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Reducing loss for Brain tumour detection and classification in MRI using deep learning techniques

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Abstract:

The signs of a brain tumour might be general or specific. The typical symptom is brought on by a tumour pressing against the brain or spinal cord. When the tumour has impacted a certain section of the brain and that area is not working correctly. Identification of brain tumours was extremely difficult and complicated due to the location, kind, shape, and size of the tumour in the brain. Brain tumour diagnosis is difficult since the tumor's size and resolution cannot be clearly evaluated in the early stages of growth. However, if a tumour is found and diagnosed early in the stage of tumour growth, there is a good chance that the patient will be treated. As a result, early tumour diagnosis is essential for successful treatment. To solve this problem, we suggested an automated method that can more help detect and classify three different types of brain tumours on MRI using deep learning techniques, faster RCNN+ResNet50.

Keywords: Brain tumour, detection, classification, deep learning, faster RCNN, ResNet-50, automated, MRI.

1. Introduction

Due to its rising presence and high death rate across all age groups [1] [2] [3][4][5], brain tumours are among the world's worst illnesses [6] [7]. It is noted in [3] as India second-most frequent type of cancer. 5 to 10 brain tumours per 100,000 persons are seen in India. According to "International Association of Cancer Registries (IARC)," over 28,000 instances of brain tumours are detected more than 24,000 individuals die due to brain tumour every year in India. [8]. Increased usage of electronic devices like mobile phones, tablets, and other devices, has made this disorder more prevalent among children as well[9].

1.1 Brain tumour

Two kinds of brain tumours exist: benign (noncancerous) and malignant (cancerous). The patient's health may deteriorate as a result of the malignant tumours' fast spread to other brain areas [10]. When the majority of the cells are worn out or harmed, they are destroyed and changed out with fresh ones. Problems may arise if damaged and old cells are not removed when producing new ones. The growth or tumour is referred to as a mass of tissue that forms as extra cells are produced.

1.2 Brain tumour causes

Although cause of the brain tumour is frequently unclear, table 1 specifies the things may increase a person's chance of getting one [17].

Table 1: Risk factors which cause brain tumour

Risk Factors	Supportive reasons
Head injury and seizures	There has long been research on the relationship between brain tumours and serious head injuries.
Ionizing radiation	It has been demonstrated that prior ionising radiation therapy, including x-rays, to the head or brain increases the likelihood to develop brain tumour.
Electromagnetic fields	Majority of research examining the effect of electromagnetic fields, like energy generated via power lines or by using a cell phone, don't find any evidence of a connection to an elevated risk of adult brain tumour development.
Exposure to allergen, viruses and infections	In tissue of brain tumours, high concentrations of the common virus cytomegalovirus (CMV) have been discovered.
Family history	Brain tumours may be caused by inherited genetic factors or circumstances in around 5% of cases.
Home and work exposures	Exposure to lubricants, pesticides, oil-based chemicals, latex, or vinyl chloride increases the risk of brain tumour.
Gender	In general, men are more likely then women to get the brain tumour. One specific type of brain tumour which affects women most frequently is the meningioma.
Age	Although anybody can acquire a brain tumour, youngsters and older individuals are more likely to do so.

1.3 Brain tumour symptoms and signs

Brain tumour symptoms might be generic or specialized. The common symptom is caused by tumor's pressure on spinal cord or brain. When the particular area of brain is affected by the tumour and is not functioning properly, distinct symptoms are brought on [18].

General symptoms includes:

- Pressure/head ache near the tumour
- Partial or complete vision loss
- A change in one's capacity for walking or carrying out everyday tasks
- Sleep problems
- Memory problems
- Loss of balance
- Difficulty in swallowing

- Fatigue
- Vomiting
- Seizures

1.4 Brain tumour detection

Due to location, kind of tumour, form and size in brain, identification of brain tumours was exceedingly intricate and challenging. Since the tumor's size and resolution cannot be precisely measured in the early stages of development, diagnosing brain tumours is challenging [11]. However, the likelihood of a patient being treated is quite great if tumour is identified and diagnosis early in tumour growth phase. As the result, early tumour detection is crucial for effective therapy [12].

The diagnosis is frequently made by the physical examination utilizing magnetic imaging or computer tomography (CT). Most popular, crucial techniques to identify and assess patient brain is MRI imaging, which produces precise pictures of the brain. MRI images outperform other imaging modalities like CT in the field of "Medical Detection Systems (MDS)" because of their better contrast in muscle tissue in humans[13].

