IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 8 June 2024, accepted 25 June 2024, date of publication 9 July 2024, date of current version 20 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3425469

RESEARCH ARTICLE

A Transfer Learning-Based Approach for Brain Tumor Classification

NADIA BIBI[1], FAZLI WAHID[1,2,3], YINGLIANG MA[3], SIKANDAR ALI[1], IRSHAD AHMED ABBASI[4], (Member, IEEE), AHMED ALKHAYYAT[5,6,7], AND KHYBER[8]

[1]Department of Information Technology, The University of Haripur, Haripur 22620, Pakistan
[2]College of Science and Engineering, School of Computing, University Derby, DE22 3AW Derby, U.K.
[3]School of Computing Sciences, University of East Anglia, NR4 7TJ Norwich, U.K.
[4]Department of Computer Science, Applied College at Belqarn, University of Bisha, Sabt Al Alayah 61985, Saudi Arabia
[5]College of Technical Engineering, The Islamic University, Najaf 100986, Iraq
[6]College of Technical Engineering, Islamic University of Diwaniya, Al Diwaniyah 58001, Iraq
[7]College of Technical Engineering, The Islamic University of Babylon, Babylon 51002, Iraq
[8]Department of Information Technology, Kabul University of Medical Sciences "Abu Ali Ibn Sina," Kabul 1006, Afghanistan

Corresponding author: Yingliang Ma (yingliang.ma@uea.ac)

This work was supported by the Engineering and Physical Sciences Research Council under Grant EP/X023826/1.

ABSTRACT In order to improve patient outcomes, brain tumors—which are notorious for their catastrophic effects and short life expectancy, particularly in higher grades—need to be diagnosed accurately and treated with care. Patient survival chances may be hampered by incorrect medical procedures brought on by a brain tumor misdiagnosis. CNNs and computer-aided tumor detection systems have demonstrated promise in revolutionizing brain tumor diagnostics through the application of ML techniques. One issue in the field of brain tumor detection and classification is the dearth of non-invasive indication support systems, which is compounded by data scarcity. Conventional neural networks may cause problems such as overfitting and gradient vanishing when they use uniform filters in different visual settings. Moreover, these methods incur time and computational complexity as they train the model from scratch and extract the pertinent characteristics. This paper presents an InceptionV4 neural network architecture-based Transfer Learning-based methodology to address the shortcomings in brain tumor classification methods. The goal is to deliver precise diagnostic assistance while minimizing calculation time and improving accuracy. The model makes use of a dataset that contains 7022 MRI images that were obtained from figshare, the SARTAJ dataset, and Br35H, among other sites. The suggested InceptionV4 architecture improves its ability to categorize brain tumors into three groups and normal brain images by utilizing transfer learning approaches. The suggested InceptionV4 model achieves an accuracy rate of 98.7% in brain tumor classification, indicating the model's remarkable performance. This suggests a noteworthy progression in the precision of diagnosis and computational effectiveness to support practitioners making decisions.

INDEX TERMS Tumor detection, DL, CNN, transfer learning, inception V4, tumor classification.

I. INTRODUCTION

The most significant and architecturally essential part of the human body is the brain, which has 50–100 trillion neurons. The CNS (Central Nervous System), which also includes the spinal cord, serves as brain of the human neurological system [1]. It is also the body's eighth-most important organ. The human body has five senses and the brain outputs information to the muscles after receiving information from these senses, often several at once as shown in Figure 1. It is also referred to as the nervous system's processor or kernel and embodies the essence of the mind and soul [2]. It assembles the messages in a fashion that can be remembered and makes sense to us. Furthermore, the brain regulates multiple body processes, such as our ability to think, speak, remember, and move our arms and legs [3].

The associate editor coordinating the review of this manuscript and approving it for publication was Ajit Khosla.

The average human brain weighs approximately three lbs. (1.4 kg), making up for about 2% of a person's total body weight [3]. The two hemispheres that make up the cerebrum comprise most of the human brain. The parietal, temporal, occipital, and front lobes constitute each hemisphere. The irregular surface of the cerebrum is known as the cortex. The cerebrum is in front of the brainstem, whereas the cerebellum is behind it [4], [5]. The frontal lobe is involved in the regulation of voluntary movement as well as cognitive functions including reasoning and future planning. The temporal lobe is responsible for producing feelings and thoughts. The parietal lobe, which combines data from several types of perception, is essential for spatial orientation and navigation [6]. The bones of the skull in the head house and guard the brain [7]. Figure 1 shows the structure and functions of the Human Brain.

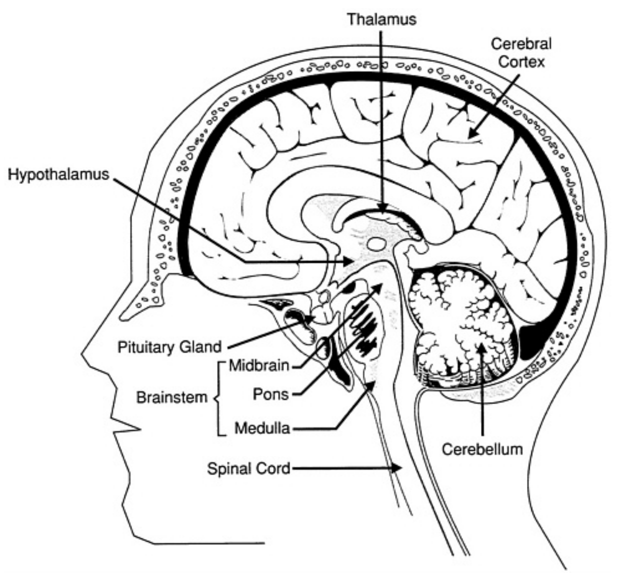


FIGURE 1. **Structures and functions of the brain.**

A. BRAIN DISEASES

Distinct functions of the brain are gradually damaged by neurodegenerative illnesses, and the damage gets worse with age [8]. Typical causes of dementia include Alzheimer's syndrome, dementia brought on by alcoholism, Parkinson's syndrome, and other less typical infectious, genetic, or metabolic conditions like Wilson's syndrome, Huntington's disorder, conditions affecting the motor neurons, HIV dementia, and dementia associated with syphilis. Alzheimer's syndrome is a passed down through generations, incurable brain condition that progressively decreases logical reasoning, memory, and cognitive ability [9].

Dementia is the failure of brain function, understanding, recognizing, and reasoning, to the point where a person faces difficulties in day-to-day activities and behavior [10]. Movement, memory, and cognition can all be impacted by neurological disorders that can affect different regions of the brain [11].

The brain is often regarded as the most sensitive organ in the human body. When brain cells proliferate improperly or in enormous quantities, it can lead to significant changes in both personality and brain function, unlike other illnesses [12]. The brain's capacity to function is also hampered by it. This anomaly or dysfunction indicates the presence of a brain tumor, or it may be the result of uncontrolled brain cell growth. It causes cancer, which is one of the plausible causes of death, and accounts for about 13% of all fatalities worldwide [13].

The danger posed by a tumor in the brain relies on a number of variables, including the tumor's appearance, behavior, size, location, and its level of growth [14]. At higher rates than other nerve ailments, brain and other tumor resulted in human death. It is the tenth most frequent reason for mortality in humans [15]. Last year, primary malignancy of CNS is expected to have been clinically tested in 23,890 individuals (13,590 men and 10,300 women) in the US. Additionally, primary malignant brain and CNS tumor are predicted as the compelling cause of death for 18,020 persons in 2021 (10,190 men and 7830 women). Additionally, 'the endurance percentage for persons with a malignant brain tumor is roughly 36% for five years and 31% for ten years' [16]. Figure 2 shows the brain MRIs for Normal and Abnormal MRI images.

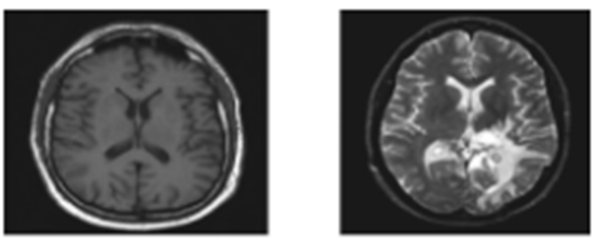


FIGURE 2. **(a) Normal brain MRI (b) Abnormal brain MRI.**

A brain tumor's type is determined by the sorts of cells that comprise it [17]. The types of brain tumors are as follows. Glial cells envelop and sustain nerve cells within the brain tissue and growth in glial cells are called gliomas. Gliomas are mostly malignant, but they can be benign as well. Meningiomas, the most widespread type, are tumors that start in the membranes that wrap the brain and spinal cord [18]. Though benign in most cases, meningiomas can sometimes be malignant. Pituitary tumor may originate in or around the pituitary gland. This little gland is situated close to the brain's base. Most tumors that develop in or near the pituitary gland are benign. The pituitary gland itself can develop tumor [19].

B. TUMOR DETECTION TECHNIQUES

Brain tumors come in the benign and malignant types. "Benign" refers to tumors that do not contain malignant cells and are less dangerous to humans. Malignant tumors, on the other hand, are those that contain cancerous cells that are more dangerous to humans [20]. The position, size, and growth status of the tumor must be determined by radiological study and predict whenever a malignancy in the brain is medically indicated. It is simple to make a choice for the patient's right treatment, such as surgical procedure, radioactivity, and chemotherapy, based on this information. The most key factor, however, is that a patient with an infection has a better chance of life if a tumor is accurately and early diagnosed [21]. The medical world has seen a meaningful change because of the advent of multiple new imaging techniques. Common imaging techniques include CT, MRI, PET, ultrasound, and X-ray. These diagnostic imaging methods are employed to identify complex disorders in people, such as brain tumors, COVID-19, malignant cells, and brain tumors or cancer [22]. The more widely used non-invasive method for identifying anomalies in tissue composition is MRI. As it provides the highest pixel-resolution images of brain cells and cancer tissues, it is favored above other medical imaging techniques [23].

Meningiomas, gliomas, and pituitary tumors are examples of intrinsic brain tumors that can cause severe damage and are the hardest to identify early enough for effective treatment. Furthermore, if ignored, these can worsen into dangerous circumstances [24]. Early detection and accurate diagnosis of brain tumors with high predictive value are critical steps in diagnosis and treatment. However, radiologists and medical professionals manually analyze brain MR images to find the tumor and normal tissues, classify the tumor, and detect and focus the tumor which is laborious and time-consuming task [25]. To overcome this issue, a computer-based diagnostic (CBD) system is required. It must be put into operation to lighten the effort and assist radiologists or other medical professionals with medical image interpretation. Researchers have already put forward a number of precise ways to automate the process of identifying brain tumors.

For analyzing brain tumors, conventional ML based algorithms have been used. However, ML-based algorithms use lesser amounts of data and require human feature extraction and categorization. On an extensive amount of labelled data, Deep Learning (DL) combines feature extraction and classification in a self-learning manner, substantially enhancing performance [26], [27].

Furthermore, CNN is an aspect of Deep Learning that was developed especially for two-dimensional (2D) or picture data. It automatically extracts various features from MR images after accepting datasets that have a minimal degree of preparation [28]. Brain tumor detection mostly makes use of deep CNN models. However, brain tumor analysis is quite challenging and requires a strong DL-based brain tumor analysis system to assist the radiologist's judgment due to the anatomical structure, tumor appearance in an image, and brightness effects. In this regard, by modifying the CNN models to take advantage of features to brain tumor seen in the brain MRI dataset, we build a deep transfer learning-based strategy to get beyond these constraints [29]. CNN has demonstrated commendable performance in both the detection of tumor using medical imagery and the classification of tumor infected from normal individuals [30]. Furthermore, performance is significantly improved by deep feature boosting, ensemble learning, and ML classifiers. According to experimental findings, the proposed deep transfer learning-based system might help radiologists to identify tumor and other anomalies from medical images [31].

C. MACHINE LEARNING TECHNIQUES

ML is a research field of computer algorithms that examine and correlate data using statistical models and algorithms that learn from past experiences without being explicitly programmed [32]. ML Techniques inevitably become better with training. It develops methodologies, trains models, and uses the learned strategies to automatically identify the result [33]. Systems built on machine learning could potentially change to fit their environment.

ML model is an artificially intelligent system that has been trained using a technique in a machine learning system to identify particular types of patterns [34], [35]. This indicates that it analyses the data and identifies any hidden dataset structures [36]. To create the algorithm that applies the Input Output functions to fresh data to anticipate the outcome, feature extraction and the dataset's known responses are employed [21]. Consequently, the algorithm of the model employs a set of data for training, develops a method to forecast the result, and then saves that method for use in the future [15], [37].

The procedure of instructing a computer to solve a problem based on its past knowledge is known as machine learning. Because of the convenience of less expensive processing power and memory, the concept of employing ML in several areas to solve issues quicker than humans has sparked a lot of attention. This allows for the handling and analysis of incredibly massive amounts of data, enabling the exploration of concepts and connections between the data that are not immediately apparent to the human eye [38]. Its ability to think is built on a number of algorithms that allow the computer to abstract from experience and create meaningful judgements. While using a more advanced technique called Deep Learning (DL), computers can now automatically accomplish features extraction process, analyze, and grasp the applicable output from the raw data [8]. Particularly, a class of techniques referred to as "Deep Learning" is driven by neural data and relies on autonomous feature engineering techniques by which these methods can acquire highest performance [23].

