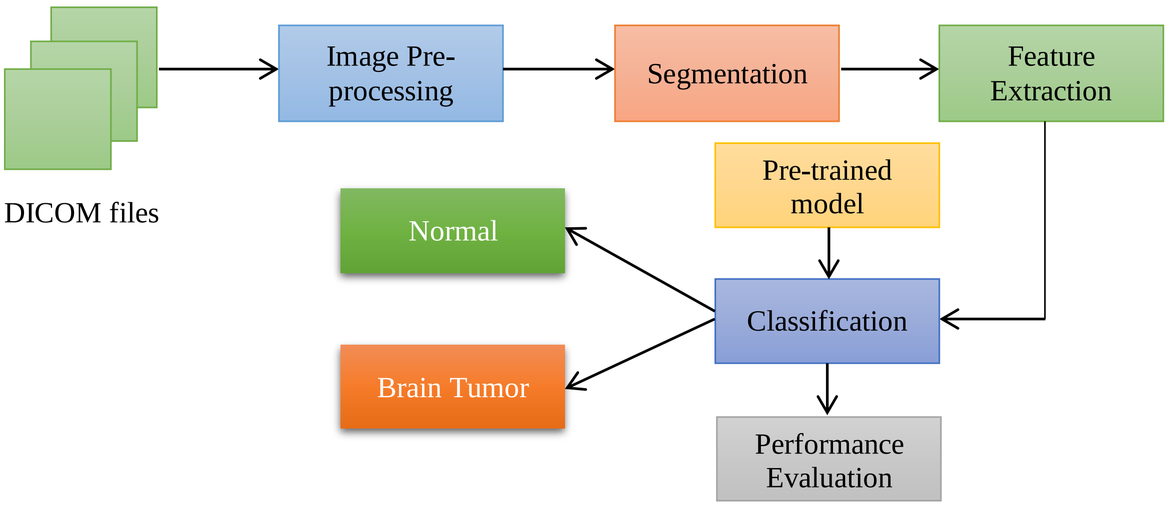

Figure 2. Overall workflow of Proposed System

There are primarily DICOM files in the images collected, which is a format used in the medical field for computer storage. It is first necessary to process these DICOM files so that images may be extracted. In the 2-D array format, all images are shown after being pre-processed.

3.1 Pre-Trained Fast Mask RCNN Learning

Presented in this section is a detailed discussion of Pre-Trained Fast Mask RCNN learning using propagation method as shown in fig 3. For each occurrence of an entity throughout the image, the framework establishes class labels as well as masks. It is built on a FRCNN backbone as well as the Region Proposal Network (RPN).

