Classification of Brain Tumors using MRI images based on Convolutional Neural Network and Supervised Machine Learning Algorithms

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***Abstract*—Brain tumor is abnormal cells that originate from cranial tissue and is considered one of the most destructive diseases, and lead to the cause of death, where the early diagnosis is crucial for accelerating the therapy of brain tumors. Examining the patient's MRI scans is one traditional way of distinguishing brain cancers. The conventional approaches take a long time and are prone to human error, especially when dealing with huge amounts of data and diverse brain tumor classes. Artificial Intelligence (AI) is extremely useful for the strict detection and classification of several diseases in the brain. Convolutional Neural Network (CNN) is one of the modes techniques which act as a tumor classifier due to it shows high effectiveness for diagnosing brain tumors. That's why, in this research, we presented a hybrid method that merged a group of pre-trained deep learning CNN patterns with a group of supervised classifiers in machine learning called, k-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA). We used an MRI image that consist of images of four brain tumor classes, namely glioma, meningioma, pituitary, and no tumor. We deduced the features extracted from the images by hiring three types of CNN called (GoogleNet, Shuffle-Net, and NasNet-Mobile). Depending upon the experimental consequences, ShuffleNet with SVM achieved the highest results according to the four categories of metrics evaluation that are Accuracy of 98.40%, Precision of 97%, Recall of 96.75%, and F1-Score of 96.75%. Finally, we compared our results with different state-of-the-art papers recently published and our proposed method show outperforms compared them.**

Keywords—Deep Learning, Brain Tumors, CNN, Machine Learning, Classification Brain Tumors

I. INTRODUCTION

The purpose behind the invention of Artificial intelligence (AI) is to achieve emulation of human intelligence, behavior, conciseness, and to bring into existence robots akin to a human brain. AI has many applications in various fields, including analysis of image, natural language processing, robotics, and expert system [1]. As complex tasks require artificial intelligence systems, thus, Deep Learning (DL) and Machine Learning (ML) essentially constitute the cornerstone of the entire AI field and sub-domain. By simulating human learning behavior, ML employs synthesis and induction to confer recent information to computers and then coordinate the existing information to ameliorate performance of computer [1]. ML has the capability to achieve higher accuracy in prediction. Many types of ML algorithms that used for prediction and classification [2]. Where the data play an important role especially in gathering data and preparing it to be ready for training and testing ML algorithms. ML has made a successful entry into many fields, such as computer aided-detection of disease [3], bioinformatics [4], and computer vision [5]. Machine learning models are capable of various types of learning such as reinforcement learning, supervised learning, and unsupervised learning [6]. Ongoing medical and scientific research all over the world continue to update and refine techniques to detect brain tumor that can provide an advantage of using ML.

Brain tumor is divided into primary tumors (usually benign) and secondary tumors (often malignant) [7]. Brain tumor universally established that uncontrolled diffusion out of cells in the brain can produce brain tumors and can result into death unless diagnosed accurately and treated early. Primary brain tumors, known as Meningioma, are benign tumors for the most part usually develop in the spinal cord and the membranes that cover the brain [8]. While Pituitary tumors and Glioma are more serious compared to the previous two types which can be life-threatening [9]. Medical research attested that if a collection of tumors grows within the substance of the brain and mix with normal brain tissues, then it is another brain condition called Gliomas, which can result into death especially if the size of the tumor is large. Pituitary tumors are the result of abnormal growth of the brain in the pituitary gland which can seriously impact the hormones and impair important functions of the body [10]. These tumors which can originate in different locations of the brain, appear in different sizes and shapes. One of the widely applied non-invasive medical imaging techniques for early diagnosis and treatment tumors of brain is the Magnetic Resonance Imaging (MRI). The MRI images sagittal, axial, and coronal are taken from three different directions. Magnetic Resonance Imaging (MRI) identify location, shaping, and sizing of brain tumor [11].

One can use the advantages of deep learning to increase the accuracy of diagnosis brain tumors. There are various kinds of deep learning models used to detect tumors [12]. Transfer learning is one of the most familiar deep learning techniques used to classify tumors based on images or two-dimensional (2D) data. Many different models used to classify different types of diseases such as (GoogleNet [13], Xception [14] , U-Net [15] , VGG19 [16] , RestNet50 [17] , MobileNet [18], DenseNet [19], ResNet18 [20], and Shuffle-Net [21]).