D. MOTIVATION

The complex pattern of the tumor's abrasive has led to much research on brain tumor detection, however there are still limitations in this field. Furthermore, it is challenging to extract and choose key features because doing this right away reduced classification accuracy. Convolutional neural networks aid in the extraction of relevant features yet these models are computationally demanding. However, a simple model is still required for the study of brain tumors.

Therefore, to overcome the existing limitations, this research aimed to create a less expensive, dependable, and efficient diagnostic tool that could not only identify tumors but also classify them. As a result, it may be employed to help medical diagnostic centers' decision-makers. Transfer learning is the ideal method for training sophisticated Deep Learning models since there are few publicly accessible MR images of brain tumors. To the best of the authors' knowledge, we used a well-known and fine-tuned deep transfer learning-based method, Inception-v4. It has not yet been investigated for the detection and classification of brain tumors.

E. PROBLEM STATEMENT

Despite recent advances in Deep Learning, accurate classification of brain tumors using MR images remains a challenge. Lack of non-invasive diagnostic support system for brain tumor detection and classification in the scenarios where there is data scarcity issue. CNN has shown promising results in image classification tasks but usage of same size filters, serially, in images where information containing area is different ultimately leading to gradient vanishing problem and overfitting. Furthermore, Deep Learning approaches train the model from scratch and extract the relevant features, leading to time and computational complexity. Additionally, no simple and efficient model is available which may be used to assist the decision makers with higher accuracy rate and less computational time.

In this research paper, we addressed the research questions below.

(i) How can brain tumor detection and classification be acquired with fewer training samples?
(ii) What would be the right size of filters while extracting features in images where information containing area is different?
(iii) Which simple and efficient architecture can be applied to accurately detect and classify brain tumors MR images in minimum computational time?

F. SUMMARY

The proposed system's main contributions are brain tumor detection and classification using machine learning techniques. Below listed are the main contributions.

(i) Review the literature on using CNNs in medical imaging and, specifically, in brain tumor classification using MR images.
(ii) We evaluate the performance of various CNN architectures, including inception-v4, for brain tumor classification using MR images.
(iii) Optimize the hyperparameters of the inception-v4 architecture for MR image classification of brain tumors.
(iv) Compare the performance of the optimized inception-v4 architecture with other state-of-the-art CNN architectures for brain tumor classification using MR images.
(v) Validate the proposed approach by evaluating it on an independent dataset and compare it with the results reported in the literature.
(vi) Analyze the interpretability of the optimized inception-v4 architecture by visualizing its activation maps and identifying the regions of the brain that contribute most to the classification.
(vii) We conducted extensive experiments on four different TL-based models and compared the effectiveness of each model on brain MRI dataset.
(viii) Discuss the potential clinical implications of the proposed approach for improving the accuracy and efficiency of brain tumor diagnosis and treatment planning.

In Section II. We will cover the relevant earlier work based on ML and Deep Learning models for the approaches presented for identifying and classifying brain tumors. There are several methods for existing approaches that can identify tumors in content. A gap analysis review is done for the research's contribution to the problem. Various models for identifying brain tumors are also being researched. The obstacles faced by various brain tumor detection approaches are provided with associated research topics at the conclusion of this chapter, and those challenges are extensively examined. The proposed solution framework and model diagram will be thoroughly covered in Section III. The creation and application of the suggested research implementation schemes—both theoretical and practical execution of the proposed brain tumor detection and classification using Transfer Learning model—are provided based on the existing research mechanism. Multiple blocks and their associated CNN Layered architecture and model diagrams are used to clearly describe the whole functioning system of the suggested solution. Additionally, we will assess our ideas in Section IV using an appropriate simulation environment in our instance, this was Jupiter, Anaconda. The experimental approach and the parameters of the confusion matrix are used to describe the experimental setup and various experiment components. In Section V, we will provide our conclusion and talk about the next steps.

II. LITERATURE REVIEW

The scientific field of medical imaging is where innovative approaches are used, and current technologies strive to simplify and improve the functionality of segmenting, classifying, and other diagnostic instruments [24]. Because it is crucial for radiotherapy treatment to discriminate the benign and malignant tissue, brain tumor segmentation plays a role in the identification process [25], [26]. Here is a summary of the most popular and effective machine learning ML approaches and the results they have produced. The results of recent research are encouraging and have huge implications for the detection and treatment of brain tumors. However, despite the positive outcomes that the authors mention, some studies have cogency in the actual clinical setting because of significant constraints [27]. The authors highlight that the results cannot be generalized because of the restricted admittance or slightly low data used for training [28]. For instance, Islam et al. said that the models employed for tumor detection were trained using modest data sets, have the limitation of no more than 40 MR images [38]. Like this, Rinesh et al. work with just 273 MR images, claiming that the data is limited and that a greater performance would be implied if the quantity of data were increased [39]. The number of MR images with brain tumor that Cinar and Yildirim is restricted to 253; however, they get around this issue by employing transfer learning and enhancing the data via data augmentation [40]. In general, researchers executed the applications using a small amount of data, but they did not use any Transfer Learning (TL) or methods for data enhancement.

A more effective brain tumor detection method based on the template-based K-means (TK) algorithm using PCA was proposed by Islam et al. in their article they proficiently detect brain tumor with low cost. Initially, key features that reliably detect brain tumors were extracted using PCA. Ultimately, the brain tumor is located by segmenting the images using the TK-means clustering technique. Database has 40 MR images with a 95.0% accuracy rate, a 97.36% sensitivity rate, and a 100% specificity rate [38]. Hyperspectral imaging was recommended as an imaging modality by Rinesh et al. [39]. Utilizing k-based clustering techniques like KNN and k-means clustering, the tumor is detected. Both methods use the firefly algorithm, an optimization technique, to determine the value of k. The various areas of the brain are labelled using a multilayer FNN. The suggested method is examined using the 250 samples open-access brain tumor dataset obtained through Kaggle. This model achieved better performance measures with 96% accuracy. Different filters with wavelet bands are used in this work to preprocess and enhance the input slices. Amin et al. [41] with the help of Potential Field (PF) clustering, tumor pixel subsets are discovered. Furthermore, the tumor is isolated using a global threshold and several mathematical models. Unique features are combined for precise and better classification. BRAT's publicly available datasets containing 273 images and one locally obtained dataset having 86 MR images was used to assess the provided technique. Specificity obtained was 92, sensitivity 93%, accuracy 96, area under the curve (AUC) was 98%.

Cinar and Yildirim [40] presented a CNN model with the collaboration of Resnet50, to diagnose tumor in the brain MRI. The model's final 5 layers have been eradicated, and 8 additional layers have been added. The Kaggle dataset is used with 98 MRIs without a tumor, and 155 with tumor and model acquire 97% accuracy on test dataset. An enhanced architecture of CNN, Visual Geometry Group (VGG 16) was used by Younis et al. [25] to find brain tumor and setting parameters over this challenge were the objectives of this study. The proposed methodology was evaluated using a dataset of 253 MR images, 155 of which had tumors, used for the diagnosis of brain tumor using MR images. The system beat existing traditional methods for identifying brain tumor in the testing data and obtained an accuracy of CNN 96%. By leveraging the best qualities for brain tumor detection, Arunkumar et al. demonstrates automated brain tumor detection, segmentation and classification identification using ANN over brain MRI. To generalize the images and mark the districts and areas according to their grey scale, K-means clustering is applied [26]. Then Artificial Neural Network is applied to choose the best value based on the training. Thirdly, the division step will extract the textural feature of the brain tumor area. To diagnose brain tumor and discriminate between benign and malignant cases, grayscale features are used to identify brain tumor. In the implementation phase, they employed training on a dataset of 89 MR images and 70 images for testing purposes and accomplished an accuracy of 94%. An image improvement method that consists of three stages: greyscale to RGB image conversion, contrast enhancement using histogram equalization, and noise removal using a median filter is presented by Ullah et al. This method divides the MR pictures into normal and pathological categories. A dataset of 71 brain MR images used to identify brain tumors was utilized to verify the proposed model, and the findings revealed that the model had 95.8% accuracy and 95.65% specificity [27].

The comparison of data augmentation techniques with a proposed method based on PCA led to the development of an experimental framework for the identification of brain tumor in magnetic resonance imaging [28]. The study proposed that FLAIR imaging is the preferred sequence for data augmentation in this group of 110 participants using three different image acquisition modalities. The resulting images still had some spatial information, which made it possible to train the ResNet50 network to attain F1 score of 92.34%. A. H. Khan suggested an intelligent and efficient method for identifying brain tumors [42]. The study's innovative aspect is its use of a hierarchical Deep Learning technique to classify brain tumors into three distinct categories. For a speedy and effective cure, the diagnosis and tumor classification are crucial, and medical image processing utilizing a sequential CNN is producing remarkable results in this area. CNN trains the data and classifies the tumor types using the visual fragments. For the aim of detection and classification of brain tumor, a sequential or hierarchical structure of CNN is used. The proposed approach classifies the tumor with an accuracy of 92.1% using the dataset of 3264 MR images. In 2022, Zailan et al. [43] presented a Deep Learning and TL Model for brain tumor detection. Three Deep Learning approaches—VGG-16, Inception V3, and MobileNet V2—are used in this study, and is implemented on the Python platform. The dataset only contains 253 image samples of malignant brain tumor, but the algorithm can only predict tumor from a small number of MRI medical images. The confusion matrix criteria are used to determine the performance evaluation outcomes. Since the recall value of the MobileNet-V2 is 86.00%, its classification results are typically better than other state of the art methods.

TABLE 1. Comparison of results with STATE-OF-THE-ART existing methodologies.

S. No.	Authors and Years	Methodology	Classification	Dataset	Accuracy
1	[38]	Template-based K-means (TK) with SVM	Binary classification using Super pixels and PCA	40 MR images	Accuracy = 95.0% Sensitivity = 97.36%
2	[39]	K-based clustering processes	Tumor and detection using K-nearest neighbor and k-mean clustering	250 samples	Accuracy = 96.47% Sensitivity = 96.32%, Specificity = 98.24%
3	[4]	Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT)	SVM with quadratic kernel function is used for the classification of the brain tumors as tumor/non-tumor	the local dataset contains 86 images, while BRATS 2015 has 273 cases	Sensitivity = 92% Accuracy = 96% AUC = 93%
4	[5]	Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT)	classify the MR images into normal and tumor	Two datasets of 98 images and 155 MR images	Accuracy = 97.2%
5	[40]	Resnet architecture of CNN	Detection of tumor from MR images yielding yes/no tumor	253 MR images	Precision = 96%, F1-score = 91.78%, Accuracy = 96%,
6	[25]	VGG-16 with CNN	Classification of brain tumor from MR images into benign and malignant	89 MR images	Accuracy = 94.07% Sensitivity = 90.09% Specificity = 96.78%
7	[26]	ANN	classifies the MR images into normal and abnormal	71 MRI brain images	Accuracy = 95.8% Sensitivity = 96.0%, Specificity = 95.65%
8	[27]	Feed Forward neural network	Image augmentation and binary classification of brain tumor	110 MR images	F1 score = 92.3%
9	[28]	PCA	Multiclass Classification	3264 MR Images	Accuracy = 92.13 %
9	Proposed Methodology	InceptionV4 model	Accelerometer, RWIS Sensor, Global Positioning System Brain Tumor Detection and Classification	Dataset Comprising 7063 MRI Images	Accuracy = 98.9%

The second-highest accuracy for Inception-V3 was 84.00%, and VGG-16 had the lowest accuracy at 79.00%.

Afshar et al., presented a framework based on Capsule Network (CapsNets) for brain tumor detection and classification. Based on a realistic set of MRI pictures, they then look at the over-fitting issue using CapsNets. The researchers next investigated if CapsNets can provide a better match for entire brain pictures rather than only segmented tumor images, and in the end, they built a visual model for the output of the CapsNet to illustrate the learnt characteristics more clearly. The proposed model was evaluated on 3064 brain MR images and acquire an accuracy of 86% [31]. Using magnetic resonance brain imaging, Saeedi et al. suggested ML and Deep Learning algorithms for identifying brain tumors, allowing doctors to detect tumors at initial stages with maximum accuracy [44]. In this study, a dataset encompassing 3264 MRI brain pictures was employed, including images of gliomas, meningiomas, pituitary tumor, and with no tumor or healthy brains. First, MRI brain pictures were subjected to preprocessing and augmentation methods. They created a Deep Learning architecture, 2D CNN and a convolutional auto-encoder network, and both were trained using the given hyper parameters. Convolution layers are then included in the 2D CNN, which is a hierarchical network with all its levels having a 2∗2 kernel function. This network has four pooling layers, eight convolutional layers, and batch-normalization layers on top of all the convolutional layers. The modified auto-encoder network consists of the last output encoder layer of the previous part's last output encoder network as well as a CNN for classification. Deep Learning models had training accuracy of 95% while KNN achieved an accuracy of 86 %.

