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A Deep Learning Approach for Brain Tumor Detection usingMagnetic Resonance Imaging

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Abstract

Brain Tumors are brought on by the proliferation of aberrant cells in the tissue of the brain. One of the most serious conditions that can affect both adults and children is brain tumours. It progresses rapidly, and if the patient is not given the right care, there is little chance of survival. Improving a patient's life expectancy requires accurate diagnosis and well-planned treatment. Magnetic resonance imaging (MRI) is the primary method used to diagnose brain tumours. The suggested model has an activation function, a modified hidden layer architecture, and an automatic feature extractor. After running a number of test cases, the suggested model had a low cross-entropy rate and scored 97.8% precision and 98.6% accuracy. The suggested model has demonstrated superior tumour detection performance when compared to alternative methods including YOLOv5, mask region-based CNN (mask RCNN), adjacent feature propagation network (AFPNet), and Fourier CNN (FCNN).

Keyterms:

MNET, Convolutional Neural Network, Magnetic Resonance Imaging, Brain Tumors

Introduction

One of the most deadly types of cancer is brain cancer. Its near closeness to the human primary neuronal motor—a location where even a minor failure may have a huge impact—explains its potent effects.[1] It is crucial to develop methods for early diagnosis or warning of the possibility of a brain tumour because of this. [2] This topic is very important since a proper diagnosis significantly increases the chance of treating an illness and keeping a patient from dying from it. Cancer treatments have come a long way in the last few years, especially in the early stages of the illness. [3] Those who receive early therapy have a far higher chance of surviving than those who do not have this opportunity during the early stages of their illness. [4] A brain tumour is an accumulation of biological cells in the brain. These cells differ from normal brain cells in ways that lead to the assumption that they are aberrant. [5] The hard skull that covers the brain keeps these cells contained as they proliferate and enlarge. As this cell cluster expands inside the hard skull bone, the brain cells are squeezed, causing excruciating pain and other issues.

Brain tumours can be categorised into two different categories, much like any other type of cancer. [6] A benign brain tumour, also known as a non-cancerous tumour, is the first type of development, while a

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malignant tumour, also known as an extremely dangerous and cancerous growth, is the second type of growth. [7] These two distinct tumour kinds are growing inside the skull, which burdens the patients' brains and puts their lives in danger.[8] It is also possible to distinguish between two different types of cancers using the genesis of a tumour. These are the body's primary and secondary tumours, respectively. [9] Because primary cancers begin in the brain, they are frequently benign tumours. Metastatic or secondary tumours are those that start in another organ and go to the brain via the blood vessels or lymphatic system. Examples of these organs include the lungs. [10] Given that early diagnosis increases a patient's chances of recovery, it is imperative that patients receive this kind of care from the start.

However, early tumour diagnosis is a process that needs the involvement of skilled professionals in every facet of the patient's evaluation. [11] Not only is this incredibly costly, but it is also nearly impossible to do for a big number of people. It is necessary to have the factor that makes the application of computer-assisted brain tumour diagnostics increasingly significant. [12] Through the use of specialised software, the initial step in the diagnosis process, known as computer-aided diagnosis (CAD), can be completed automatically. [13] The software is responsible for identifying any of the numerous unique sections or regions of the brain that are created by the magnetic resonance imaging machine.