Images of brain tumors are extracted from the brain via MRI and are applied to the deep learning technique and classified into respective categories. Such techniques enable to extract features, analysis, and image interpretation. In addition to tissue classification, tumor detection, tumor size assessment as well as operation preparation. MRI images are also used in the timely diagnosis and treatment of Alzheimer's disease [22], schizophrenia[23], and dementia [24]. Brain tumor classification consists of two major parts are (extract the hidden information from the images and Classification). Deep learning provides an accurate diagnosis for different diseases. Lately, many specialists used deep learning for the diagnosis of brain tumors by MRI.

One of these studies has been done by M.S Fuad, et, al [25], they used MRI images with three tumor types: meningioma, glioma, and pituitary for classification using two convolutional neural networks namely GoogleNet and Alex Net. They obtained accuracies for the Alex Net is 94.6% and for the GoogleNet is 92%. For AlexNet sensitivity is 94%, specificity is 95.2%, precision is 94.6% and recall is 46.9%. While sensitivity is 96.3%, specificity is 96.8%, precision is 87.3% and recall is 45.9% for the GoogleNet. AlexNet gave higher accuracy which is 94.6%.

Toqa A. Sadoon and Mohammed H. Ali Al-Hayani [26] classified three types of brain tumors using MRI images glioma, meningioma, and pituitary gland based on convolution neural network(CNN) and compared between convolution neural network(CNN) and other models. The highest results accuracy achieved was 96.1%. Likewise. Nyoman Abiwinanda et al[27] used dataset MRI images collected from Figshare Cheng. They employed a CNN for training and detecting different types of brain tumors glioma, meningioma, and pituitary. They get accuracy for accuracy of training was 98.51% and the accuracy of validation of 84.19%.

Asaf Raza et al [7] introduced a new deep learning structure based on GoogleNet they called DeepTumorNet. The final five layers of GoogleNet were removed during the development of the hybrid DeepTumorNet technique, and fifteen recent layers were inserted in their place. In addition, they used a leaky ReLU activation function in the feature map to boost a model's expressive. For evaluation reasons, the introduced model was evaluated on an available published research dataset, and it received 99.67 % accuracy, 99.6 % precision, 100 % recall, and a 99.66 % F1-Score. When compared with other classification results produced with Alex Net, Resnet50, darkNet53, ShuffleNet, GoogleNet, SqueezeNet, ResNet101, Exception Net, and MobileNetv2, the proposed methodology achieved the greatest accuracy.

Mirza Mumtaz Zahoor et. al [28] suggested a unique two-phase of deep learning-based system to characterize and detect cancers of the brain in magnetic resonance imaging. A novel deep-boosted features space and ensemble classifiers (DBFS-EC) approach is introduced in the first phase to effectively detect tumor MRI images in healthy people. While, a recent approach of hybrid features fusion for the classification of brain tumors is proposed in the second phase, which combines features of dynamic and static with a machine learning classifier to graded distinct tumor kinds. Validation occurs in a two-phase analysis framework of a brain tumor that is introduced. Using benchmark datasets obtained from Figshare and Kaggle, which including several forms of tumors including pituitary, glioma, and meningioma. The suggested DBFS-EC detection technique beats the standard in terms of accuracy (99.56%), precision (99.91%), recall (98.99%), F1-Score (99.45%), MCC (98.92%), and AUC-PR, according to experimental data (99.90%). In terms of recall (99.13%), precision (99.06%), accuracy (99.20%), and F1-Score (99.09%).

Mohamed Ait Amou et al [29] suggested an effective hyper-parameter optimization strategy for CNN based on Bayesian Optimization. MRI images were classified into three categories of brain cancers to test this strategy (Glioma, Meningioma, and Pituitary). The CNN utilize transfer learning improved when compared with performing of five known deep pre-trained networks. Without augmentation of data or cropping lesion approaches, the CNN scored the best is 98.70 % validation accuracy, while VGG19, InceptionV3, VGG16, DenseNet201, and ResNet50 obtained 96.43 %,92.86 %, 97.08%, 94.81 %, and 89.29% validation accuracy respectively.

Imayanmosha Wahlang et al [30] used deep learning architectures to classify into normal or pathological brain MRI pictures. For more precise and meaningful classification, age and gender have been added as higher characters. Deep Neural Network (DNN) and deep learning Convolutional Neural Network (CNN)-based techniques are also introduced for effective classification. To examine and compare the results, another architectures of deep learning including Le Net, ResNet, and AlexNet as well as classic methodologies like SVM, are used. In general, accuracy 88 % of (Le Net Inspired Model) and 80% of (CNN-DNN) when matched to AlexNet (64%) and SVM (82%). Ghazanfar Latif et al [31] proposed deep-learning-based features and an SVM classifier, it presented classification techniques for different kinds of Glioma tumors. The features of the MR images are extracted using a deep convolution neural network, which is then input into an SVM classifier. Classification of four Glioma kinds, the suggested technique achieved an accuracy of 96.19 % for the High-Grade Glioma (HGG) kind.

