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Brain tumor classification for optimizing performance using hybrid RNN classifier

Boya Nethappa Gari Kalavathi, Umadevi Ramamoorthy
School of Science Studies (SOSS), CMR University (OMBR Campus), Bengaluru, India

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ABSTRACT

Tumor is the uncontrolled growth of cancer cells in any part of the human body. Brain tumoris the leading cause of cancer deaths worldwide among adults and childrens. Early detection of brain cancers is essential. To prevent more issues, early defect detection is essential. Healthcare physicians may discover and categorize brain tumors with the use of computational intelligence-focused tools. An essential task for diagnosing tumors and choosing the right type of therapy is classifying brain tumors. Brain tumor identification and segmentation using magnetic resonance imaging (MRI) scans is now recognized as one of the most significant and difficult research areas in the world of medical image processing. The field of medical imaging has gained greatly from the use of artificial intelligence (AI) in the form of machine learning (ML) and deep learning (DL). DL has shown significant presentation, especially in the areas of brain tumor classification and segmentation. In this work, brain tumor classification for optimizing performance using hybrid recurrent neural network (RNN) classifier is presented. Different types of brain tumors are classified using a mix of RNN and inception residual neural network (ResNet). This strategy will produce improved F1-score, precision, accuracy, and recall scores.

Corresponding Author:

Boya Nethappa Gari Kalavathi
School of Science Studies (SOSS), CMR University (OMBR Campus)
Bengaluru, Karnataka, India
Email: bnkalavathi123@gmail.com

1. INTRODUCTION

An abnormal cell development in the brain results in the creation of a brain tumor, sometimes referred to as an intracranial neoplasm. Headache, vomiting, vision problems, and mental abnormalities are possible symptoms. A tumor is essentially the body's cells growing abnormally and uncontrollably [1]. A brain tumor is an abnormal mass of tissue in which cells grow rapidly and uncontrollably inside the brain's tissues. Early identification of brain tumors is important. When it develops, it becomes extremely life-saving. If a brain tumoris discovered early on, the patient's chances of survival will increase. The possibility of a person surviving a brain tumor is definitely increased by early detection and immediate treatment [2].

Brain tumors may spread throughout the brain at different rates. Its growth rate is dependent upon the brain tumor's location. Regarding harm to the human nervous system, the tumor's location is equally essential [3]. The tumor's size, location, and type all affect the way it is treated at the same time. The patient's various symptoms are the first step towards a brain tumor diagnosis. A physician makes an assessment of the nerves, strength, reflexes, balance, and senses. Additional examination methods are used to diagnose brain tumor if the physician believes there is a tumor. Brain tumor is one of the most typical kinds of brain disease. It is occurred due to the development of unregulated brain cells. Generally, the tumor classified in to primary and secondary brain tumors. The first starts in the brain and stays there while the latter starts as cancer at somewhere in the body and spreads to the brain [4]. There are two types of tumors: benign tumors, which are made up of malignant cells and are less dangerous since they do not spread to other cells. On the other hand, malignant tumors are masses of cells that are dangerous, cancerous, and more susceptible to spread to other tissues and cells. A tumor is essentially a collection of cells that create a tissue that has an unrestricted growing of development and lacks the control that normal cells have [5]. Brain tumors can be categorized into numerous types, including pituitary, glioma, and meningioma. One type of tumor that affects the brain and spinal cord is called a glioma. Brain and other parts of the nervous system, such as the brain stem and spinal column, can develop gliomas.

The symptoms of gliomas vary depending on this type. Headaches, seizures, irritability, vomiting, vision problems and numbness or weakness in the extremities are a few of them. A tumor that develops in the meninges, the tissue layers protecting your brain and spinal cord, is known as a meningioma. Although they are often benign (not cancerous), they can occasionally be malignant (cancerous). Meningiomas can be managed. One of the most devastating forms of cancer is Malignant brain tumor which can be marked as dismal survival rates and remained unchanged over the decades [6]. Unusual growths in the pituitary gland are called pituitary tumors. Headaches or abnormalities in vision are signs. Hormones may also be impacted in some situations, disrupting menstrual cycles and leading to sexual dysfunction. Surgery and medication are used as treatments to reduce the tumor or stop the overproduction of hormones. Radioactivity may also be utilized in certain situations [7].