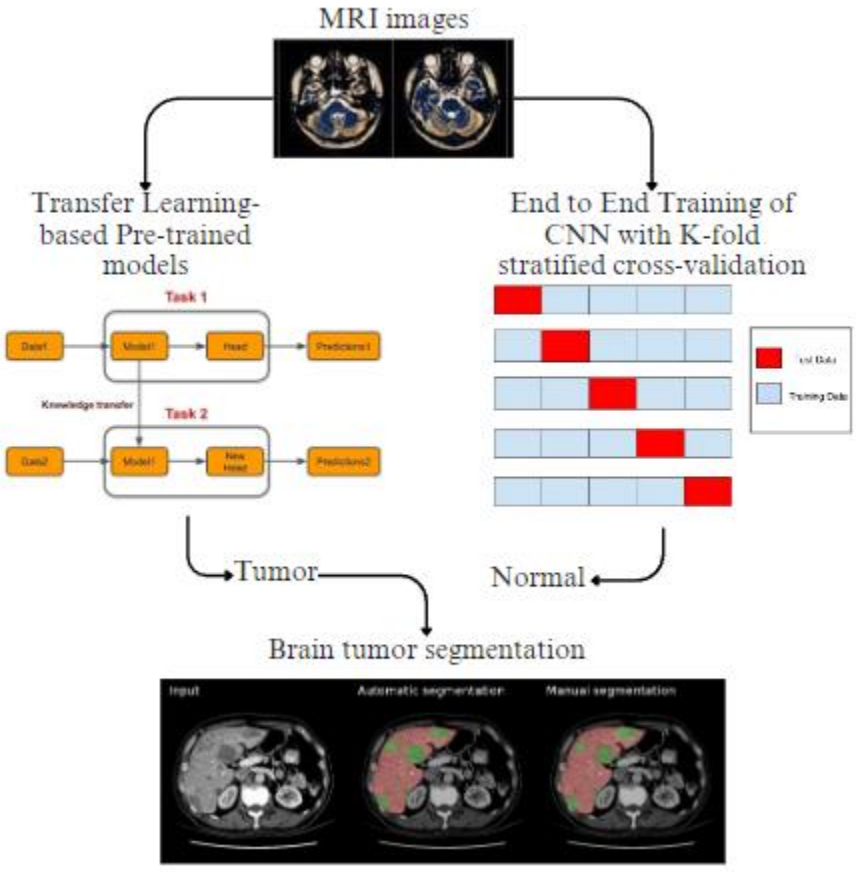

Figure 1. Brain tumor detection and segmentation

The study of techniques for the automated identification of different malignancies has received a great deal more interest in the last several years. [14] It is highly recommended that researchers explore for new methods that will enable automated tumour identification and MR image classification to function with greater precision. [15] Artificial neural networks have been widely used in image processing and medical imaging in recent years. In recent years, they have become an essential part of the analysis of medical images and the identification of illnesses. Artificial neural systems have proven to be quite effective at tasks that are thought to be difficult for humans to do but are frequently necessary habits for the brain to establish.

The effectiveness of Artificial Neural Networks (ANN) architectures has allowed researchers to establish themselves in a variety of medical subfields. With the continuous development of digital technology and ANN simulators, it is expected that the use of artificial intelligence based on neural networks would soon become the most important early detection method for malignant tumour masses. The main focus of this research is on brain tumours and how to detect them early with artificial neural systems and image processing techniques. The examination of different images of brain tumours will be the main focus, along with their processing, segmentation, and classification as benign or malignant. Many researchers from many nations throughout the world are interested in learning more about malignant tumours. Each year, hundreds of papers are published that address the wide range of issues surrounding brain tumours and the several methods available for detecting them early.

A patient's diagnosis is based on both the results of their tests and the doctor's manual evaluation of the patient. There is not just a longer wait time for patient appointments, but there is also a higher chance that a doctor may diagnose a patient incorrectly because there are fewer automated diagnostic tools and fewer doctors available. Rather than spending time with patients, physicians must mechanically assess test results and images. This consumes important appointment time. A doctor's manual evaluation of a patient and the results of their tests are what determine the patient's diagnosis. Patients have to wait longer to be seen, which contributes to the increased risk that a doctor would diagnose someone incorrectly due to the lack of automated technology that can help with diagnosis and the shortage of doctors. Doctors are forced to manually review test results and images rather of spending time with the patient. This eats up important time for appointments. A doctor must examine multiple picture slices when assessing photos in order to detect possible health issues, which necessitates months away from more challenging diagnosis. In order to ease the burden on physicians and allow them to tackle the most challenging diagnosis, we would like to be able to correctly identify the many types of brain cancer.

The process for detecting brain tumours

Data Collection

To train the deep learning model, 30,000 photos were gathered into a dataset. There were two classes in the dataset: brain MRI scans that were recent and images that showed a brain tumour. There are 15,000 photos of normal brains and 15,000 photos of brain tumours among the data that was gathered. Relevant photos were gathered from Google to test the dataset. 3,200 photos of the brain were taken with a tumour, and 4,400 images were obtained without one. A portion of the gathered photos is displayed in Figure 1. The BRATS datasets (BRATS_2018, BRATS_2019, and BRATS_2020) were used for comparison.