In 2022, Yazdan et al. [45] Put up a two-part solution first to use Multi-Scale CNN-model to build a reliable architecture for diagnosing brain tumor. The suggested approach performs multi class classification and categorize tumor among four different classes. Researchers aimed to develop a model that will improve the precision and effectiveness of the current tumor detection methods. To further enhance the classification outcomes, MRIs are denoised. According to the findings, the suggested model attained an F1-score and an accuracy of 91% on a dataset of 3264 MR images. An architecture containing a residual network and is based on attention modules and hyper column technology is proposed by Toğaçar et al. [33]. First, BrainMRNet performs preprocessing. This procedure is subsequently transmitted to attention modules for each image using picture augmentation techniques. CNN layers receive the picture after identifying key portions of the image. One of the main techniques used by the proposed model's convolutional layers is hyper parameters. This method allows the vector structure in the final layer of the BrainMRNet model to maintain the characteristics that were retrieved from each of the earlier layers. With the use of the BrainMRNet

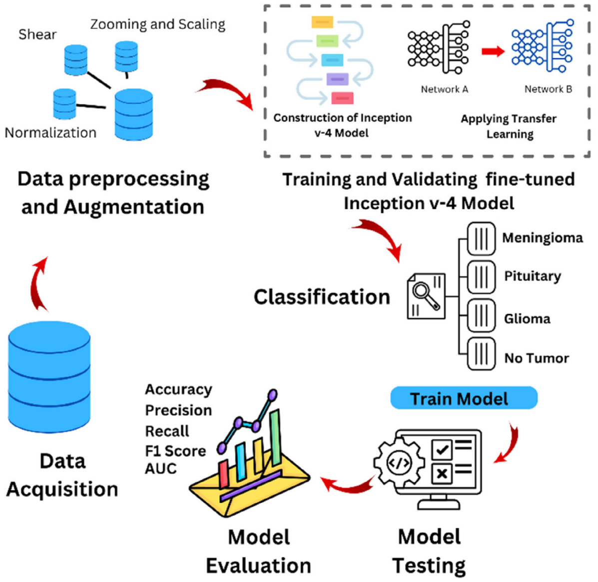


FIGURE 3. Proposed model diagram.

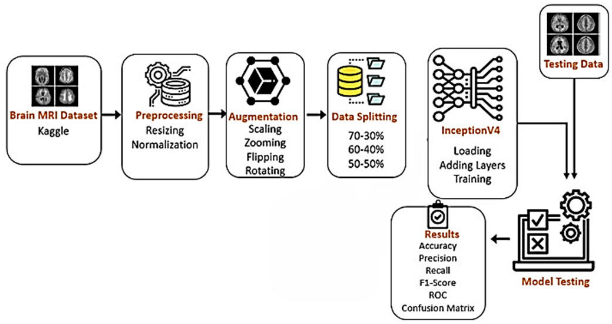


FIGURE 4. Proposed work flow I diagram.

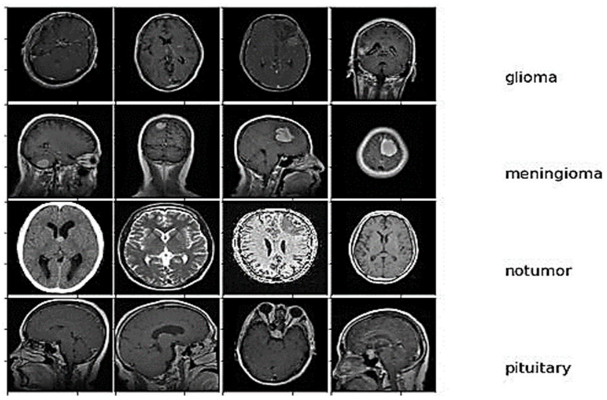


FIGURE 5. Sample dataset architecture.

model, brain tumor was diagnosed over a dataset of 253 MR images and attained an accuracy of 96%.

Based on the ResNet50 model and had a modified layer structure with three FC layers and five convolutional layers, Kumar et al. suggested an approach in 2022 [11]. After extracting the deep features and providing them as input to the classifier, this study creates a comprised feature set. The hybrid ResNet50 characteristics included in the proposed model. With a dataset of 253 images using various imaging modalities, the recommended modified ResNet50 model successfully recovered the images of brain tumor tissue with a classification accuracy of 90%. ANN are employed for the identification of brain tumor by Santos [46]. Authors used a publicly available dataset containing 3762 MR images and performed binary classification of images. This study achieved an accuracy of 89%. A Multi scale CNN architecture was proposed by Yazdan et al. Additionally, pre-trained models based on transfer learning, such AlexNet and ResNet, were employed to identify brain tumor. The model that has been presented divides MR images into multi class classification. The many parallel convolutions models with various filter sizes make up the projected multi-scale CNN model. Architecture's primary goal is to examine how different-sized convolutional filters affect the identification of brain tumors. As a result, several filter sizes are considered, including CNN1's 3×3 filter, CNN2's 5×5, and CNN3's 7×7 filter. The dataset, which includes 3264 MRIs from multi class classifications, had accuracy rates of 89%, 92%, and 90%, respectively. Table 1 shows the state-of-the-art comparison of existing techniques with Proposed Methodology.

III. PROPOSED CURVE CRASH AVOIDANCE PROTOCOL

One of the most prevalent cancers is a brain tumor, which makes for 15% of all cancer diagnoses in the US. For a patient to get appropriate care and achieve positive results, a quick and accurate identification of a brain tumor is crucial. Due to the high-pixels contrast scans of the brain that an MRI gives, it is frequently used to diagnose brain tumors [46]. Various ML and Deep Learning models are proposed for the accurate classification of innumerable types of brain tumor. The timely and accurate detection of brain tumor is very necessary in order to take precautionary measures [47]. The accuracy of various proposed models is discussed in the literature review Section. Inception v4 is not used yet for brain tumor detection. This study aimed to improve tumor detection accuracy and gauge how well InceptionV4 performs for the specified problem.

The InceptionV4 neural network architecture will be used in this project to identify and categorize brain tumors. We will pay particular attention to images of three different tumor types, including gliomas, meningiomas, pituitary tumors, and normal brain tissue. We used a publicly available dataset of brain MRI scans, consisting of 7022 brain MR images [29], [30]. Figure 3 shows the suggested detection and classification strategy for brain tumors.

Recent years have seen some of the biggest advances in image recognition performance, mostly due to deep convolutional networks. In the proposed work, an efficient Deep Learning-based approach for autonomously classifying brain tumors with minimum clinician interaction is provided. The goal of this research is to employ Deep Learning algorithms and TL techniques to increase the accuracy of MR image identification in the brain. Fig. 4 depicts the process of our proposed brain tumor classification system. The suggested framework model has four steps. First, the input MR picture is preprocessed (brain cropping and image resizing, and image normalization). Second, the data augmentation (shear, horizontal flipping and scaling) approach is employed to enhance the size of the dataset. Third, we evaluated the unique Deep Transfer Learning-based model, Inception V4, employing preprocessed MR images from Brain Tumor and applied the TL approach to extract features. The softmax layer classifies the characteristics retrieved by the CNN models.

A. DATA ACQUISITION

In the context of image processing, the process of getting images from a source, called the process of image acquisition. The first stage of the process is image collection, which comprises acquiring MRI scans of the three different types of tumor and healthy brain images. We used a publicly available dataset of brain tumor. Dataset used in the proposed study is an amalgamation of three brain tumor datasets, including figshare, SARTAJ dataset, and Br35H, and contains 7022 brain MRI images. The dataset is classified into four classes, including glioma, meningioma, no tumor, and pituitary. It must be remembered that images from the Br35H dataset were used for the no tumor class. This dataset is publicly available on Kaggle platform. Figure 5 presents the dataset classification [29], [30].

The outcome of a DeepLearning model can be significantly impacted by the distribution of classes in the dataset. If there is a large class imbalance, where some classes have significantly fewer examples than others, the model may struggle to learn the less represented classes. Plotting the ratios of categories in the dataset can help identify if there is a class imbalance and guide strategies for addressing it. The ratios of classes in the used dataset for this study is demonstrated in Figure 6.

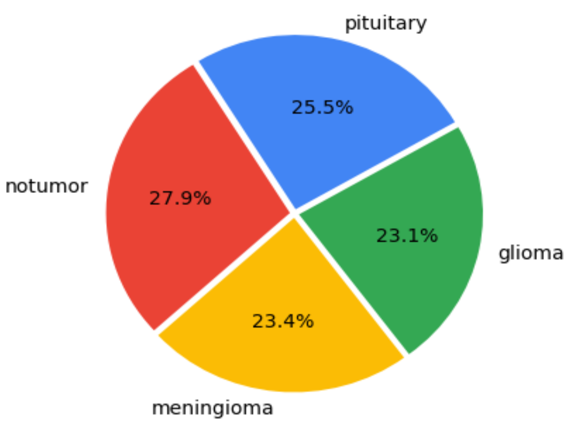


FIGURE 6. Ratios of classes used in the proposed system.

B. DATASET DIVISIONS

The dataset is divided into train and test ratios using the Sklearn Library of Python. The division of the dataset is as follows:

- 70% train and 30% test.
- 60% train and 40% test.
- 50% train and 50% test.

C. PREPROCESSING STEP

The first step of the study will involve data preprocessing, including image normalization and augmentation. We preprocess the MRI images to make them suitable for model training. Data normalization is a step in the preprocessing process that involves setting the mean and standard deviation of pixel values to 0 and 1, respectively [36], [48]. By adding new, slightly different versions of the current data, we may expand the dataset. This is accomplished by performing a number of modifications to the original data, such as rotating, scaling, cropping, flipping, or adding noise to photos, or altering the pitch or tempo of audio files. By exposing a machine learning model to more varied samples of the same data, data augmentation aims to increase the generalization capability of the model, which might prevent overfitting and increase the model's accuracy [31]. The model learns to be resilience to tiny fluctuations in the input by applying random modifications to the data during training, and hence can handle unknown data better during testing. To increase the variety of the training data and enhance model generalization, we employed data augmentation techniques including rotation, flipping, and zooming. The images are resized into 299×299 dimensions that is standard size of image for inceptionv4 model.

D. MODEL TRAINING PHASE

Inception-v4 is a deep transfer learning-based CNN architecture that was introduced by Google researchers in 2016. It is a model from the Inception family, which was initially launched in 2014, which aimed to improve the performance of CNNs. Convolutional layers (Conv.), pooling layers, and fully connected layers (FC) are stacked to make up the Inception-v4 model. The use of an Inception module, a building block that enables the network to learn both spatial and channel-wise dependencies within the input data, is the main innovation of the Inception-v4 model. The Inception module consists of a combination of 1×1, 3×3, and 5×5 convolutions, as well as pooling layers, which are used for feature extraction at multiple scales. The Inception-v4 model also includes several architectural innovations such as the Stem network, which uses a small set of convolutional layers to extract features from the input images and reduce their spatial dimensions. The Reduction modules are specialized modules that are employed to increase the depth of the feature maps while reducing their spatial dimensions. Residual connections are also included, which bypass one or more layers and allow gradients to flow more easily through the network.

This model uses global average pooling, which averages the values in each feature map across its spatial dimensions, producing a single value for each feature map. The network's parameter count is reduced because of this pooling procedure,

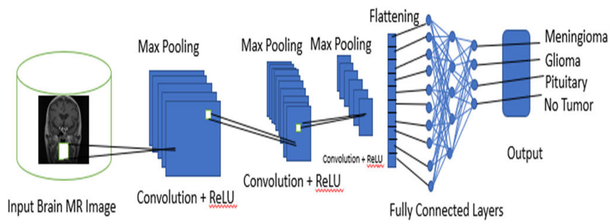


FIGURE 7. Implemented sequential CNN architecture for brain tumor.

TABLE 2. The proposed architecture of sequential CNN for brain tumor classification.

Layer (Type)	Output Shape	Parameter #
conv2d (Conv2D)	(None,198,198,64)	640
conv2d_1(Conv2D)	(None,196,196,64)	36928
max_pooling2d	(None, 98, 98, 64)	0
(MaxPooling2D		
Dropout (Dropout)	(None,98,98,64)	0
conv2d (Conv2D)	(None, 96, 96, 64)	36928
conv2d_1 (Conv2D)	(None, 94, 94, 64)	36928
max_pooling2d	(None, 98, 98, 64)	0
(MaxPooling2D)		
dropout (Dropout)	(None, 98, 98, 64)	0
conv2d_2 (Conv2D)	(None, 96, 96, 64)	36928
conv2d_3 (Conv2D)	(None, 94, 94, 64)	36928
dropout_1 (Dropout)	(None, 94, 94, 64)	0
max_pooling2d_1		
(MaxPooling 2D)		
	(None, 47, 47, 64)	0
dropout_2 (Dropout)	(None, 47, 47, 64)	0
conv2d_4 (Conv2D)		
	(None, 45, 45, 128)	73856
conv2d_5 (Conv2D)	(None, 43, 43, 128)	147584
conv2d_6 (Conv2D)	(None, 41, 41, 128)	147584
max_pooling2d_2		
(MaxPooling 2D)		
	(None, 20, 20, 128)	0
dropout_3 (Dropout)		
	(None, 20, 20, 128)	0
conv2d_7 (Conv2D)		
	(None, 18, 18, 128)	147584
conv2d_8 (Conv2D)	(None, 16, 16, 256)	295168
max_pooling2d_3	(None, 8, 8, 256)	0
(MaxPooling 2D)		
dropout_4 (Dropout)	(None, 8, 8, 256)	0
flatten (Flatten)		

which also helps to avoid overfitting. Finally, auxiliary classifiers are inserted to the network at intermediate layers, which improve gradient flow through the network and offer additional supervision during training. Several image classifications benchmarks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), were competed using this model, and it demonstrated state-of-the-art performance. It is an advanced architecture for a variety of computer vision problems due to its combination of effective and expressive features [32].