The patient's various symptoms are the first step towards a brain tumor diagnosis. Next, a physician makes an assessment of the nerves, strength, reflexes, balance, and senses. Additional examination methods are used to diagnose brain tumors if the physician believes there is a tumor. The diagnosis of brain tumor is proved to be challenging due to the resemblance between cancerous and healthy cells and the similarities between different kinds of brain tumors [8]. Untreated of brain tumors can result in death. Health care providers have difficulties in detecting and treating people that have brain tumordue to their complexity. To start treatment as early as possible, it is essential to identify the type of tumor that a patient has [9]. Image processing-based brain tumor detection has been a major field of study in recent years. Even though, numerous researches work described, still a reliable technique for detecting brain tumors is challenging.

Patients are now treated with surgery, radiation, chemotherapy, or a combination of treatments. Because brain tumor biopsies need surgery, they are more difficult than biopsies of other body areas [10]. It is therefore essential to have a different technique for obtaining a precise diagnosis without surgery. The most effective and widely used method for identifying brain cancers is magnetic resonance imaging (MRI). Diagnostic imaging techniques including computed tomography (CT) scans and MRIs can identify brain tumor [11].

Utilizing image processing, one may gather and separate important information from a range of datasets. In the field of image diagnostic research, many machine learning (ML) techniques are used for MRI image segmentation [12]. Utilizing MRI to segment brain tumors is important and significant for medical field since it supports in diagnosis and prognosis, general growth forecasts, tumor density measurements, and patient treatment plans. Three different directions are used to capture the MR images. These perspectives are known as corona, axial, and sagittal [13].

In the domains of computer vision and medical image analysis, image segmentation is a crucial phenomenon. The goal of brain tumor segmentation is to separate abnormal brain tissues from normal brain tissues, such as white matter (WM), gray matter (GM), and cerebro-spinal fluid (CSF), including active cells, necrotic core, and edema [14]. The existence of non-homogeneous intensity distribution surrounding the tumor, noisy background, complicated structure with fuzzy boundaries, and low contrast relative to other brain tissues make tumor segmentation extremely challenging. Automatic tumor segmentation algorithms are faster, more accurate, and aid in tumor analysis and diagnosis compared to manual tumor segmentation [15].

Radiologists detect and diagnose cancers using the traditional approach for tumor detection, which is extremely laborious and time-consuming. Computer-aided medical diagnosis (CAMD), which may help physicians analyze medical images in a matter of seconds, has advanced significantly as a result of recent advancements in artificial intelligence (AI) and ML. Medical imaging patterns have been recognized and categorized due to recent developments in ML. One of the areas of success in this field is that information can now be retrieved and extracted from data instead of having to be learned from specialists or scientific texts [16].

The identification and categorization of medical imaging patterns is the result of recent developments in ML, particularly deep learning (DL). One of the successes in this field is that knowledge can now be retrieved and extracted from data instead of being taught by specialists or scientific texts [17]. A number of medical applications are finding DL to be a useful technique for improving performance, such as the tissue segmentation, illness prediction and diagnosis, cellular and molecular structure identification, and image classification [18].

ML-based segmentation and classification of brain tumors was demonstrated. In order to reduce the small possibility of miss categorization error, this research focuses on accurately classifying tumors from MRI images utilizing several segmentation methods. When compared to a single segmentation algorithm, the results produced by many segmentation algorithms are more exact and accurate. In order to do this, the support vector machine (SVM) classifier is combined with the watershed, K-means, and threshold segmentation algorithms, and the end result is a 90% above classification result [19].

To detect the brain tumors deep neural network (DNN) algorithm is employed. A DNN structure that makes use of stacked auto-encoders is shown. Biopsies are not often done before conclusive brain surgery; instead, they are used to categorize brain tumors. Without requiring invasive procedures, radiologists will have additional help in tumor diagnosis due to the development of ML. They use its speed and benefits for the human being to enhance medical imaging facilities. Medical professionals may find new opportunities with ML's increased training speeds and accuracy. By avoiding the computational strain of manually going through medical images, it simplified the process of understanding the human brain and save a significant amount of time [20].