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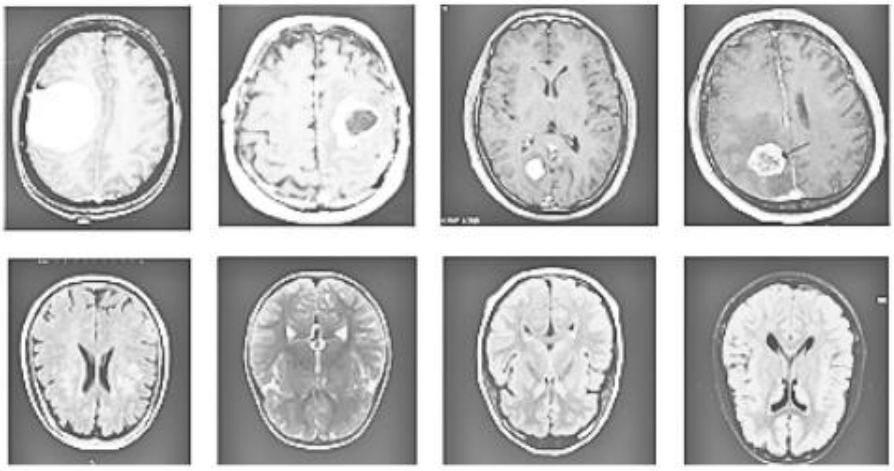

Figure 2. A part of collected images

Data Processing

The preprocessing stage seeks to improve contrast, clean up data, and improve image quality. By removing noise, the median filter preserves important data. A nonlinear method for keeping crisp features in MRI pictures is median filtering. In this work, an MRI image was preprocessed utilising (1) to improve image quality by turning the image into greyscale and removing noise using a 3x3 median filter.

$$(x, y) = medi_{(s,t)eSxy}\{g(s, t)\} \quad (1)$$

To find edges in the acquired MRI picture, a high pass filter was employed. The improved image was created by combining the edge-identified MRI scan with the original image. In order to avoid overfitting, the dataset was expanded through the use of data augmentation. Four different strategies were used to enhance the dataset: flipping each image once, rotating left -90 degrees, rotating left -180 degrees, and rotating left -270 degrees.

Architecture of the CNN model

In this work, MR images were used to detect brain tumours using CNN. CNN is an artificial neural network (ANN) that is intended to extract meaningful images by analysing image pixels. CNNs are utilised in artificial intelligence, natural language processing, and image and video recognition. Figure 2 shows the basic design of the proposed CNN. Typically, the input layer consists of an image filled with pixels. A feature map is created and then slid over the pixels to create a convolution layer. The correlation between nearby pixels is increased and the number of features is minimised during the pooling stage. The proposed

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technique downsamples images and extracts important features, including edges, using the max-pooling methodology. This study contrasts the triangular and rectangular designs depicted in Figures 3(a) through (c) with the assessment score of the suggested recto-triangular design for the concealed layer.

Figure 3. Model architecture of CNN

Triangular Architecture

256 nodes make up the first hidden layer of the modified triangular design, 512 nodes make up the second hidden layer, and the number of nodes decreases to form a triangle from the third layer to the seventh layer. There are 256, 512, 256, 128, 64, 32, and 16 nodes in the buried layers. All seven hidden levels are activated by the ReLU activation mechanism. The output layer makes use of the SoftMax activation function to make probability distribution modelling easier. The architecture is shown in Figure 3(a).

Rectangular Architecture

The rectangular construction has six concealed layers. The architecture is rectangular in shape and consists of six levels, each having a comparable node in a separate layer. Figure 3(b) presents an architectural illustration. For the rectangular architecture in this article, six hidden layers with 256 nodes in each layer are used. Only the output layer employs the SoftMax activation function; the other hidden layers use the ReLU activation function.