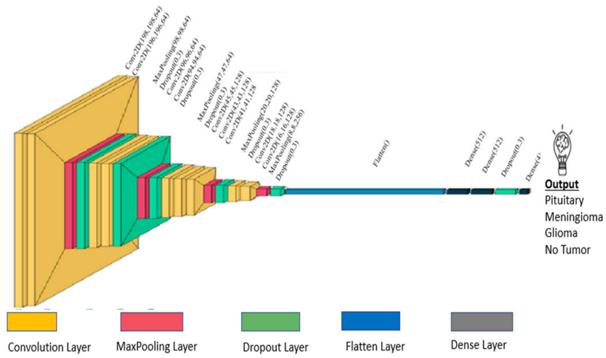


FIGURE 8. The proposed sequential architecture of CNN for brain tumor.

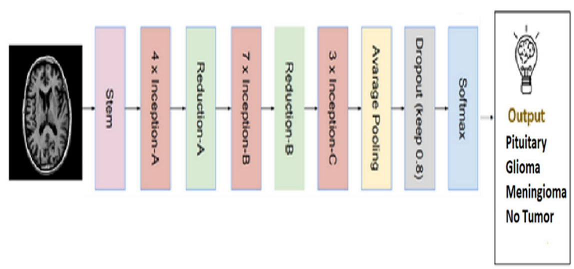


FIGURE 9. The architecture of inception V4 for brain tumor classification.

E. SEQUENTIAL CNN AND INCEPTION V-4 IMPLEMENTATION

The sequential CNN layout for a brain tumor has nine convolutional layers, as demonstrated in Figure 7. The network's spatial variance attribute is realized by using an activation function called RELU or rectified layer unit in these layers following the convolutional layers max-pooling. To give an intellectual form of representation and prevent overfitting, max pooling is employed. Likewise, it reduces the cost of computation by reducing the amount of parameters. The pool size (2×2) for all max-pooling operations over the whole network is often referred to as the stride size. The flattening function added by the pooling function is employed to turn the frame pixel into a vector column after the ninth convolutional layer. After flattening, the suggested model employs two completely linked layers. Both completely linked layers employ the dense function, which has 512 units and rectified layer units with a drop rate of 30% as activation functions. The class of the brain image is determined by the last FC layer. After all the functions have been added to a sequential model, the call model compiles the function using three parameters: loss, optimizer, and metrics. During data training, the weights are repeatedly updated using the Adam optimizer. The loss and accuracy are then measured

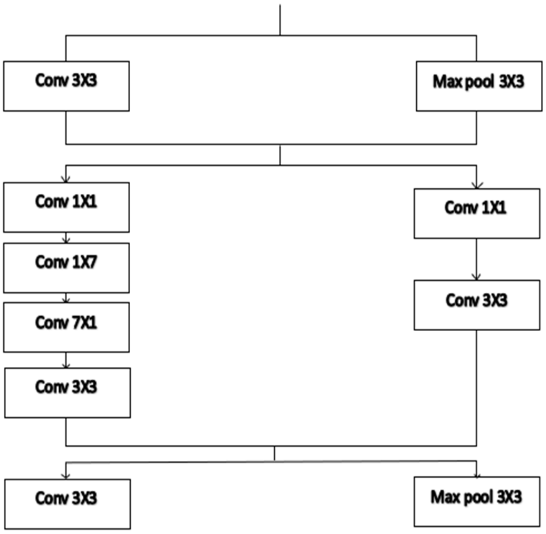


FIGURE 10. The internal architecture of base block.

TABLE 3. Simulation parameters.

S.No.	Parameters	Used Values
1	Windows OS	LINUX OS
2	Language	Python 3.6, JAVA, XML
3	Processor	X64 bit
4	Platform	Google Collaboratory
5	Learning rate	0.001
6	Batch size	32
7	Number of epochs	50
8	Dropout rate	0.3
9	Weight decay	0.0001
10	Optimizer	Adam
11	Activation Function	Relu and softmax
12	Loss Function	Categorical Cross entropy

as evolution metrics for assessment using categorical cross-entropy. Figure 8 shows the proposed sequential architecture of CNN for brain tumor.

F. PROPOSED INCEPTION V4 ARCHITECTURE

The complete Inception v4 network architecture for identifying brain tumor from stipulated MR data is shown in Figure 9. Employing parallel multidimensional convolutional layers, Inception is a deep architecture of CNN. The stem or base, A, B, C blocks make up the Inception v4 architecture. Two reduction blocks, A and B, are placed after the initialization blocks A and B. The input for the inception block is split into four branches, B0 to B3, each of which comprises convolutional layers. All blocks are listed from Table 3, along with their branches and convolutional layer sizes. After integrating the outputs from each block, the flattening and FC layers determine the output class of the input picture [32].

G. ARCHITECTURE OF BASE BLOCK

The Inception v4 input portion is the schema or base block, also known as the stem of pure Inception modules. This stem accepts input images in the 299 $\times$ 299 format, which is the standard layout for Inception V4 as shown in Figure 10.

IV. PERFORMANCE EVALUATION

Inception-v4 is a deep CNN architecture that was proposed by Google researchers in 2016. It is an extension of the Inception models that were first introduced in 2014, which aimed to enhance the efficiency and accuracy of CNNs. The inception-v4 model comprises a stack of convolutional, pooling, and FC layers. The key innovation of the Inception-v4 model is using an Inception module, which is a building block that allows the network to learn spatial and channel-wise dependencies within the input data. The Inception module consists of a combination of 1 $\times$ 1, 3 $\times$ 3, and 5 $\times$ 5 convolutions and pooling operations, which are used to extract features at multiple scales. The Inception-v4 model also includes several architectural innovations, such as the Stem network, which uses convolutional layers to extract features from the input images and reduce their spatial dimensions. The Reduction modules are specialized modules that are used to reduce the spatial dimensions of the feature maps while increasing their depth. Residual connections are also included, which bypass one or more layers and allow gradients to flow more quickly through the network. Table 3 defines the model's parameters with their description.

The importance of Inception-v4 for brain tumor classification lies in its ability to extract and learn complex features from input images, which can be used to accurately classify diverse types of brain tumor. In our study, we used the pre-trained InceptionV4 model, which has been trained on the ImageNet dataset for image classification. The proposed model is trained on the dataset for 50 epochs, with a batch size of 32. All 3 ratios are used for the model training and results are evaluated using different evaluation metrics. With a learning rate of 0.001 and a decay rate of 0.0001, the model is optimized using the Adam optimizer. We also used early stopping to prevent overfitting, based on validation loss. Fine-tuning is a technique that involves taking a pre-trained neural network, in this case Inception-v4, and updating its weights to adapt it to a new task or dataset. In the context of brain tumor detection, fine-tuning Inception-v4 involves taking the pre-trained model and updating its weights on a new dataset of brain MRI images, which allows the model to learn to recognize the specific features and patterns associated with brain tumor. The values of hyper parameters of proposed model are listed in Table 3.

A. CLASSIFICATION AND MODEL EVALUATION

After training the InceptionV4 model on the using the discussed hyper-parameters, the next step is to evaluate its performance on the test dataset and classify the brain tumor into their respective categories. To do this, we applied the pre-trained model to predict the test pictures' class labels and compared those predictions to the ground truth labels to derive several assessment measures, including accuracy, precision, recall, and F1-score. When a model is tested, its performance on a different test set that was not used during the training phase is assessed. This is crucial to make sure the model is not overfitting to the training data and has learnt to generalize to new, unexplored data. We evaluate the performance of the InceptionV4 model using validation data. For each class, we additionally evaluate the model's F1 score, recall, accuracy, and precision. The effectiveness of the model at various thresholds was further evaluated using the receiver operating characteristic (ROC) analysis. We compare the performance of InceptionV4 to other innovative models described in the literature in order to assess its potential for the identification and classification of brain tumors. InceptionV4 performed better than other models when it came to accuracy, precision, recall, and F1 score.

1) CONFUSION MATRIX

The Matrix is one of the most simple and natural ways to assess the model's accuracy and accuracy. It is used to tackle problems involving categorization in which the result can be separated into two classes.

2) CLASSIFICATION ACCURACY

Accuracy in problems of classification refers to the total number of correctly predicted events across all the classes. It can be calculated using the confusion matrix using equation 1.

$$Accuracy = \left(\frac{Correctly\ Classified\ Records}{Total\ Records}\right) \times 1 \quad (1)$$

3) PRECISION

In contrast to the confusion matrix, the precision matrix shows the proportion of accurate predictions for positive occurrences. Being specific is the core of precision. So, even if we were only able to accurately identify one case of cancer, we would still be 100% accurate. The precision in the proposed methodology is computed using equation 2.

$$Precision = \frac{TP}{TP + TF} \quad (2)$$

4) SENSITIVITY

A measure of true positives and genuine positive, are compared to false negatives is called sensitivity. When "cancer" is the response, the recall concentrates more on compiling every case. It means recall is not so much focused on correct predictions so, if each case will be referred to as "cancer," we will have a 100% recall rate. The sensitivity is computed using equation 3.

$$Sensitivity = \frac{TP}{FP + FN} \quad (3)$$

5) SPECIFICITY

The fraction of cases that the model categorized as non-cancerous but those did not yet have illness is known as specificity. The recall is the polar opposite of this using equation 4.

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

6) F1 SCORE

We do not want both Recall and Precision in our accounts while building a model to tackle a classification challenge. Therefore, it would be ideal (R) if we could obtain a single score that accurately reflects both precision (P) and recall (R). The harmonic mean of recall and precision is a form of average if x and y are equal. However, if x and y are not equal, the smaller figure resembles the lower number more closely than the bigger number. It can be calculated using equation 5.

$$F1Score = Harmonic\ Mean\,(Precision, Recall) \quad (5)$$

7) ROC

Graphically, a receiver operating characteristic (ROC) curve shows how well a classification model performs. It is a plot of the true positive rate (TPR) against the false positive rate (FPR) for different classification levels. The ROC curve may be used to assess the effectiveness of the model in identifying tumor and differentiating between various tumor kinds when classifying brain tumors using the Inception-v4 model. By analyzing the curve and calculating the AUC, it is possible to assess the accuracy of the model and identify areas for improvement.

B. EXPERIMENTAL SETUP

We utilize a corei5 7th generation system with 16 GB of RAM, 512 GB of SSD storage, and a 4 GB Nividia GPU for simulation purposes. Anaconda and a Jupyter notebook running Python 3.9 are the tools employed for simulation. Various libraries are used during simulation process including pytorch, TensorFlow, Keras, Pandas, Matplotlib etc. The dataset was loaded and split into different ratios for testing the model effectiveness in different scenarios [35].

C. ABOUT DATASET

In image processing, retrieving a picture from a source (hardware-based source) is a generally called image acquisition. The initial phase is image collecting, which entails gathering MRI images of three categories of tumors and standard brain images. We used a publically available data set of brain tumors. The dataset combines three brain tumor datasets, including figshare, SARTAJ dataset, and Br35H, and contains 7063 images of human brain MRI scans. The dataset is classified into four classes: glioma, meningioma,

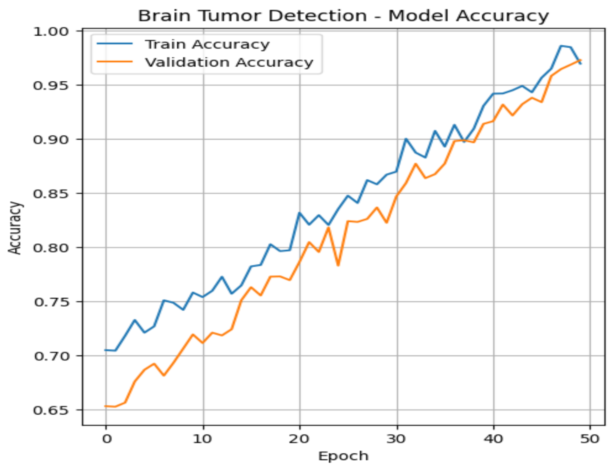


FIGURE 11. Training and validation accuracy of 70-30 ratio.

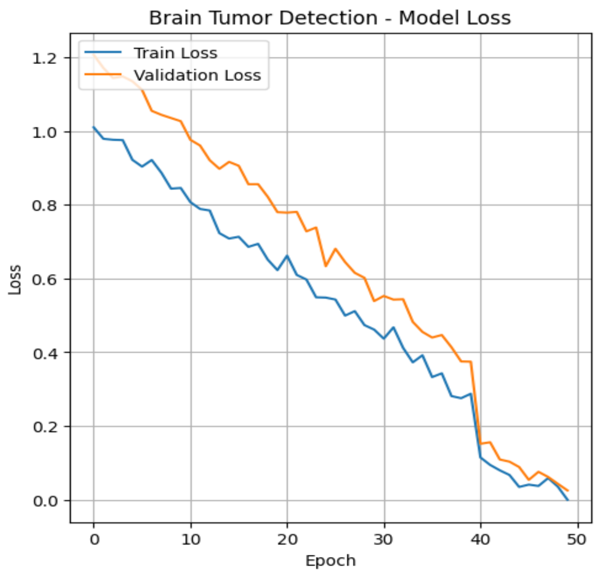


FIGURE 12. Training and validation loss of proposed model on 70-30 ratio.

no tumor, and pituitary. It is important to note that the no tumor class images were taken from the Br35H dataset. This dataset is publically available on the Kaggle platform. Figure 2 presents the dataset classification.