Currently, the majority of MRI anomaly identification is manual, and it takes more time for doctors for locating and segmenting tumours to surgical, therapeutic purposes[14] [15] [16]. This manual method might endanger life and is also prone to mistakes. To solve these issues, research has started to focus on various deep learning and machine learning techniques for computer-based cancer segmentation and diagnosis.

2. Related work

In [19], they proposed a technique based on genetic algorithms (GA) and CNNs to noninvasively aggregate different assessments of glioma using MRI. They explained how a specific strategy was used to construct the CNN's architecture using GA as well as how stowing was used to reduce change in expectation error.

Glioma is a form of brain tumour that is extremely lethal and has a lifespan of just two years. In [20], authors published automatically estimate the longevity of patients with glioma. The doctor gave the patient's projected number of days to live up until the patient was given the Glioma diagnosis. To avoid any human mistake, the technology automated the process for the impartial prediction. MRI imaging data with ground-truth segmented label identifies region-of-interest (ROI).

In [21], author developed acquiring CNN highlights, such as images of the brain and liver, includes “discrete wavelet transform (DWT)” intensity, descent while signal processing, and included LSTM intensity for signal analyzing. To arrange those MRIs of brains with tumours and group CT images of livers among tumours, a CNN+LSTM+DWT method had been developed. Element vector pertaining to those pictures are obtained by configuring AlexNet architecture for the first half and second half as CNN+LSTM+DWT technique.

For increasingly precise new disease detection, the author of [22] suggested a data processing method for maintaining data of the entire cortical covering inside deep networks. To categorise Alzheimer's disease, a 3D MRI of brain is used. Cortical covering is then straightened as 2D plane and deep networks are placed over this 2D cortical covering. Leveled cortical pictures were used on several deep networks, including ResNet, together with ADNI collection of brain MRI filters.

In [23], the author used reliable and conventional procedures to identify brain tumour, determine characteristic, categorize glioma by MRI. As a consequence, they created the model which uses synthetic neural networks and image processing to assist in the diagnosis of brain tumours. Primary picture has been made more complexity by using Histogram Balance (HE) method.

In [24], they presented the MV-KBC deep technique, which uses limited chest CT data to distinguish dangerous from favourable knobs by multi-view knowledge-based collaboration. Their approach disassembles a 3D knob into nine predetermined views to study the features of the 3D lung knob. Authors created “knowledge-based collaborative (KBC)” subsystem to every scene, three different image types are used to change 3 different ResNet-50 systems which depict overall character, voxel, and form heterogeneity of knobs independently. Authors used 9 KBC submodels to describe lung knobs using the flexible weighting strategy learned by error back-propagation, allowing MV-KBC model to produce in the comprehensive manner. Role of punitive misfortune was applied to GA with minimal influence on overall MV-KBC execution in order to significantly reduce bogus erroneous valuation.

Regarding brain tumour localization and containment, unique dual platforms multi-modelled program conclusion structure was provided by the author of [25]. The initial stage of framework construction includes pre-processing, feature extraction by CNN, and feature analyses by ECOC-SVM method. Goal is to identify brain tumours by categorising MRIs as common and unusual MRI. Purpose of succeeding system stage was to use the fully prepared 5 layer location-based R-CNN to limit tumour inside abnormal MRIs. They obtained an 87% on the dice[35][38].

Convolution neural networks are used in [26] to split brain tumours into smaller segments by breaking them out into short 3x3 kernels.

Three distinct CNN strategies for glioma segmentation to MICCAI BraTS challenge against dataset were put up by the author in [27]. By using pre-ordered patterns from BraTS dataset for segmenting images from Rembrandt dataset, they looked at differences in the way information was received between several other datasets and BraTS dataset. The outcomes show that segmentation's only dice score is 86%[36][37].

In [28], CNN methods evaluated the effectiveness of using more under CNN topologies for brain tumour segmentation. By inserting a few 3 x 3 estimated channel into convolution phases, this process is demonstrated. As a result, more advanced convolution stages may be added to system without reducing robust open field of conventional upper channels. Additionally, deep designs employ more non-linearity and have lower channels load due to usage of smaller channels, which reduces the risk of overfitting. “Leaky rectified linear unit (LReLU)”, the ReLU altered model, was used as non-linearity initiating task. Rascal dice records of 88 percent, 83 percent, and 77 percent were obtained to whole tumour, center tumour, dynamic tumour, respectively, using suggested CNN which creates Eleven layers of profundity “6 six convolutional covers followed by 3 completely associated stages with two maximum pooling stages isolating them into squares of three”.