The use of ML to detect brain tumors was presented. This method offers a model that uses ML techniques to accurately identify brain tumors using magnetic resonance imaging. Segmentation and feature extraction have been performed using a convolutional neural network (CNN). The utilized dataset was obtained from a website on the internet [21].

A transfer learning method for classifying brain cancers using AI was discussed. This article proposes the use of DL algorithms for AI-based categorization of brain tumor types using datasets that are readily available. These databases categorize brain tumors as either benign or malignant. For testing purposes, the datasets consist of 696 images on T1-weighted images. The predicted configuration achieves an impressive result with the finest accuracy [22].

ML-based pixel-level feature space modeling was designed for brain tumor identification. In order to improve the ability of a ML approach to identify brain tumor areas at the pixel level in an MRI brain image, a feature learning technique is provided. The brain tumor segmentation (BraTS 2015) datasets were modified in order to create and verify the suggested computational framework. Using a range of quantitative and qualitative measurements, the authors assessed the random forest (RF), artificial neural network (ANN), and SVM models. Based on the precision-recall curve, they found that the RF model learned 92% of the perfect model's tumor detection abilities, whereas ANN and SVM learned 90% and 88% of the perfect model's tumor detection skills [23].

A computational method based on internet of medical things (IoMT) was presented for brain tumor detection. Brain tumors are classified into grades I through IV using the Partial Tree association rule learner, which has an extensive feature set. 10-fold cross-validation is used to validate the suggested model, and it is contrasted with the current approaches random tree, RF, classification and regression trees (CART), and Naive Bayes (NB). The results show that the above methods are surpassed by incomplete trees with improved feature sets. The measures of performance that are used for evaluation include F-measure, precision, and recall [24].

Brain tumor detection and segmentation of MRI images using neural networks was described. In an effort to improve yield and precision, this work has implemented an automated brain tumor detection approach; however, the diagnostic time is decreased. The objective is to divide the tissues into two groups: normal and abnormal. It is possible to efficiently use this technique to identify the tumor's geometrical dimensions. The aimed at neural network approach consists of several phases, including detection, segmentation, classification, dimensionality reduction, and feature extraction. The suggested approach for the identification and segmentation of brain tumors in this study is more precise and efficient [25].

The active contour model and self-organizing-map was used to segment brain tumors from MRIs efficiently. In order to effectively separate brain tumors from MR images, this work provides a combination method using the self-organizing map (SOM) and active contour model (ACM). Energy-based image segmentation techniques known as ACMs approach the task of segmentation as an optimization issue. This is done iteratively during the optimization process to help choose whether to reduce or increase the current contour. It performs this by correctly integrating the global data generated by the trained SOM neurons weights or prototypes [26].

Over the years, many approaches have been presented to detect and classify the brain tumor. However, there is a need of a technique that might identify a brain tumor with excellent accuracy. The main problem with current models is their accuracy, which is important for intelligent health care systems. To address this problem, a very accurate model will be designed i.e., brain tumor classification for optimizing performance using hybrid RNN classifier is presented. The remaining work is arranged as follows:

the section 2 presented the brain tumor classification for optimizing performance using hybrid RNN classifier. The validation of the results of the analysis of the suggested framework is done in section 3. Lastly, section 4 provides the conclusion.