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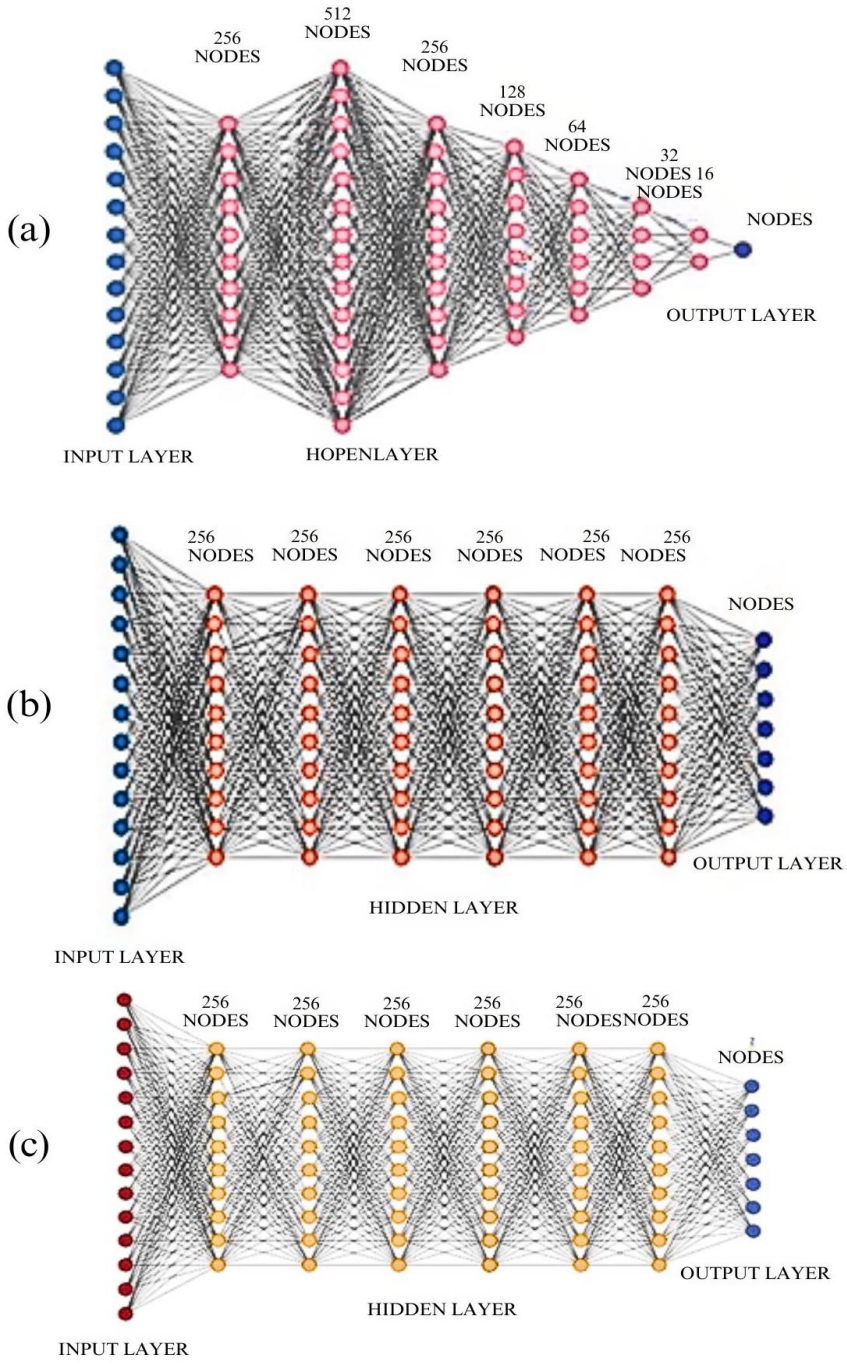

Figure 4. Hidden layer architecture (a) triangular, (b) rectangular, and (c) recto-triangular

Proposed recto-triangular architecture

This article proposes the recto-triangular, a hybrid of rectangular and triangular architecture. The concealed layer of the architecture consists of six layers. The form and strata of the suggested recto-triangular design

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are shown in Figure 3(c). The 512, 256, 128, 128, 256, and 512 nodes are found in the first, second, third, fourth, fifth, and sixth hidden levels. In the hidden layer's popular structure, the number of nodes decreases initially before increasing to the output layer. To activate each of the six hidden layers, ReLU is used. To precisely reflect the probability allocation, the output layer makes use of a SoftMax activation function.