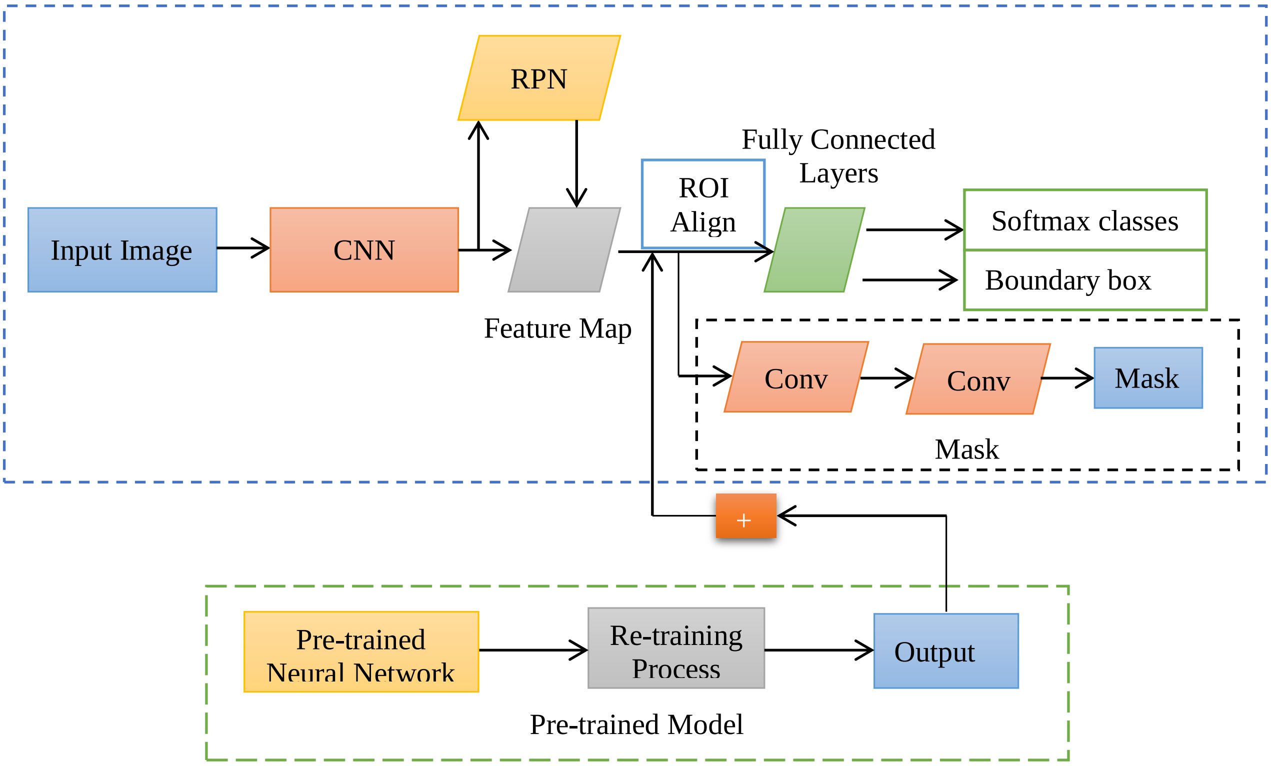

Figure 3. Architecture of Pre-Trained Fast Mark RCNN Learning

Propagation estimation: Hyperplanes are constructed in P-FRNNs using hidden layer activation, which is based on the activation of the hyperplanes:

$$H_{(k)}^{i(T)} = e^{\left(-\eta \frac{di_{(k)}^{(T)}}{\mathrm{MAX}(di_{(k)}^{(T)})}\right)} \quad (1)$$

Where, i varieties from 1 to ek, which characterizes the number of unknown units at time T, k^th hidden layer H (t) (k), η - activation strength is controlled and adjusted by this parameter. Here, η is secure as 0.05 for all sets. di(t) (k) is the space between (t − 1)^th, the data point is i^th hyperplane feature k^th hidden layer. The following information is provided as:

$$d_{(1)}^{i(T)} = \frac{\left|y^{(T-1)}\right|_1 s(b_{(1)}^{i} + U_i x^{(t)})}{\sqrt{1+\sum_{j=1}^{D} U_{ij}^2}} \quad (2)$$

where k = 1, |y|1 is the 1-norm of y, S signifies the output dimension, b(1) ∈ R e1is equal to the bias at level 1, regarding the addition of a feature plane dimension.

$$d_{(1)}^{i(t)} = \frac{\left|y^{(T-1)}\right|_1 s.(b_{(k)}^{i} + V_{(k-1)i}) h_{(k-1)}^{(t)}}{\sqrt{1+\sum_{j=1}^{e_{k-1}} V_{(k-1)ij}^2}} \quad (3)$$

where b(k) ∈ R ek is the bias atblevel kin respect to the additional dimension to (k − 1)^th feature plane. This hyperplane-based activation is noteworthy in that, without requiring external weights or parameters, and a teacher-forced training approach is employed by default when training the model.

In order to estimate the un-normalized output at time t, the activations of the hidden layer must be obtained:

$$O^{(T)} = C + v_{(K)} \cdot h_{(k)}^{(t)} \quad (4)$$

where k = l, and c ∈ R The output layer's bias is indicated. In general, log probabilities are un-normalized and normalized by the softmax function in order to achieve the output predicted by yb(t).

$$\hat{y}^{(T)} = softmax\ (O(t)) \quad (5)$$

In order to calculate the reduction of cross entropy, we use the following equation:

$$Loss(Y, \hat{Y}) = -\sum_i Y_i . \log(\hat{Y}) \quad (6)$$

Where Y band YPredict and observe the output at the designated time.

Algorithm:

Input: *DICOM images of Brain*

Output: *Brain tumor classified Image*

Step 1: Preprocessing of DICOM Images

Step 2: Extract images to 2D-array format.