2. METHOD

In this section, brain tumor classification for optimizing performance using hybrid RNN classifier is described. The presented framework's block diagram is displayed in Figure 1. For the purpose of brain tumor identification and classification, this method uses a hybrid RNN that combines Inception ResNetv2 with RNN. The dataset used in this paper is the brain tumor MRI. One of the main and most important tasks of every MLproject is data collection. Considering that the data serves as the algorithms input. Thus, the quality and accuracy of the data that is gathered determines the efficiency and accuracy of the algorithm. Thus, the result will be the same as the data. For every patient, a variable number of images is required. Brain tumors, traumatic brain injury, anomalies in development, multiple sclerosis, stroke, dementia, infection, and headache reasons can all be identified using MRI. The process of transforming unprocessed datasets into a readable, understandable format that may be used for additional analysis is known as data pre-processing. For ensuring the accuracy, consistency and completeness of input datasets is a crucial stage in every data analysis effort. To improve the model's accuracy at this point, noise from the MRI images will be removed. A lot of noise is present in MRI images, which increases redundancy and reduces model accuracy.

noise on its borders of an MRI increases the possibility that a tumor won't be identified. So has an impact on the model's accuracy. They performed pre-processing by being reduced, scaled, and grayscaled. Images pre-processing is done to improve the image's quality, looks, and features. One of the most fundamental preprocessing steps for every segmentation method is noise reduction. The given dataset has noise pre-filtered out of it already. Thus, they first preprocess every image using our own noise reduction technique. The image enhancement approach is used since the dataset contains a few dark images. MRI data is subjected to a thresholding-based technique to eliminate bias field artifacts. The preprocessing stage also makes advantage of the histogram explained. Each image in the dataset is the first histogram that the individual image from the dataset specifies. Each region of interest (RoI) in the image has its own set of characteristics that are extracted. In this research, the tumor is segmented using statistical and neighborhood feature extraction approaches. These retrieved characteristics have a number of uses in the field of image processing, such as evaluating the image's quality.

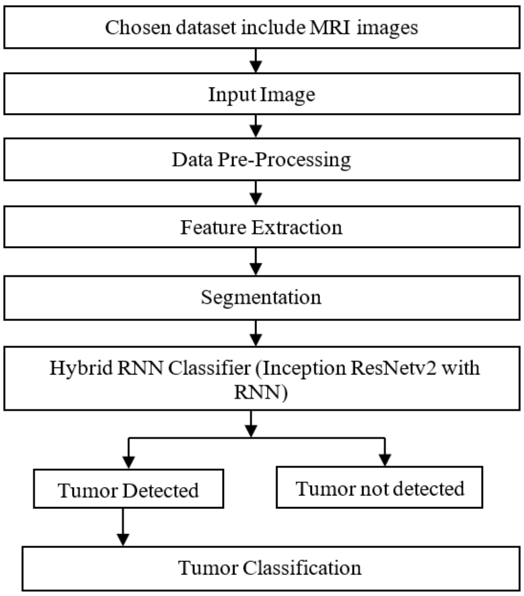


Figure 1. Block diagram of brain tumor classification for optimizing performance using hybrid RNN classifier

The MRI scans are used to extract two groups of features: first order and higher order. The many statistical characteristics Pixel intensities are calculated using extraction techniques, such as standard deviation, histogram, kurtosis, skewness, etc. In the higher-order example, the connectivity relation between pixels is determined. Insight segmentation and registration toolkit (ITK-Snap) provides manual delineation, image navigation, and semi-automatic segmentation utilizing active contour approaches in preprocessing. It will supply the two-directional image is needed for additional image processing methods related to the segmentation phase.

The brain image RoIis developed using image processing techniques. Segmented brain tumor images are then utilized to extract form features such as the tumor region's solidity, center of gravity, convexity, and ratio of circularity to rectangularity. Only the brain tumor remains in these extracted brain tumors after all other things have been eliminated. By applying morphological processes such as erosion, open, close, and filtering, this tumor area's RoIis retrieved. The procedure to extract meaningful information from an image is called feature extraction. Utilizing pixel-based feature extraction, data is extracted and categorized as either tumor or non-tumor. The quantity of redundant data in the data collection is decreased with the support of feature extraction. Ultimately, the process of data reduction speeds up the learning, generalization phases and aids in the construction of the model with less computational effort.

Improving on the Inception family of architectures, Inception-ResNet-v2 is a CNN architecture that adds residual connections (which take the place of the Inception architecture's filter concatenation stage). The suggested approach applies segmentation through the use of k-means clustering. The distance between a point and the centroid is expressed in Euclidean terms. The closest new centroid and the identical data set points are binding. After that, a loop is created. The places with comparable pixel values are divided into two or more clusters as a consequence of this loop. Using Inception ResNetV2 with RNN, brain MRI images are classified as non-tumor or tumor.