Another novel strategy was used to a two-pathway CNN design in [29]. In order to figure out a fallen CNN that analyses neighbourhood nuances of brain MRI in addition to larger settings of brain tissues, smaller measured patches and larger estimated fixes must be extracted concurrently. In order to position the mark of the focus pixel, patches measuring 65 x 65 were extricated to globe pathway and patches measuring 33 x 33 pixel are extricated to local pathway from each individual MRI approach. Multi-method 2D design A CNN initially prepared globe input patches with 65 x 65 x 4 size to produce 33 × 33 x 5 sized patches. Later, these patches are connected to 33x33x4 neighbour patches which where sent as input to the 2 track CNN with convolution stages that had 7 x 7 estimation channels in one manner and 13 x 13 measure channels in preceding one.

In [30], they built four separate CNNs' unique information-seeking bits from each single MRI technique picture by selecting several plane fixes inside every pixel and performing these steps. A RF classifier was prepared by deep stages of CNN, which are successfully linked, used as highlighted map. Only a precision stage of 67% was provided, with no information on the use of pre/post-handling levels.

A limited architecture prediction with CNN is suggested in [31], in the overall approach. First fixes of name are taken from sands precision pattern and afterwards packaged by k-implies method into N gathering to form the marking fix lexicon of size N. This method replaces the use of CNNs to define focused voxels regarding data picture pieces inside brain tissue classes. The multi-levelled model elements inside unity of those assemblages are then characterized using a 2D CNN. Whelp cube rates of 83 percent, 75 percent, and 77 percent for the overall tumour, center tumour, dynamic tumour regions were independently taken into consideration in this segmentation execution of the technique.

Another comparable strategy was published in [32] and mentioned in [33]. Two-stage preparation is also used in conjunction with this innovative compositional process to prevent class disparities in characters. CNN is retrained by expanding delegate diffusion of first metaphor during the subsequent stage after falling behind with its preparation of groups in the initial stage. The corresponding segment's technique was also implemented as a posthandling action and Maxout non-linearity was used. High Minxe cube rates 88 percent are applied to overall tumour region, 79% are applied to the centre tumour district, and 73% are applied to the dynamic tumour location.

3 Methodology

Here, the methodology for the suggested system of brain tumour detection and classification is described. A more suitable deep learning model that is "Faster R-CNN (Faster Region-based Convolutional Neural Network) and combined with deep feature extractor: Residual Network-50 (ResNet-50)" to identify and categorize various brain tumours on the Kaggle brain tumour dataset [34].

3.1 System Overview

This study uses deep learning as major component of proposed system to identify 3 different forms of brain tumours, like pituitary, meningioma, glioma, which have an influence on the human brain. Figure 1 shows a broad view of the system. Below, each stage of the proposed system is thoroughly explained.

3.2 Data Collection

A brain tumour dataset includes MRI pictures with top and side views of the brain for glioma, meningioma, pituitary, and no tumour. The symptoms of pituitary, meningioma, glioma, and samples of MRI are summarised in the table (Table 2).

3.3 Data Annotation

All tumour locations were manually labelled in all photos using the LabelImg tool, which is an excellent tool for labelling images, by the bounding-boxes and class type to which the tumour belongs. The coordinates of various sized bounding boxes with their corresponding tumour class are the output of the data annotation step, and these coordinates will be assessed by the IoU (Intersection-over-Union) using the suggested system and projected outcome during testing.

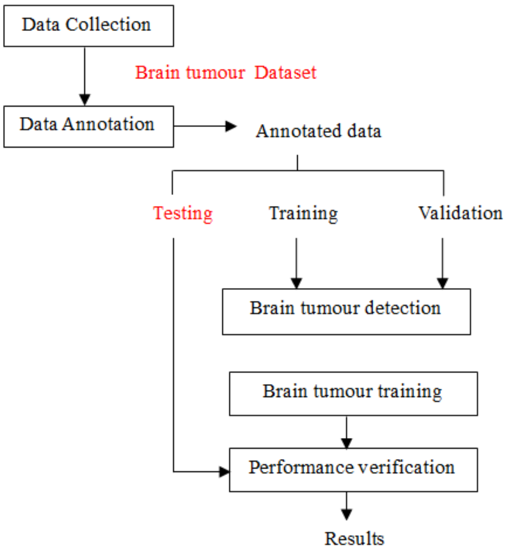
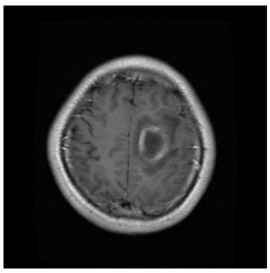
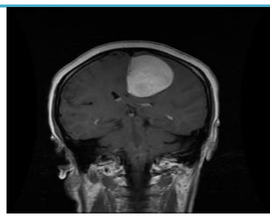
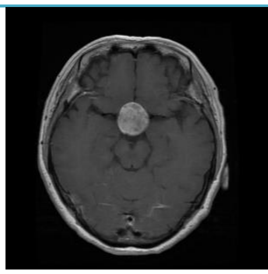