The dataset is divided into different train and test ratios, which are as follows:

- 70% train and 30% test.
- 60% train and 40% test.
- 50% train and 50% test.

D. EXPERIMENTS

We perform the experiments in three sections based on the dataset presented in section C.

E. EXPERIMENT 1

70 percent of the data, chosen at random, were used to train the proposed Inception v4 model, and 30 percent of the data were used to assess the model. The training accuracy of the proposed model was 98.9% while validation accuracy of the model on this ratio is 97.3%, which means that 97.3% of the samples in the testing set were correctly identified and classified by the model. The training and validation loss of model was also plotted. The implied Inception v4 model's training and validation accuracy is shown in Figure 11 for this ratio.

As illustrated in Figure 12 the proposed inception v4 achieved a handsome rate of on proposed data set. The model's validation loss is 0.13%, an exceptionally low value that shows the model is functioning effectively on the set that was tested. The training and validation losses of the suggested model on the 70-30 ratio are shown in Figure 12.

On the X-axis, the epoch count is shown, while the Y-axis shows the training and validation loss. The loss amount changes based on learning rate. If the learning rate is small, the loss value slowly decreases. We also evaluate proposed model by using confusion matrix that is illustrated in Figure 13. The model has a high true positive rate, a low true negative rate, and extremely few false positives and false negatives, as demonstrated by the below confusion matrix.

As illustrated in this Figure 13 the confusion matrix chart where the examples in a projected class are represented by

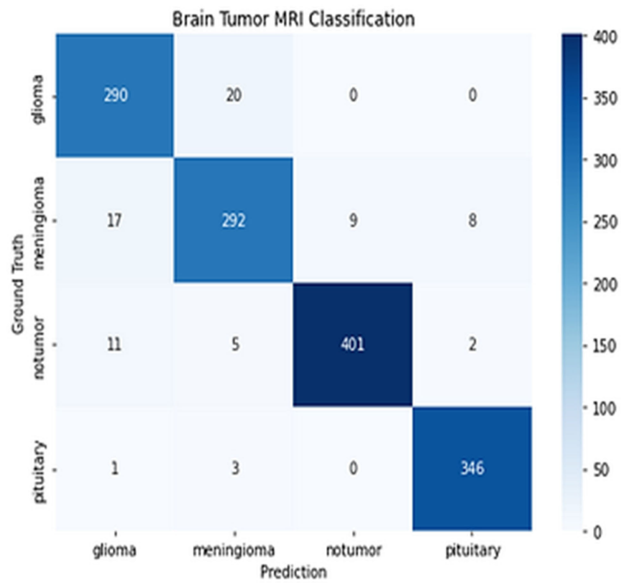


FIGURE 13. Confusion matrix for 70-30 ratio.

TABLE 4. Classification report of 70-30 ratio.

Classes	Precision	Recall	F1-Score
Pituitary	0.98	0.99	0.99
No tumor	0.98	0.99	0.99
Meningioma	0.95	0.97	0.95
Glioma	0.99	0.94	0.96

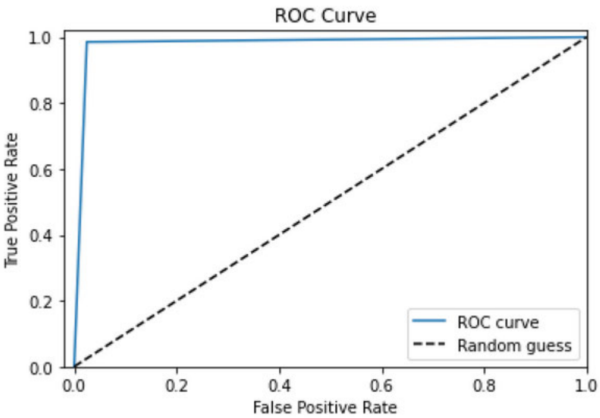


FIGURE 14. ROC for the model for 70-30 ratio.

TABLE 5. Values of sensitivity and specificity of 70-30 ratio.

Model	Data Division	Training accuracy	Validation Accuracy	Sensitivity	Specificity
Model	70% and 30%	98.9%	97.3%	97%	99%

the column, and the cases in the class label are represented by the row. Values only on the matrix diagonal display the correct predicted, whilst values outside the diagonal display the incorrect prediction. The evaluation of the model using the classification report can provide a more detailed understanding of the performance of the model for each class. The classification report comprises metrics for each class, including the overall weighted average of these metrics as well as accuracy, recall, and F1-score. The values of all these parameters are presented in Table 4.

From this classification report, we can see that the model has precision, recall and F1 score values for all classes of brain tumor. The overall average accuracy for this testing set is 0.97%, which indicates that the model is performing well overall. Figure 14 illustrates the receiver operating characteristic (ROC) curve for this testing ratio by plotting TPR vs the FPR for various threshold values. We used the one versus rest for plotting ROC and select the average curve from all. The ROC curve is above the diagonal line, which indicates that the model is performing better than a random classifier. The area under the curve (AUC) for this ROC curve is 0.972%, which is quite high and indicates that the model is performing well.

Sensitivity and specificity are also important metrics to consider when evaluating a classification model. In contrast to specificity, which measures the proportion of real negative cases the model properly identifies, sensitivity measures the proportion of true positive situations. Table 5 presents the sensitivity and specificity along with training and validation accuracy of proposed model on 70-30% ratio of data.

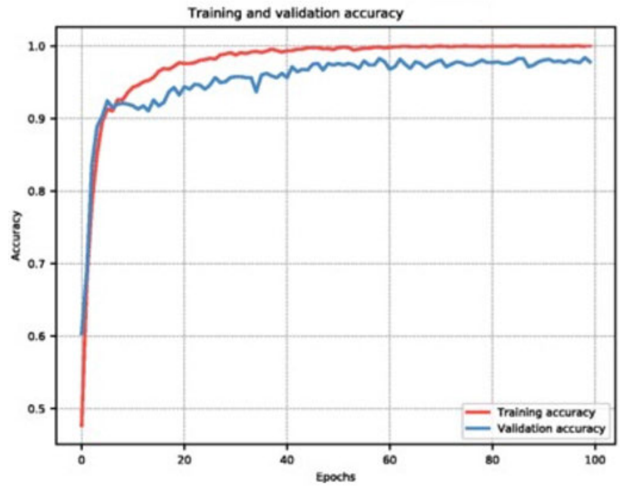


FIGURE 15. Training and validation accuracy of the proposed model on 60-40 ratio.

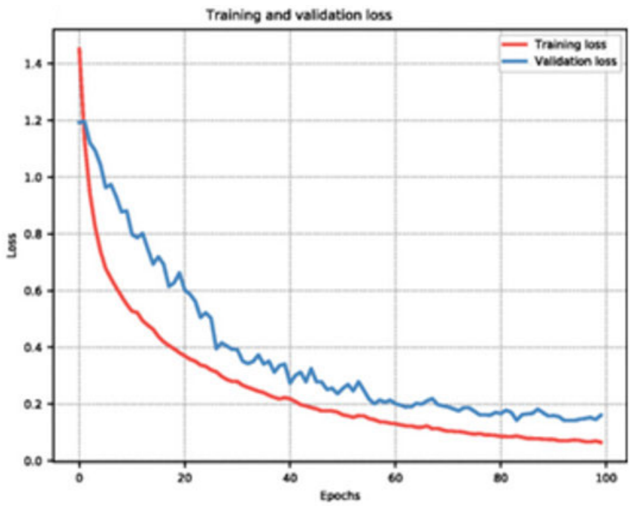


FIGURE 16. Training and validation loss of model for 60-40 ratio.

F. EXPERIMENT 2

The suggested model was further tested employing 60% and 40% to see how changing the training and validation ratios affected model's effectiveness. The training and validation accuracy of the model on this ratio is 99.6% and 98.7% respectively, which is slightly higher than the previous data ratio. The validation loss of the model is 0.17, which is slightly lower than the previous data ratio. Figure 15 illustrates the training and validation of proposed inception v4 model on 60-40 ratio of data.

The proposed Inception v4 model's training loss is 0.13 and validation loss is 0.17 as shown in Figure 16. The confusion matrix of model on 60-40 ratio is presented in Figure 17 for finding the more insights of model predictions on unseen data. As can be observed, the model still exhibits high true positive and true negative rates, but compared to the prior data ratio, there are a little bit fewer false positives and false negatives.

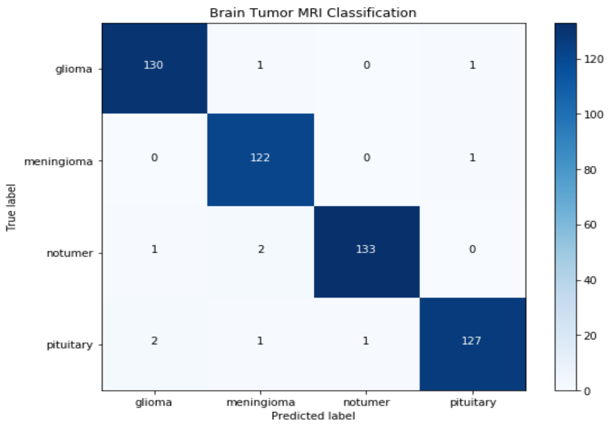


FIGURE 17. Confusion matrix of proposed model for 60-40 ratio.

TABLE 6. Classification report of model for 60-40 ratio.

Classes	Precision	Recall	F1-Score
Pituitary	1.0	0.98	0.99
No tumor	0.98	1.0	0.99
Meningioma	0.99	1.0	1.0
Glioma	1.0	0.99	0.99

As discussed earlier, by utilizing the classification report to evaluate the model can offer a more comprehensive comprehension of its performance for each class. By presenting precision, recall, and F1-score metrics for every class, as well as the overall weighted average of these metrics, the classification report furnishes an in-depth analysis of the model's efficiency. The Table 6 presents the values of all these parameters.

In the presented table, we can see that the proposed inception v4 model has achieved a sensitivity of 0.98 and a specificity of 0.99. This means that the model correctly identified 98% of the positive cases and 99% of the negative cases. When evaluated with test data, a high sensitivity shows that the model is effective at identifying the brain tumor. A low sensitivity means that there is a higher chance that the model may misclassify the input data, which can be problematic, particularly when it comes to medical diagnosis. The proposed model is also evaluated on the basis on ROC curve for analyzing the effectiveness of model on test data. The ROC curve of the proposed model on 60-40 ratio is illustrated in Figure 18.

A Deep Learning model's sensitivity and specificity are essential measures used to assess its performance. Sensitivity, also known as recall or the actual positive rate, measures the percentage of genuine positive cases correctly identified by the model. The proportion of actual negative that the model accurately identifies as being negative, is measured as specificity. Table 7 explains the sensitivity, specificity, training, and validation accuracy for 60-40 ratio.

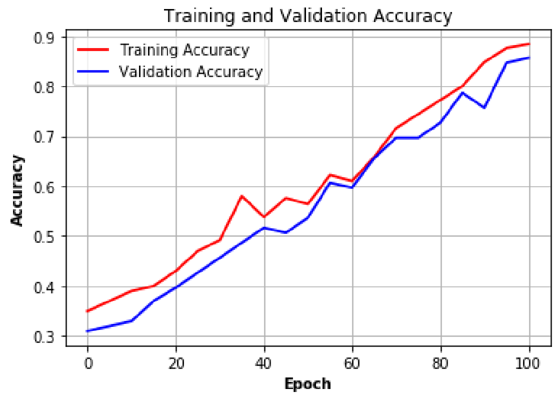


FIGURE 18. Training and validation accuracy of the model on 50-50 ratio.

TABLE 7. Values of sensitivity and specificity of 70-30 ratio.

Model	Data Division	Training accuracy	Validation Accuracy	Sensitivity	Specificity
Model	60% and 40%	99.6%	98.7%	98%	99%

As illustrated in Figure 8, the ROC shows a false positive rate and true positive has maximum value of 1.0. The red line depicts AUC of proposed model that has a high value of 0.98 from range of 1.0.

G. EXPERIMENT 3

The results of training and evaluating a model on a 50-50 split of data set to see the insights of model performance. The results obtained from the evaluation metrics, including training and validation accuracy, confusion matrix, classification report, and ROC curve will be covered in this section. One important parameter used to assess the model's ability to predict is its accuracy on the training and validation sets of data. The training accuracy is obtained on the training set during training, while the validation accuracy is the accuracy obtained on the validation set during training. The training and validation accuracy of proposed model of 50-50 ratio is illustrated in Figure 19.

In this study, we discovered that the model had an 89% training accuracy and an 88.4% validation accuracy. The model performs well in terms of its capacity to produce accurate predictions, but less than in earlier tests, according to the relatively high values of both measures. Figure 20 displays the training and validation loss of the suggested model on the 50-50 ratio.