A CNN design called Inception-ResNet-v2 expands upon the Inception family of architectures by adding residual connections, which take the place of the Inception architecture's filter concatenation stage. The Inception RestNetv2 is trained on the ImageNet database which contains over a million images. The network can categorize the images into 1,000 various object types and has 164 layers. Consequently, a wide range of image rich feature representations have been trained by the network. A complex architecture is used by the Inception-Resnet-v2 to extract important information from the images. A list of estimated class probabilities is the network's output, and the input image's size is 299 by 299 pixels. Starting prior to the weight matrix (convolution operation) multiplication, residual network version 2 (ResNet V2) performs batch normalization and rectified linear unit (ReLU) activation to the input.

The way a recurrent neural network (RNN) functions is by gradually processing sequential data. It keeps a hidden state that operates as a type of memory, at each time step, the hidden state from the previous time step and the input data are updated. RNNs utilize patterns to identify the sequential features of data and predict the most likely pattern of developments. One type of neural network that is useful for representing sequence data is the RNN. Similar to the behavior of human brains, RNNs are derived from feed-forward networks.

All lengths of inputs may be processed using RNN. Any time series predictor can benefit greatly from an RNN model's ability to retain all of the data throughout time. The model size remains constant, whatever the amount of the input. When dealing with sequential data, RNNs can predict results those other algorithms can't.

Inception ResnetV2 with RNN can classify the brain tumor better than previous models and it is almost the best model for image classification. This approach has very effectively detected and classified the brain tumor. If the tumor is detected and classified correctly then proper diagnosis is provided as a result patient's lives will be saved.

3. RESULTS AND DISCUSSION

In this section, brain tumor classification for optimizing performance using hybrid RNN classifier is implemented. The brain tumor MRI dataset, which includes 7,023 MRI images of the human brain, is used in this method. Brain scans of the collected patients are pre-processed to increase accuracy and reduce noise.

To detect and categorize the brain tumor, CNN is used with the segmented data. When a brain tumoris discovered, it is categorized into several categories, including pituitary, glioma, and meningioma. The precision, recall, and F1-score of the proposed method are used to assess its performance.

- Precision: the level to which the model produced accurate predictions. The ratio of real positives to all positive predicts is known as precision.
- Recall: it can also know as sensitivity or true positive rate (TPR). It is expressed as the ratio of the total number of positive cases to the number of accurately recognized positive instances.

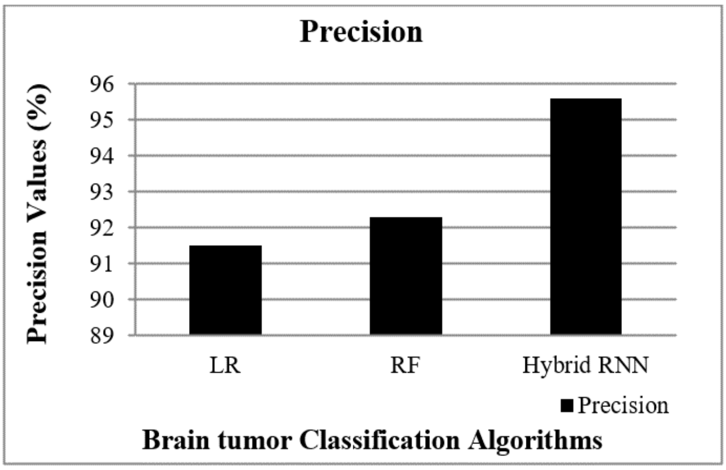
– F1-score: the accuracy of a model is determined by the F1-score, an assessment metric. It integrates a model's accuracy and recall ratings. The number of times a model correctly predicted throughout the whole dataset is calculated by the accuracy measure.