Figure 1. High-level picture of proposed system for brain tumour detection and classification

Table 2. Dataset for brain tumour detection and classification

Tumour	Common Symptoms	Collected sample
Glioma tumour	Seizures, behavioural changes, nausea and vomiting, hemiparesis, headaches, dizziness, difficulty walking, cognitive problems, vision loss, aphasia	
Meningioma tumour	Language difficulty, changes in vision, headaches, hearing loss, memory loss, loss of smell, seizures, legs or arms weakness	

Pituitary tumour	Sudden weight gain or loss, Increased amount of urine, sexual dysfunction, less frequent or no menstrual periods, feeling cold, weakness, nausea and vomiting	

3.4 Faster-RCNN+ResNet50 Brain Tumour Detection and Classification

The objective is to identify three different groups of brain tumours and their locations in brain MRI scans. The system's bounding boxes that include the tumour must be accurately established in order to get reliable findings. Using Region Proposal Network (RPN), faster R-CNN produces crucial Region of Interest (ROI) for the identification of brain tumours.

In a Faster RCNN technique for brain tumour detection in MRI, the following stages are carried out:
1. Provide an MRI to the ConvNet, which will then provide feature maps to RPN for the MRI.
2. RPN generates k fixed size anchor boxes in a brain tumour MRI by sliding windows on collected feature maps at each window, and predicts the likelihood that an anchor is a tumour as well as the bounding-box regressor that will most closely fit the anchor for a tumour.
3. After getting various types and sizes of bounding boxes and cropping each proposal such that it includes a brain tumour, ROI gathers fixed-size feature maps to all of the anchors.
4. The gathered fixed size feature mappings are sent to a fully connected layer that has a softmax and a linear regression layer. With the use of the ResNet 50 classifier, the brain tumour is ultimately classified as (glioma tumour, meningioma tumour, pituitary tumour, and no tumour), and bounding-boxes to detect the location of the brain tumour in an MRI are predicted.

3.5 RPN training and loss functions

An anchor is considered a "positive (tumour)" sample if it satisfies one of the two requirements listed below: With a ground-truth box, which have the highest “Intersection over Union (IoU)”; when the IoU is greater than 0.5 with any ground-truth-box. Anchor is labelled as "negative (no tumour)" if IoU on other ground-truth-boxes is substantially lesser than 0.5. During RPN training, all anchors are disregarded (either negative or positive). A single MRI serves as the basis for each RPN mini-batch. A batch should be created with 128 negatives and 128 positive samples to prevent bias learning. The loss of RPN training is calculated by:

$$Loss(\{ p_i \}, \{ t_i \})= 1/N_{cls} \sum_i Loss_{cls} (p_i, p_i^*)+ \lambda^*(1/N_{reg})\sum_i p_i^* Loss_{reg}(t_i, t_i^*) \qquad (1)$$

Here,

$Loss_{reg}(t_i, t_i^*)$ – Regression loss

$Loss_{cls} (p_i, p_i^*)$ - Classification loss

i - Anchor index in the mini-batch

p_i - output score for anchor i from the classification branch

p_i^* - Ground truth label (0 or 1)

4 Experiments and results

Using labelImg, manually annotated all MRI in the brain tumour dataset, the total number of labels for class considered for the proposed system for training and testing is shown in table 3.

Table 3. Total number of labels considered for training and testing for each class

Class	No. of labels for training	No. of labels for testing
Glioma tumour	826	100
Meningioma tumour	822	115
Pituitary tumour	827	74
No tumour	395	105
Total	**2870**	**394**

The suggested approach employs ResNet-50 and Faster R-CNN to identify three types of common brain tumours. First, IoU and AP (Average Precision) analyze the proposed system's performance.

$$\text{IoU}(B, S) = \left| (B \cap S)/(B \cup S) \right| \qquad (3)$$

Here,

B – Annotated Coordinates of Ground-truth-box

S – Predicted result by system

When calculated IoU exceeds the threshold value of 0.5, projected result was classified as either the "true positive (TP) or the false positive (FP)". When there are few FPs from MRI's including tumour locations, the suggested approach is deemed effective. Mean Average Precision (mAP) is AP determined for glioma tumour, meningioma tumour, pituitary tumour, and no tumour. AP is generated by calculating precision average across the range of [0, 0.1,..., 1] recall levels.