Result and Discussion

Model training

A cross-validation approach was employed in training to assess the performance of the training session. Two distinct methods were used to train the data. In order to guarantee that every component was equally available, the initial strategy divided the data into ten equivalent sections. To partition the data into ten equal pieces, each comprising data from a single participant, another approach was used. The ability to generalise in clinical practise means that a diagnosis can be made using data collected from participants who did not show any symptoms during training. To address the problem of class inequality, the focused loss function (2) was used.

$$Focal = -(1-P)^{\gamma} \sum_{n-1}^{n} l_n * \ln(P_n) \ldots$$

The focus loss was described in terms of pixel weights, where p represents a high probability that is more challenging to detect precisely, P_n represents the anticipated probability, and n is the number of classes, indicating that the pixels belong to the kth class. To successfully classify pixels, weights are assigned and the focus loss function value is ten.

Measures of performance

We developed our model using the four assessment parameters and the validation results. True negative (TN) and true positive (TP), which represent correctly recognised aberrant and standard brain pictures, respectively, are the correct values. There are two types of erroneous classifications: false-positive (FP) and false-negative (FN), where FN denotes abnormal brain imaging and FP denotes usual brain imaging. Using (3) to (6), the accuracy, dice score/F1, recall, and precision of our proposed model are assessed.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (5)$$

$$F1 = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}} \quad (6)$$

Evaluation of performance

Three sets of MRI data were obtained: training, testing, and validation. The recommended framework used a size 16 minibatch for training. Figure 5 displays some of the images produced by the suggested strategy for detecting tumours.

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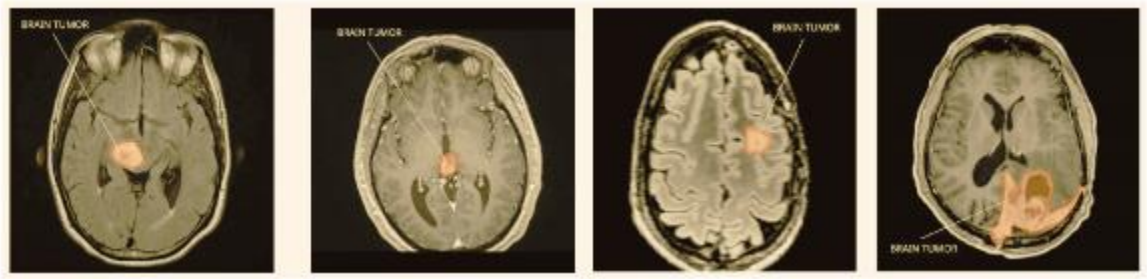

Figure 5. Tumor detection by the proposed model

Evaluation of various architectures

This study covers architecture that is triangular, rectangular, and recto-triangular. All three architectures were trained and evaluated using the same dataset. With six hidden layers, the rectangular architecture achieved a precision of 91.2% and a training accuracy of 97.9%. By comparison, the training accuracy of the triangle design with seven hidden layers was 97.5%, which was 0.4% lower than that of the rectangular architecture. Nevertheless, the precision score of the triangular building was 2.6% higher than that of the rectangular architecture. Three distinct architectures are compared in Figure 6. The suggested recto-triangular architecture, as seen in Figure 6, has the highest training and precision scores (98.6% and 97.8%, respectively), outperforming the other two. Based on the evaluation, it can be said that the suggested architecture works better at detecting brain tumours and yields satisfactory results.

Evaluation of various methodologies and datasets

The performance of the proposed model was compared with some current methods. The proposed method was benchmarked against FCNN, mask RCNN, YOLOv5, and AFPNet. Table 1 provides a full comparison based on the prepared dataset. The results demonstrate how much better the suggested architecture performs than earlier studies. The constructed model outperforms the state-of-the-art model as it stands now. The performance of the suggested model was evaluated using the BRATS 2018–2019, 2020 brain tumour dataset. The model's performance on BRATS datasets is displayed in Table 2.