The confusion matrix, as previously explained, provides a summary of the model's performance by indicating the number of TP, TN, FP, and FN. The proposed model for a 50-50 split is shown in confusion matrix form in Figure 21. The relatively high values for both true positives and true negatives but as compared to the other ratios of data the model

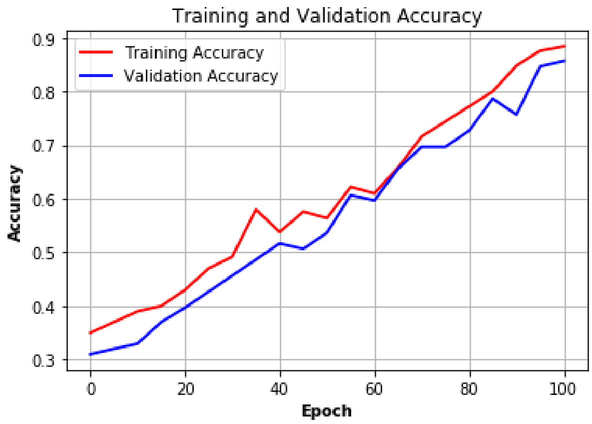


FIGURE 19. Training and validation loss of model on 50-50 ratio.

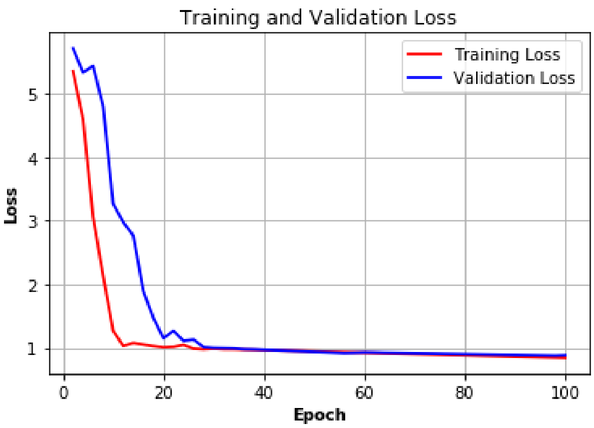


FIGURE 20. Training and validation loss of model on 50-50 ratio.

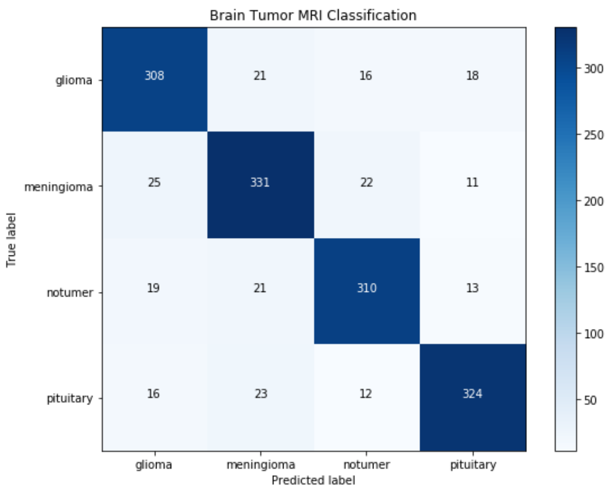


FIGURE 21. Confusion matrix for 50-50 ratio model.

is not performing well. So, this data division is not good for the proposed model.

To assess the value of precision, recall and F1 score we use the classification report that shows the values of these parameters for all categories of brain tumor used in the proposed dataset. The classification report for the 50-50 data partition proposed inception v4 model is shown in Table 8.

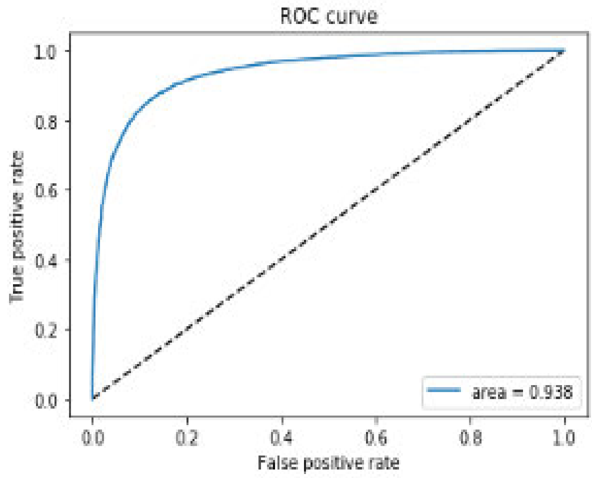


FIGURE 22. ROC of the proposed model for 50-50 ratio.

TABLE 8. Classification report of model for 50-50 ratio.

Classes	Precision	Recall	F1-Score
Pituitary	0.83	0.82	0.83
No tumor	0.96	0.92	0.94
Meningioma	0.78	0.64	0.70
Glioma	0.78	0.97	0.87

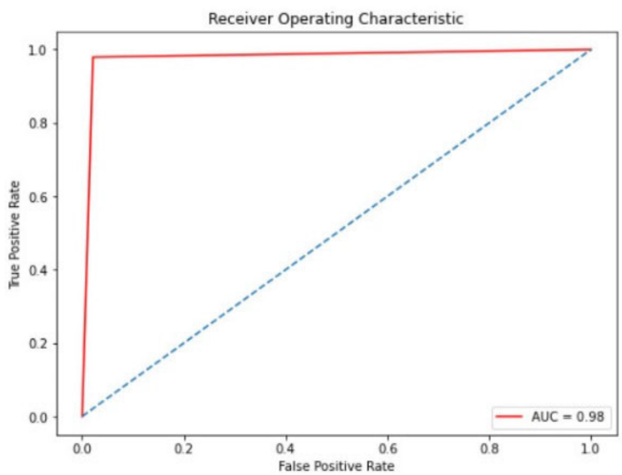


FIGURE 23. ROC of the model on 60-40 ratio.

As shown in Table 8 the proposed model on 50-50 ratio is not performing well on the detection of Meningioma and Pituitary tumor that is the reason of less accuracy of model on this ratio. This model is also evaluated on ROC curve as others. The ROC curve of the proposed model is demonstrated in Figure 23.

The sensitivity and specificity of proposed model on this ratio along with training and validation accuracy is presented in Table 9.

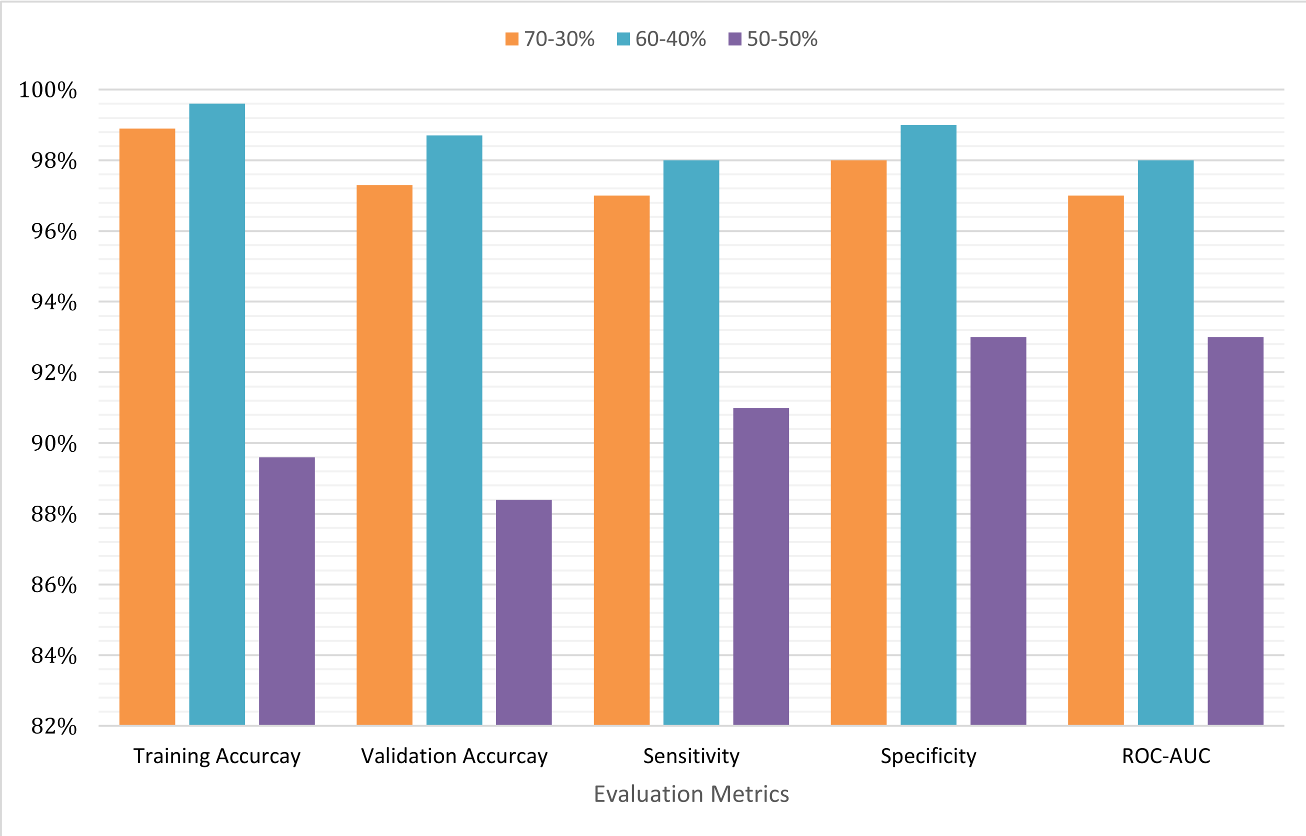


FIGURE 24. Comparison of proposed models.

TABLE 9. Sensitivity and specificity of 50-50 ratio model.

Model	Data Division	Training accuracy	Validation Accuracy	Sensitivity	Specificity
Model	50% and 50%	89.6%	88.4%	91%	93%

The proposed model performance as presented in table 4.6 has achieved 91 and 93 percent sensitivity and specificity values, respectively. We can see that the proposed model on this ration achieved low level of sensitivity and specificity as compared to other experiments.

H. RESULTS COMPARISON

The proposed inception V4 model experiments are compared for finding the best model. The performance of all experiments on the basis on accuracy and other metrics are illustrated in Figure 24.

As shown in Figure 25 the data ratio of 60-40 achieved a higher level of accuracy and other metrics values. So, the 60-40 ratio model outperformed other models in the identification and classification of different brain tumors.

The proposed model for the detection and classification of brain tumor from MRI images is also compared with previous techniques discussed in chapter 2. After the analysis and comparison based on different metrics, we found that the Inception V4 is effective and outperformed previous machines and Deep Learning models. Deep convolutional neural network Inception v4 was created to offer superior accuracy in image classification tasks. Due to its distinctive design, it has performed better than previous versions. The comparison of the suggested model with existing models for the identification of brain tumors is shown in Figure 25.

In this part, we evaluate how well the proposed Inception v4 model for classifying brain tumors performs in comparison to other suggested Deep Learning models. This section aims to demonstrate insights into the advantages and strengths of the Inception v4 model in acquiring high accuracy in the proposed problem. The deep models have been widely used in medical image analysis; they heavily rely on the manual extraction of features. It may hinder their ability to detect subtle differences and complicated patterns in the data. The Inception v4 model, on the other hand, automatically learns structure from the unprocessed input data, allowing it to effectively capture intricate features that are crucial for accurate brain tumor classification.

The Deep Learning model CNN employs a convolutional architecture like the Inception v4 model. However, it utilizes a shallower network with fewer layers and parameters. The deeper architecture of the Inception v4 model allows it to

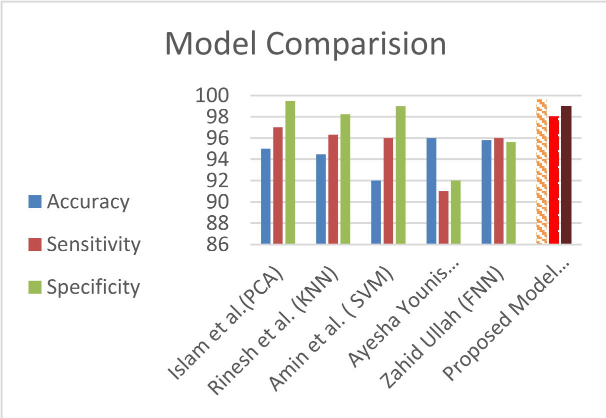


FIGURE 25. Comparison of proposed model with sequential CNN.

TABLE 10. Result from comparison with sequential CNN.

Models	Accuracy	Sensitivity	Specificity	Precision	Recall	F1-Score
CNN	86.33 %	89.28%	88.62%	89.32 %	87.93 %	88.21 %
Inception v4	98.7%	98.0%	99.0%	99.0%	98.2 %	99.1 %

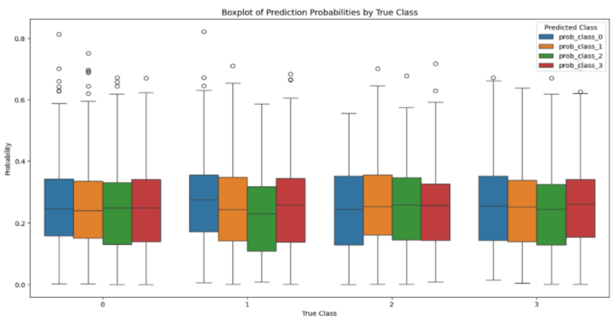


FIGURE 26. Comparison of proposed model with sequential CNN.

acquire greater abstraction and discriminatory features from incoming images. The highly deep architecture of Inception v4 model allows for better representation learning, resulting in improved performance compared to CNN. Table 10 presents the comparison of other proposed models with inception v4.