$$AP = 1/11 \sum_r P_{inter}(\text{r}) \qquad (4)$$

$$P_{\text{interp}}(r) = \max_{\check{r}:\, \check{r} \geq r} p(\check{r}) \qquad (5)$$

Here, p(ř) is accuracy measure at recall for each brain tumour. Suggested detection mechanism and mAP calculated to IoU = 0.5 obtained more than 94%. Table 4 displays the faster RCNN with ResNet50 findings for pituitary, meningioma and giloma tumours. Performance of suggested system, mAP, exceeded 94%. The performance can be improved by training proposed system with more samples. Figure 2 displays resultant loss curve for the fifty four thousand epochs and demonstrates that the proposed is capable of learning brain tumour data by achieving a smaller error-rate less than 0.1 at fifty two thousand epoch. Tensorboard is a tensorflow visualization toolkit that provides visualization and tracking of total loss. Table 5 displays the qualitative outcomes obtained by the suggested approach to identify three common brain tumours.

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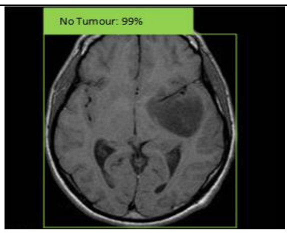
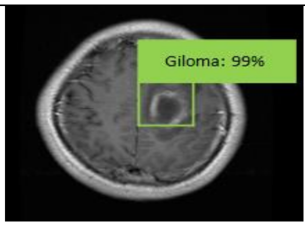
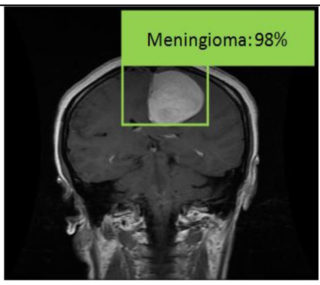
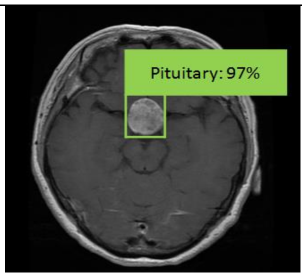
Table 5. Qualitative results predicted by the proposed system

Result predicted the system	Whether prediction is correct or not
	Correct prediction
	Correct prediction
	Correct prediction
	Correct prediction

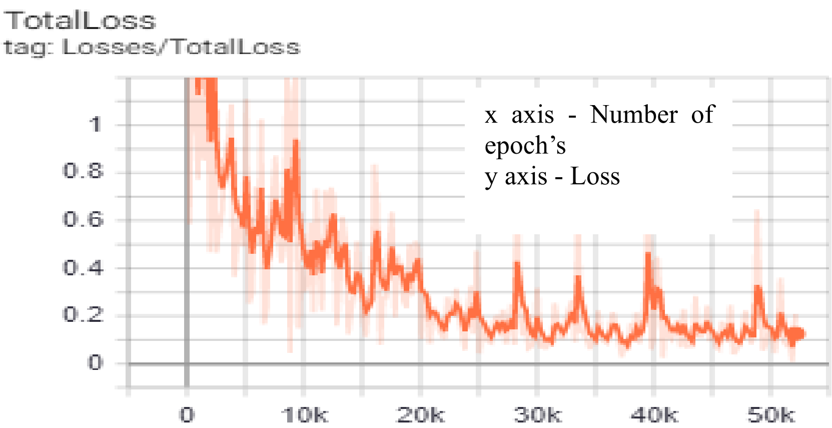


Figure 2: Total loss curve of the proposed system

Table 4. Proposed system results achieved for brain tumour detection

Class	ResNet50
Glioma tumour	96.22%
Meningioma tumour	93.50%
Pituitary tumour	92.09%

No tumour	94.48%
Total mean AP	**94.07%**

5. Conclusion

Over 28,000 cases of brain tumours have been found, and more than 24,000 people in India lose their lives to brain tumours each year, according to the IARC. The increased use of electronic gadgets like tablets, smartphones, and other devices has increased the prevalence of this illness among kids as well. However, if a tumour is found and diagnosed early in the stage of tumour growth, there is a good chance that the patient will be treated. As a result, early tumour diagnosis is essential for successful treatment. The better deep learning model, "Faster R-CNN (Faster Region-based Convolutional Neural Network) and combined with deep feature extractor: Residual Network-50 (ResNet-50)" is suggested for the detection and classification of various brain tumours, including pituitary, meningioma, and glioma, on the brain tumour MRI dataset. For glioma, meningioma, pituitary, and no tumour, an MRI image collection of the brain's top and side views is available. The proposed system, achieved mAP 94%.

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