Table 1. Performance comparison of several approaches

Name	F1	Precision	Accuracy	Recall
YOLOv5	93.99	90.11	98.42	**97.91**
AFPNet	92.77	87.45	98.50	**98.75**
FCNN	95.08	93.57	98.83	**98.40**
Mask RCNN	**91.29**	**84.84**	**99.96**	**99.60**

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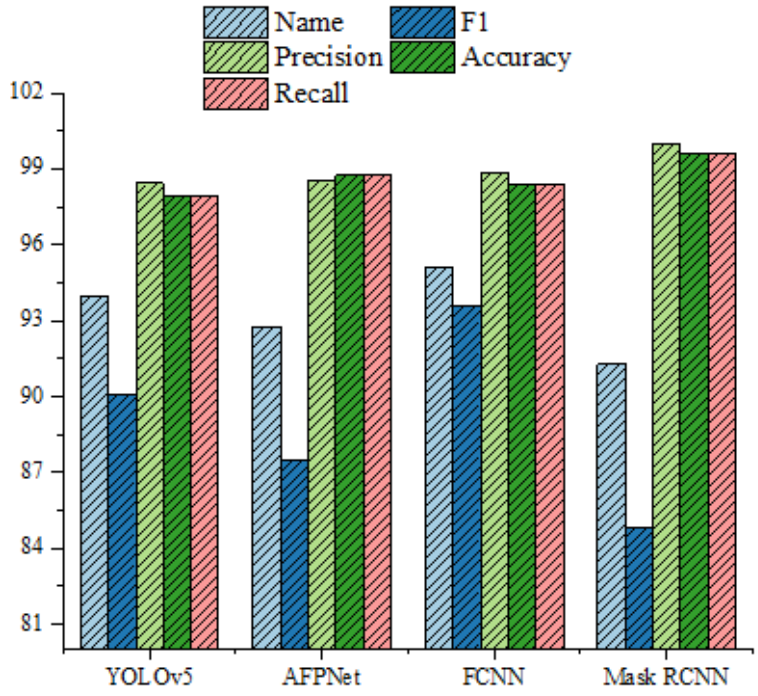

Figure 6 Comparison of several approaches

Table 2. Proposed model's performance on BRATS dataset

Name	F1	Precision	Accuracy	Recall
BRATS_2020	96.42	95.20	97.45	**96.27**
BRATS_2021	97.33	97.46	98.80	**96.90**
BRATS_2022	**98.51**	**97.63**	**98.79**	**96.78**

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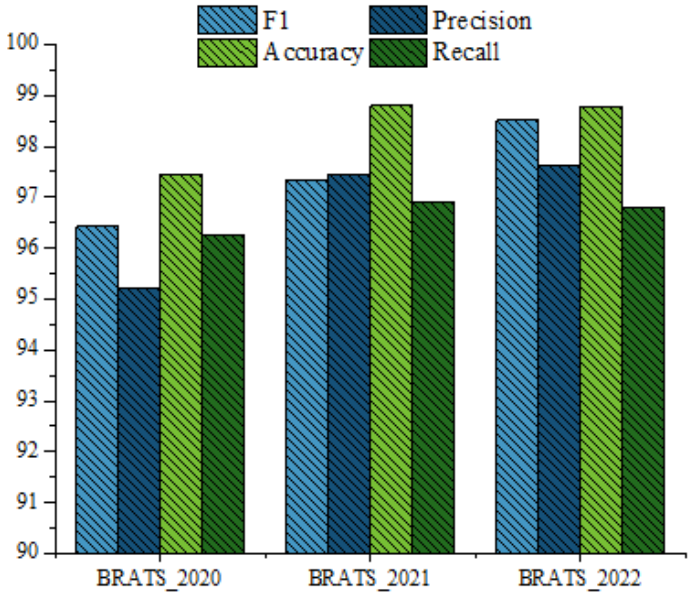

Figure 7 Performance on BRATS dataset

Conclusion

This study proposes a modified architecture for brain tumour identification that makes use of the processed MRI dataset and the suggested recto-triangular architecture in the hidden layer. The suggested CNN model focuses on a region of the brain image close to the tumour tissue, which may help it outperform human observers. To cut down on processing time and capacity, the suggested preprocessing techniques eliminate a large number of unnecessary pixels from the photos. The suggested model with the suggested hidden layer architecture and the processed dataset has outperformed state-of-the-art alternatives. We intend to upgrade the filters in the future to increase accuracy.

Abbreviation

MRI - Magnetic resonance imaging

AFPN - adjacent feature propagation network

CAD - computer-aided diagnosis

FCNN - Fourier Convolutional Neural Network

ANN - artificial neural network

CAD - computer-aided diagnosis

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable

Ethics approval and consent to participate

Not applicable

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Availability of data and materials

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Authors' contribution

Author A supports to find materials and results part in this manuscript. Author B helps to develop literature part.

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