Step 3: Image ← Train_classifier (Features, Label)

Step 4: for i=1; n // number of iterations

Step 5: Classifer : (label) → Image (unlabelled)

Step 6: for each classifier (Image)

Step 7: label_image ← merge (label, Image (unlabelled))

Step 8: unlabled ← mask (unlabled_image)

Step 9: Image ←Train_classifier (labelled, features)

Step 10: end for

4 RESULTS AND DISCUSSIONS

An array of n_array datatypes is used to store the image data in the variable named information. Moreover, the images' class labels have also been generated into a variable called data_target, which is also a collection of n-arrays. Once the dataframe has been created, the images will be placed inside of it. Training, validation, and testing datasets are divided into the image dataset. In order to provide enhanced end results in the evaluation of brain tumor images, a well-established method of brain segmentation is desirable. According to the following description, accuracy refers to being true to the results.

$$Accuracy = \frac{(Tp + TN)}{(TP + TN + FN + FP)} \times 100 \quad (7)$$

Signal fidelity or image fidelity is measured by mean square error (MSE). A signal reliability measure or fidelity measure refers to assessing the degree of similarity or consistency expressed by two images on the basis of numerical calculation. In the event that MSE is pre-meditated, we assume that one image is flawlessly unique, whereas the remaining image is distorted by some means and is characterized as follows:

$$MSE = \frac{1}{M} \times N\varepsilon\left(f(x,y) - F^r f(x,y)\right)^2 \quad (8)$$

It is a database that provides information on Peak Signal-to-Noise Ratios. In general, it serves as a measure of how well a processed image can be reconstructed. The formula for this can be found below.

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$$PSNR = \frac{20log10(2N-1)}{MSE} \quad (9)$$

When the MSE is lower and the PSNR is higher, the signal-to-noise ratio is considered to be good. In the Boundary Displacement Error, pixels are distanced from the nearest pixels in boundaries and then the values of both pixels are summed. The following results are output steps which are useful to detect brain tumor. An input image of MRI brain image is shown in fig 4.

Figure 4. Input Image

The purpose of pre-processing would be to improve the picture data by eliminating undesired distortions or enhancing certain visual elements that are essential for subsequent processing as shown in fig 5.

Figure 5. Data Preprocessing

Image segmentation is the subject of the subsequent step. An input image is segmented into its individual items or sections in order to analyse it more thoroughly as shown in fig 6.

Figure 6. Image Segmentation

Figure 7. Classification of Brain Tumor

Image classification involves doing numerical analysis on a variety of image attributes and then organising the results of that analysis into distinct groups as shown in fig 7.

Table 1: Performance Evaluation of Various Algorithms vs Proposed Algorithm

Algorithms	MSE	PSNR	Accuracy
CNN	24.1	21.4	93.2
Fast RCNN	23.2	18.6	94.6
Proposed (Pre-Trained Fast Mask RCNN)	17.0	11.2	98.3

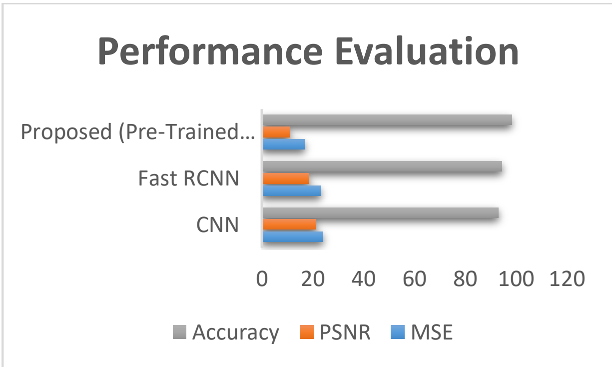

Figure 8. Comparison Results

The results of the present work are presented in Table 1 and fig 8 where two algorithms are compared with our proposed algorithm and the accuracy is increased by 98.3 percent when comparing CNN and Fast RCNN algorithms.

5 CONCLUSION

A critical component of medical imaging applications is the segmentation of an ideal abnormal area in brain tumor images. Brain tumor medical images are segmented using a variety of algorithms in order to enhance accuracy. In this paper, we proposed DL based Early Prediciton of Brain tumor using Pre-Trained Fast Mask RCNN for precise classification and segmentation. The performance of these algorithms is evaluated. The determination of this study is to associate a variety of performance metrics. Blood cancer images can be processed using Machine LearningML techniques to improve efficiency, shorten the time required for diagnosis, and to facilitate faster as well as more cost-effective diagnostic procedures.

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