The performance of presented approach is compared with different classifiers like RF and linear regression (LR). The Table 1 shows the performance analysis. Compared to RF, LR classifiers, presented hybrid RNN classifier has better precision. The Figure 2 shows the performance metrics comparison. The Figure 2(a) shows the precision performance and Figure 2(b) shows the recall comparison. In Figure 2(a), the x-axis indicates different brain tumor classification algorithms whereas y-axis indicates precision performance. Compared to RF and LR, presented hybrid RNN algorithm has better precision for brain tumor classification. The hybrid RNN has obtained better recall than LR and RF algorithms. The Figure 3 shows the accuracy comparison.

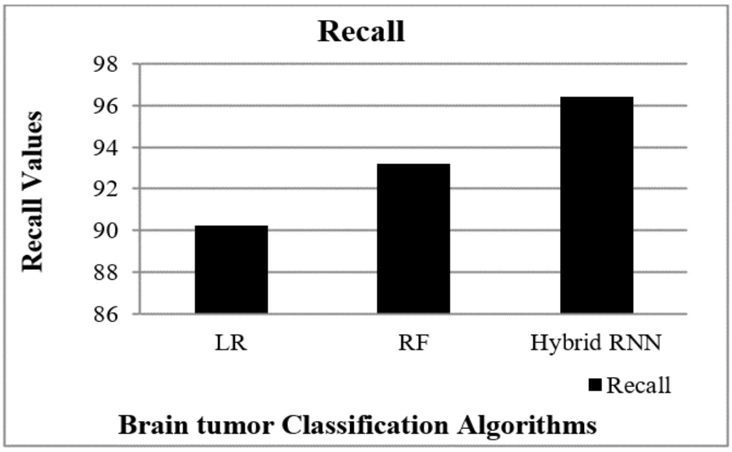
In Figure 3, x-axis indicates the different tumor classification algorithms and y-axis indicates the accuracy values. Compared to LR and RF, presented hybrid RNN has obtained better accuracy for brain tumor classification. The Figure 4 shows F1-score comparison. Presented hybrid RNN classifier has achieved better F1-score than LR and RF algorithms. Hence this approach has achieved better performance for classification of brain tumor.

Table 1. Performance comparison

Performance metrics	Linear regression	Random forest	Presented hybrid RNN classifier
Precision (%)	91.5	92.3	95.6
Recall (%)	90.23	93.2	96.4
Accuracy (%)	90.12	92.56	97.2
F1-score (%)	89.98	91.4	97.1



(a)



(b)