I. RESULTS COMPARISON WITH OTHER STATE OF ART MODELS

This research focused on using transfer learning models such as VGG16, ResNet50 and InceptionV3 for Brain Tumor detection. Proposed approach to brain tumor detection stands out for its good performance specifically for tumor detection. Through extensive experimentation, a custom architecture that includes advanced data augmentation techniques, carefully applied custom layers, and set some model checkpoints

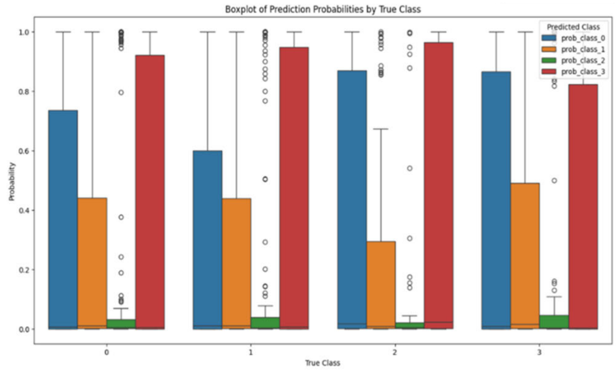


FIGURE 27. Boxplot of prediction probabilities by true class.

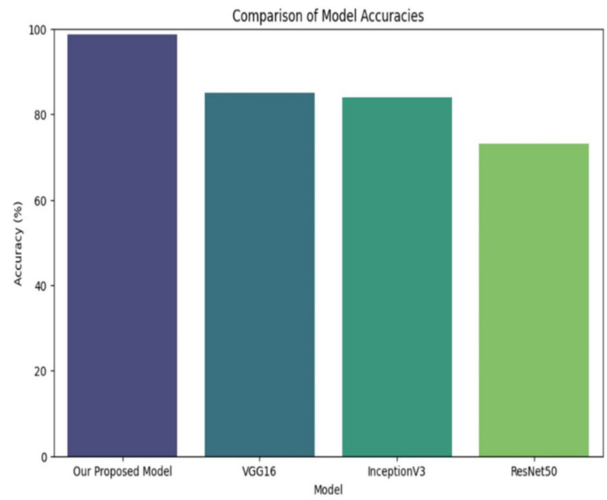


FIGURE 28. Comparison of model accuracies.

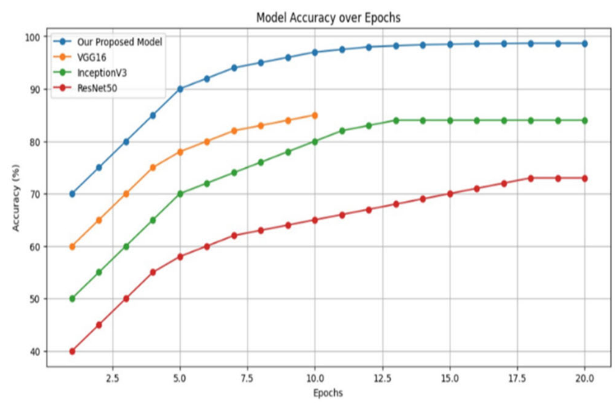


FIGURE 29. Model accuracies over epochs.

has been developed. By freezing some layers of Inception V4 and fine-tuning others leads to optimal results. Moreover, proposed architecture ensures this architecture adopts the complexities of brain tumor images. So, this iterative process allowed to continually refine and improve the architecture which leads to better results.

First of all, a simple iteration in which only dense layer with 128 units and ReLU activation along with

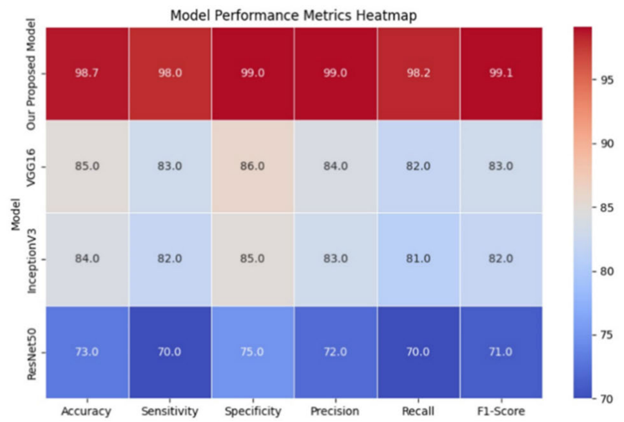


FIGURE 30. Proposed model performance evaluation using heatmap.

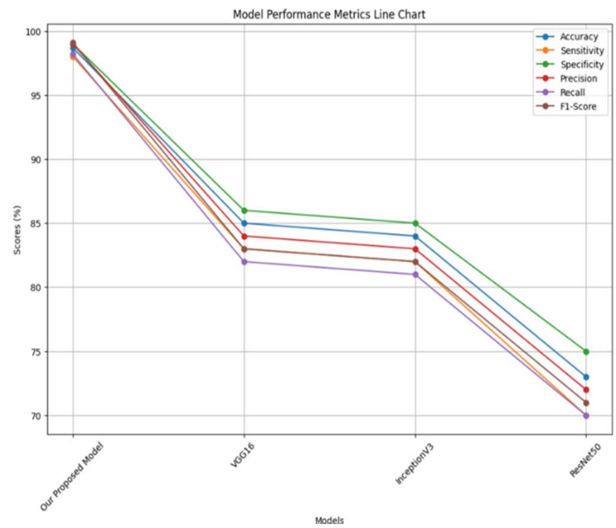


FIGURE 31. Comparison with state-of-the-art approaches using Linechart.

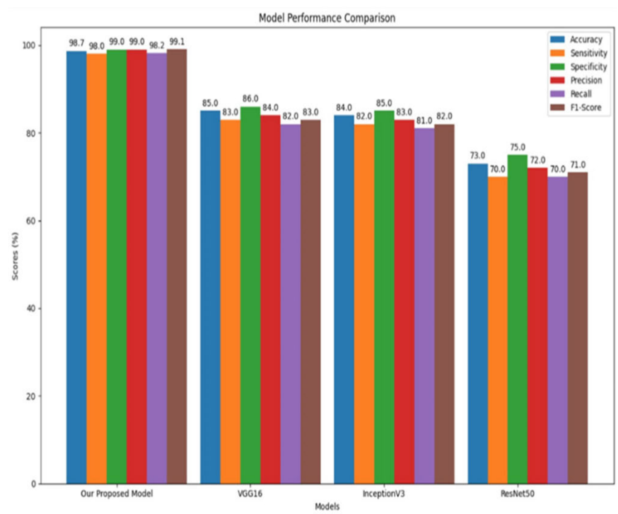


FIGURE 32. Model comparison using performance metrices.

only 10 Epochs was chosen and resulted in 0.85 accuracy. After data augmentation with an increase in custom layers such as adding the Dense layer with 512 units along with dense layer with 128 units and also applying batch normalization improved the performance. In the start of the training ResNet50 showed some potential, its return the accuracy of 0.73 only on 20 epochs but after refining and increasing the epochs its accuracy drops so for this dataset VGG16, InceptionV3 outperformed the Resnet50 model.

InceptionV4 showed the remarkable results with the custom architecture. It started from 0.52 to 0.79 in just 20 epochs after fine-tuning in the same way just 30 epochs it achieved the accuracy of 0.84 and in 50 epochs it attained highest accuracy of 0.987.

V. CONCLUSION AND FUTURE WORK

A. CONCLUSION

The results of the research demonstrate the success of the anticipated brain tumor classification approach, which is based on the Inception v4 model trained on MRI scans. The proposed system for brain tumor classification, utilizing the Inception v4 model trained on MRI images, has yielded exceptional results with an accuracy of 98.7%. This accuracy outperforms earlier DL-leading models in the field, highlighting the effectiveness of the Inception v4 architecture for accurate detection of brain tumor and classify their class. The success of the proposed system can be accredited to two key factors: the utilization of a powerful Deep Learning architecture and the availability of a diverse and well-curated dataset.

The Inception v4 model's architecture is designed to extract relevant features from images, enabling accurate classification of brain tumors. Its combination of 1×1, 3×3, and 5×5 convolutions allows it to capture both fine-grained and high-level features, contributing to its superior performance. The model's ability to recognize complex architectures and discriminate between different tumor types has been a key factor in achieving the high accuracy rate. Moreover, the availability of a diverse and well-curated dataset has played a noteworthy role in the achievement of the proposed system. A diverse dataset ensures that the model is exposed to a wide range of tumor variations, enabling it to generalize well to unseen images. The inclusion of a large number of images in the dataset enhances the model's ability to learn robust representations, improving its accuracy in real-world scenarios.

B. FUTURE WORK

Future research ought to concentrate on enhancing the model's predictability. Deep Learning models are often considered black boxes due to their complex architecture. The adoption of explainable AI techniques can provide light on the model's process of making decisions making it more transparent and interpretable for medical professionals. Techniques such as saliency maps or attention mechanisms can highlight the regions in the MRI images that contribute most to the classification, aiding in the understanding and acceptance of the model's predictions. Our study focused on MRI images, there are other imaging modalities that can provide complementary information for brain tumor classification, such as functional MRI (fMRI) or diffusion tensor imaging (DTI). Future work can explore the integration of multi model data to improve the accuracy and robustness of the system. Fusion techniques, such as combining features from different modalities or training joint models, can leverage the strengths of each modality and potentially enhance the diagnostic capabilities of the system. We can further advance the proposed brain tumor classification system by addressing these areas of future work.

ACKNOWLEDGMENT

The authors are thankful to the Deanship of Graduate Studies and Scientific Research at University of Bisha for supporting this work through the Fast-Track Research Support Program.

REFERENCES

[1] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Comput. Biol. Med.*, vol. 111, Aug. 2019, Art. no. 103345, doi: 10.1016/j.compbiomed.2019.103345.

[2] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for brain tumor classification," *Neural Process. Lett.*, vol. 53, no. 1, pp. 671–700, Feb. 2021.

[3] A. Raza, H. Ayub, J. A. Khan, I. Ahmad, A. S. Salama, Y. I. Daradkeh, D. Javeed, A. Ur Rehman, and H. Hamam, "A hybrid deep learning-based approach for brain tumor classification," *Electronics*, vol. 11, no. 7, p. 1146, Apr. 2022.

[4] J. Kang, Z. Ullah, and J. Gwak, "MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers," *Sensors*, vol. 21, no. 6, p. 2222, Mar. 2021.

[5] D. R. Nayak, N. Padhy, P. K. Mallick, M. Zymbler, and S. Kumar, "Brain tumor classification using dense efficient-net," *Axioms*, vol. 11, no. 1, p. 34, Jan. 2022.

[6] R. Zhang, J. Tan, Z. Cao, L. Xu, Y. Liu, L. Si, and F. Sun, "Part-aware correlation networks for few-shot learning," *IEEE Trans. Multimedia*, vol. 1, no. 1, pp. 1–13, Apr. 2024, doi: 10.1109/TMM.2024.3394681.

[7] K. T. K. and S. Xavier, "An intelligent system for early assessment and classification of brain tumor," in *Proc. 2nd Int. Conf. Inventive Commun. Comput. Technol. (ICICCT)*, Apr. 2018, pp. 1265–1268.

[8] M. I. Sharif, M. A. Khan, M. Alhussein, K. Aurangzeb, and M. Raza, "A decision support system for multimodal brain tumor classification using deep learning," *Complex Intell. Syst.*, vol. 8, no. 4, pp. 3007–3020, Aug. 2022.

[9] G. S. Tandel, A. Balestrieri, T. Jujaray, N. N. Khanna, L. Saba, and J. S. Suri, "Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm," *Comput. Biol. Med.*, vol. 122, Jul. 2020, Art. no. 103804.

[10] S. Athisayamani, R. S. Antonyswamy, V. Sarveshwaran, M. Almeshari, Y. Alzamil, and V. Ravi, "Feature extraction using a residual deep convolutional neural network (ResNet-152) and optimized feature dimension reduction for MRI brain tumor classification," *Diagnostics*, vol. 13, no. 4, p. 668, Feb. 2023.

[11] R. L. Kumar, J. Kakarla, B. V. Isunuri, and M. Singh, "Multi-class brain tumor classification using residual network and global average pooling," *Multimedia Tools Appl.*, vol. 80, no. 9, pp. 13429–13438, Apr. 2021.

[12] C. Srinivas, N. P. K. S., M. Zakariah, Y. A. Alothaibi, K. Shaukat, B. Partibane, and H. Awal, "Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images," *J. Healthcare Eng.*, vol. 2022, pp. 1–17, Mar. 2022.

[13] M. Li, J. Wei, C. Xue, X. Zhou, S. Chen, L. Zheng, and M. Zhou, "Dissecting the roles and clinical potential of YY1 in the tumor microenvironment," *Frontiers Oncology*, vol. 1, no. 1, pp. 1–12, 2023, doi: 10.3389/fonc.2023.1122110.

[14] Y. Xie, F. Zaccagna, L. Rundo, C. Testa, R. Agati, R. Lodi, D. N. Manners, and C. Tonon, "Convolutional neural network techniques for brain tumor classification (from 2015 to 2022): Review, challenges, and future perspectives," *Diagnostics*, vol. 12, no. 8, p. 1850, Jul. 2022.