Figure 2. Performance comparison in terms of (a) precision and (b) recall

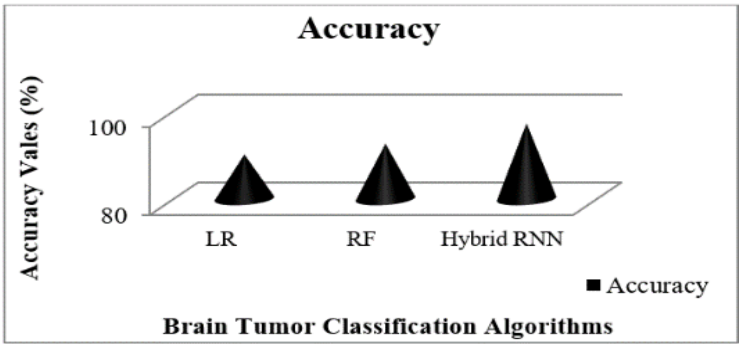


Figure 3. Accuracy comparison

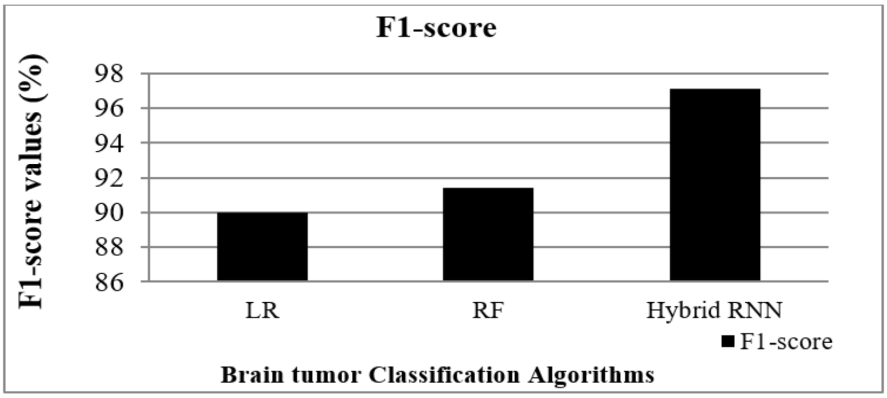


Figure 4. F1-score comparison

4. CONCLUSION

In this work, brain tumor classification for optimizing performance using hybrid RNN classifier is presented. Developing a highly accurate model to identify and categorize brain tumors from MRI images is the main aim. This model works based on the hybrid DL algorithm RNN. The tumor region has been identified by applying segmentation techniques to the segment. Using image processing techniques, the brain image's RoI is created. Segmented images of brain tumors are then utilized to extract the form features. The segmentation results are applied to Inception ResNetv2 with RNN algorithm to detect and classify the brain tumor. Firstly, it detects weather a person has brain tumor or not. If brain tumor disease is detected then classification is performed in to different types such as 0, 1, 2, 3. Finally, the approaches performances have been calculated. The F1-score, precision, accuracy, and recall of the suggested technique are used to assess its performance. Compared to previous approaches this approach has achieved better and high performance. Hence this approach has detected and classified the brain tumor very accurately and as a result patient's lives will be saved. Therefore, it will be used in real time for brain tumor detection and classification. In future, hybrid Neural network with U-nets will be designed to further improve the accuracy of brain tumor classification.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Boya Nethappa Gari Kalavathi		✓	✓		✓	✓		✓	✓	✓			✓	
Umadevi Ramamoorthy	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

- The data that support the findings of this study are openly available in [J. Shedbalkar et. al.,] at http://10.11591/ijeecs.v33.i3.pp1405-1415.org/[10.11591/ijeecs.v33.i3.pp1405-1415], [1].
- The data that support the findings of this study are openly available in [S. Kothari et. al.,] at http://10.11591/ijeecs.v26.i3.pp1651-1661.org/[10.11591/ijeecs.v26.i3.pp1651-1661], [5].
- The data that support the findings of this study are openly available in [T. Chithambaram et. al.,] at http://10.23956/ijarcsse/v7i3/0164.org/[10.23956/ijarcsse/v7i3/0164], [25].
- The data that support the findings of this study will be available in [IEEE] [DOI:10.1109/ACCESS.2024.3359418] following a [6 month] embargo from the date of publication to allow for the commercialization of research findings.
  The data that support the findings of this study are available on request from the Kaggle Platform [Masoud Nickparvar]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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BIOGRAPHIES OF AUTHORS

Mrs. Boya Nethappa Gari Kalavathi is currently working as assistant professor in the Department of Computer Science, Dravidian University, Kuppam, Andhra Pradesh, India and she is pursuing Ph.D. in SOSS, CMR University (OMBR Campus), Bengaluru, Karnataka, India. Her area of research is machine learning. She organized a UGC sponsored two-day National level conference organized on big data Technologies and Application in Dravidian University on March 2017. She can be contacted at email: bnkalavathi123@gmail.com.

Dr. Umadevi Ramamoorthy a M.S. in Information Technology and Management from Bharathiar University, has completed her M.Phil. in Computer Science and Ph.D. in Computer Science at Periyar University, Salem and presently working as associate professor in CMR University, Bangalore, Karnataka. With 18 years of teaching experience and 7 years of research experience, she has been presenting and published papers in several International and National Conferences and journals indexed by SCI Expanded, Scopus, UGC Care and UGC approved list. She is a member of IAENG. She has published patents and got design patent by Intellectual Property, Government of India. Currently she is guiding 6 research scholars and recognized with various awards such as best young scientist award, best academician award, and best paper award. She is editorial board member and review member in various reputed national and international journals. She has invited as resource person for guest talk, seminar and cultural. She has organized various events at National and International Level. She can be contacted at email: umadevi.r@cmr.edu.in.