[15] Q. Liu, H. Yuan, R. Hamzaoui, H. Su, J. Hou, and H. Yang, "Reduced reference perceptual quality model with application to rate control for video-based point cloud compression," *IEEE Trans. Image Process.*, vol. 30, pp. 6623–6636, 2021, doi: 10.1109/TIP.2021.3096060.

[16] N. F. Aurna, M. A. Yousuf, K. A. Taher, A. K. M. Azad, and M. A. Moni, "A classification of MRI brain tumor based on two stage feature level ensemble of deep CNN models," *Comput. Biol. Med.*, vol. 146, Jul. 2022, Art. no. 105539.

[17] J. Xing, H. Yuan, R. Hamzaoui, H. Liu, and J. Hou, "GQE-Net: A graph-based quality enhancement network for point cloud color attribute," *IEEE Trans. Image Process.*, vol. 32, pp. 6303–6317, 2023, doi: 10.1109/tip.2023.3330086.

[18] K. Dushyant, G. Muskan, A. Gupta, S. J. C. S. Pramanik, and D. Forensics, "Utilizing machine learning and deep learning in cybesecurity: An innovative approach," in *Cyber Security and Digital Forensics*. Hoboken, NJ, USA: Wiley, 2022, pp. 271–293.

[19] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, and J. Si, "Improving effectiveness of different deep transfer learning-based models for detecting brain tumors from MR images," *IEEE Access*, vol. 10, pp. 34716–34730, 2022.

[20] B. Badjie and E. Deniz Ülker, "A deep transfer learning based architecture for brain tumor classification using MR images," *Inf. Technol. Control*, vol. 51, no. 2, pp. 332–344, Jun. 2022.

[21] S. Ahmad and P. K. Choudhury, "On the performance of deep transfer learning networks for brain tumor detection using MR images," *IEEE Access*, vol. 10, pp. 59099–59114, 2022.

[22] N. Ullah, J. A. Khan, M. S. Khan, W. Khan, I. Hassan, M. Obayya, N. Negm, and A. S. Salama, "An effective approach to detect and identify brain tumors using transfer learning," *Appl. Sci.*, vol. 12, no. 11, p. 5645, Jun. 2022.

[23] A. I. Shahin, W. Aly, and S. Aly, "MBTFCN: A novel modular fully convolutional network for MRI brain tumor multi-classification," *Expert Syst. Appl.*, vol. 212, Feb. 2023, Art. no. 118776.

[24] I. A. E. Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. S. Ahmad, "Differential deep convolutional neural network model for brain tumor classification," *Brain Sci.*, vol. 11, no. 3, p. 352, Mar. 2021.

[25] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," *Appl. Sci.*, vol. 12, no. 14, p. 7282, Jul. 2022.

[26] N. Arunkumar, M. A. Mohammed, M. K. Abd Ghani, D. A. Ibrahim, E. Abdulhay, G. Ramirez-Gonzalez, and V. H. C. de Albuquerque, "K-means clustering and neural network for object detecting and identifying abnormality of brain tumor," *Soft Comput.*, vol. 23, no. 19, pp. 9083–9096, Oct. 2019.

[27] Z. Ullah, M. U. Farooq, S.-H. Lee, and D. An, "A hybrid image enhancement based brain MRI images classification technique," *Med. Hypotheses*, vol. 143, Oct. 2020, Art. no. 109922.

[28] A. Anaya-Isaza and L. Mera-Jiménez, "Data augmentation and transfer learning for brain tumor detection in magnetic resonance imaging," *IEEE Access*, vol. 10, pp. 23217–23233, 2022.

[29] A. Veeramuthu, S. Meenakshi, G. Mathivanan, K. Kotecha, J. R. Saini, V. Vijayakumar, and V. Subramaniyaswamy, "MRI brain tumor image classification using a combined feature and image-based classifier," *Frontiers Psychol.*, vol. 13, Mar. 2022, Art. no. 848784.

[30] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, "A deep learning-based framework for automatic brain tumors classification using transfer learning," *Circuits, Syst., Signal Process.*, vol. 39, no. 2, pp. 757–775, Feb. 2020.

[31] P. Afshar, K. N. Plataniotis, and A. Mohammadi, "Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 1368–1372.

[32] S. Das, O. F. M. R. R. Aranya, and N. N. Labiba, "Brain tumor classification using convolutional neural network," in *Proc. 1st Int. Conf. Adv. Sci., Eng. Robot. Technol. (ICASERT)*, Sep. 2019, pp. 1–5.

[33] M. Togaçar, B. Ergen, and Z. Cömert, "BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model," *Med. Hypotheses*, vol. 134, Jan. 2020, Art. no. 109531.

[34] S. Maqsood, R. Damasevicius, and R. Maskeliunas, "Multi-modal brain tumor detection using deep neural network and multiclass SVM," *Medicina*, vol. 58, no. 8, p. 1090, Aug. 2022, doi: 10.3390/medicina58081090.

[35] I. Stancin and A. Jovic, "An overview and comparison of free Python libraries for data mining and big data analysis," in *Proc. 42nd Int. Conv. Inf. Commun. Technol., Electron. Microelectron. (MIPRO)*, May 2019, pp. 977–982.

[36] F. Wahid, S. Azhar, S. Ali, M. S. Zia, F. A. Almisned, and A. Gumaei, "Pneumonia detection in chest X-ray images using enhanced restricted Boltzmann machine," *J. Healthcare Eng.*, vol. 2022, pp. 1–17, Aug. 2022, doi: 10.1155/2022/1678000.

[37] M. Nazir, F. Wahid, and S. Ali Khan, "A simple and intelligent approach for brain MRI classification," *J. Intell. Fuzzy Syst.*, vol. 28, no. 3, pp. 1127–1135, Jan. 2015, doi: 10.3233/ifs-141396.

[38] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M. S. Alam, and M. A. Hossain, "Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm," *Mach. Learn. Appl.*, vol. 5, Sep. 2021, Art. no. 100044.

[39] S. Rinesh, K. Maheswari, B. Arthi, P. Sherubha, A. Vijay, S. Sridhar, T. Rajendran, and Y. A. Waji, "Investigations on brain tumor classification using hybrid machine learning algorithms," *J. Healthcare Eng.*, vol. 2022, pp. 1–9, Feb. 2022.

[40] A. Çinar and M. Yildirim, "Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture," *Med. Hypotheses*, vol. 139, Jun. 2020, Art. no. 109684.

[41] J. Amin, M. Sharif, M. Raza, T. Saba, and M. A. Anjum, "Brain tumor detection using statistical and machine learning method," *Comput. Methods Programs Biomed.*, vol. 177, pp. 69–79, Aug. 2019, doi: 10.1016/j.cmpb.2019.05.015.

[42] A. H. Khan, S. Abbas, M. A. Khan, U. Farooq, W. A. Khan, S. Y. Siddiqui, and A. Ahmad, "Intelligent model for brain tumor identification using deep learning," *Appl. Comput. Intell. Soft Comput.*, vol. 2022, pp. 1–10, Jan. 2022, doi: 10.1155/2022/8104054.

[43] N. I. Zailan, Z. N. Mostafa, S. A. Abdulmaged, A. I. Baharum, Z. Jaber, and M. M. Hidayat, "Deep learning approach for prediction of brain tumor from small number of MRI images," *Int. J. Inform. Vis.*, vol. 6, pp. 581–586, Oct. 2022.

[44] S. Saeedi, S. Rezayi, H. Keshavarz, R. Niakan, and S. Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," *BMC Med. Inform. Decis. Making*, vol. 23, no. 1, pp. 1–17, 2023.

[45] S. A. Yazdan, R. Iqbal, N. Rizwan, A. Khan, and A. N. Kim, "An efficient multi-scale convolutional neural network based multi-class brain MRI classification for SaMD," *Tomography*, vol. 8, pp. 1905–1927, Aug. 2022.

[46] D. Santos and E. Santos, "Brain tumor detection using deep learning," *MedRxiv*, pp. 1–7, Jan. 2022, doi: 10.1101/2022.01.19.22269457.

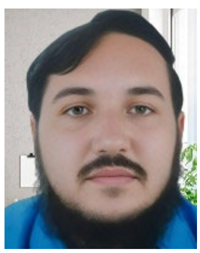
[47] C. Zhu, "Computational intelligence-based classification system for the diagnosis of memory impairment in psychoactive substance users," *J. Cloud Comput.*, vol. 13, no. 1, pp. 1–119, Jun. 2024, doi: 10.1186/s13677-024-00675-z.

[48] Q.-Y. Yao, M.-L. Fu, Q. Zhao, X.-M. Zheng, K. Tang, and L.-M. Cao, "Image-based visualization of stents in mechanical thrombectomy for acute ischemic stroke: Preliminary findings from a series of cases," *World J. Clin. Cases*, vol. 11, no. 21, pp. 5047–5055, Jul. 2023, doi: 10.12998/wjcc.v11.i21.5047.

NADIA BIBI received the Bachelor of Science degree in software engineering from Fatima Jinnah Women University, Pakistan, in 2009. She is currently pursuing the M.Sc. degree in computer science with The University of Haripur, Pakistan. She is also with SST IT, Elementary and Secondary Education Department, Khyber Pakhtunkhwa, Pakistan. Her research interests include VANETs, image processing, and machine learning for medical diagnostics.

FAZLI WAHID received the B.S. degree in computer science from the University of Malakand, Pakistan, in 2006, the M.S. degree in computer science from SZABIST, Pakistan, in 2015, the Ph.D. degree in information technology from the Faculty of Computer Science and Information Technology (FSKTM), Universiti Tun Hussein Onn Malaysia, in 2020, and the Ph.D. degree in artificial intelligence from the School of Computing Sciences, University of East Anglia, Norwich, U.K., in 2024. He is currently a Senior Lecturer in computer science with the College of Science and Engineering, School of Computing, University of Derby, U.K. Previously, he was an Assistant Professor in computer science with the Department of Information Technology, The University of Haripur, Pakistan, and an Assistant Professor in computer science with The University of Lahore, Pakistan. His research interests include evolutionary intelligence, swarm intelligence, machine learning, deep learning, medical imaging, disease detections, natural language processing, computer vision, smart buildings, smart hospitals, and smart agriculture. Related to all these areas, he has published more than 50 articles in well-reputed journals and conferences.

YINGLIANG MA received the Ph.D. degree in computer science from The University of Manchester. His research interests include the development of novel computer vision and computational geometric algorithms and applications in medical image analysis, image-guided surgery, and procedure risk assessment. As a principal investigator (PI) or a Co-PI, he has been conducting research in relation to computer vision/machine learning/AI and parallel computing funded by EPSRC and NIHR. He has been invited to give a number of talks in national and international institutions.



SIKANDAR ALI received the double Ph.D. degree from China University of Petroleum, Beijing, in 2019 and 2021, respectively. He is currently an Assistant Professor. He has authored over 70 articles in highly cited journals and conferences. His research interests include business process management, anomaly detection in multi sensor systems, software outsourcing partnership, software testing and test automation, bug prediction, bug fixing, software incidence classification, source code transformation, agile software development, and global software engineering. He served as a technical program committee member for more than 20 conferences and act as a reviewer for many well reputed journals. He also organizes many special issues. Currently, he is an Academic Editor of *Mobile Information Systems*, *Journal of Computer Information Systems*, *Intelligent Control and System Engineering*, *Journal of Intelligent Medicine and Healthcare*, and *Scientific Programming* journals.

IRSHAD AHMED ABBASI (Member, IEEE) received the M.S. degree in computer science from COMSATS University Islamabad, Abbottabad Campus, Pakistan, and the Ph.D. degree in computer science from Universiti Malaysia Sarawak, Malaysia. He was a Senior Lecturer with King Khalid University, Saudi Arabia, from 2011 to 2015. He completed his Post Doctorate at Universiti Malaysia Sarawak, Malaysia. Currently, he is an Assistant Professor with the Department of Computer Science, University of Bisha, Saudi Arabia. He has over 12 years of research and teaching experience. He is the author of many articles published in top-quality journals. His research interests include networks, VANETs, MANETs, FANETs, mobile computing, the IoT, cloud computing, cybersecurity, cryptography, soft computing, and drone security and authentication. He has received multiple awards, scholarships, and research grants. He is also acting as a reviewer of many well-reputed peer-reviewed international journals and conferences. He is serving as an editor.

AHMED ALKHAYYAT received the B.Sc. degree in electrical engineering from the University of Kufa, Najaf, Iraq, in 2007, the M.Sc. degree from Dehradun Institute of Technology, Dehradun, India, in 2010, and the Ph.D. degree from Cankaya University, Ankara, Türkiye, in 2015. He contributed in organizing a several IEEE conferences, workshop, and special sessions. He is currently the Dean of international relationship and the Manager of the word ranking with The Islamic University, Najaf. His research interests include the IoT in the health-care systems, SDN, network coding, cognitive radio, efficient-energy routing algorithms and efficient-energy MAC protocol in cooperative wireless networks and wireless body area networks, and cross-layer designing for self-organized networks. To serve his community, he acted as a reviewer for several journals and conferences.

KHYBER received the Bachelor of Science degree in computer science from the Computer Science Faculty, Nangarhar University, Afghanistan, in 2019, and the Master of Science degree in computer science from The University of Haripur, Pakistan, in 2022. His research interests include software engineering, agile software development, software bugs classification, and machine and deep learning.