Milica M. Badža and Marko Č. Barjaktarović [11] utilized the convolutional neural network and a machine learning method for classification and segmentation of brain tumors. They classify three various forms of tumor brain by demonstrating a new CNN architecture. The created network was evaluated on T1-weighted contrast-enhanced MRI images and was shown to be simpler than previously developed pre-trained networks. The network's performance was assessed using four different methods: two 10-fold cross-validation methods and two databases. The capacity of network's generalization was assessed using one of the 10-fold approaches, subject wise cross-validation, and the enhancement was significant, with an accuracy of 96.56%.

Based on the aforementioned accuracies that were achieved in previous studies, therefore, we try to increase accuracy further by applying a combination of deep learning and machine learning techniques. We used a pre-trained model namely GoogleNet, NasNet-Mobile, and Shuffle-Net to conclude the most significant features from images. And then, fed to three supervised classifiers called KNN, SVM , and Linear Discriminant Analysis (LDA). The dataset used is publicly available on Kaggle that consists of more than 6321 images.

II. DESCRIPTION OF THE DATASET

An image dataset of MRI is used in this study. The dataset consists of (6321) MRI images of four distinct brain tumors and no tumor which comprised (1621) glioma, (1645) meningioma, (2000) pituitary, and (1055) no tumor. The open-source Kaggle (MRI original dataset of brain tumor) is the source from FigShare, SARTAJ dataset, and Br35H which we gathered the dataset [32].

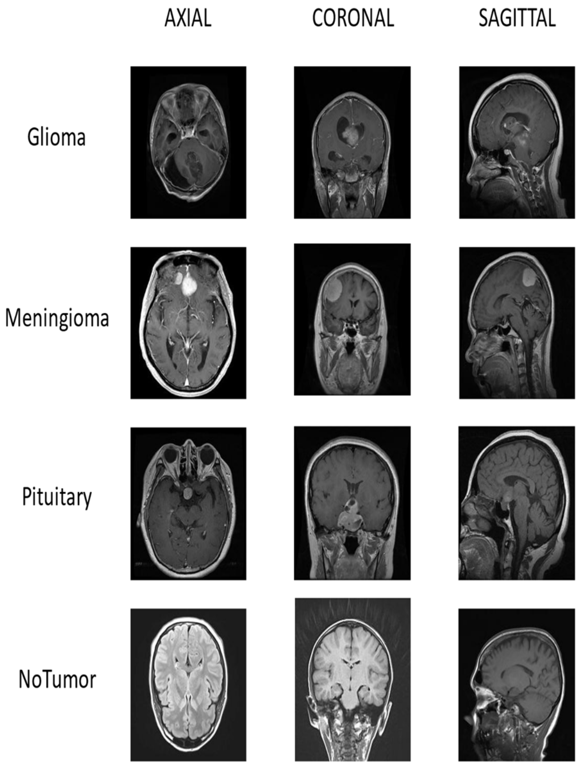

Fig. 1. Specimen of tumor and normal images from dataset

III. METHODOLOGY

First of all, dataset images of MRI should be augmented for efficient training and the enhanced capability of the models. Image-Rotation, Image-Sharing, Image-Scaling, and Image Reflection employed for augmentation techniques of data. The MRI images have different high and wide so, we resize all the MRI images into the same dimension for obtaining optimal performance. The grayscale MRI image is 224 × 224 × 3 pixels. Deep learning techniques were applied to brain MRI images for extracting their feature of them. GoogleNet, NasNet-Mobile, and Shuffle-Net are used as a model of deep learning. The extracted features are applied to classifiers of machine learning which are k-Nearest Neighbor (KNN), Supporting Vector Machines (SVM), and Linear Discriminant Analysis (LDA) for each one of the models.

GoogleNet: is defined as a kind of deep learning convolution neural network consist of twenty-two of learning layers. The learning layer contains 9 modules of inception (pooling layer and 6 convolution layer), 2 layers of pooling,2 convolution layers, and fully connected layer. Miscellaneous pattern of data capturing required different sizes of kernel and variation in the sizes of filters 1×1, 3×3, and 5×5 which occur in this modules. In the Image net, one thousand classes of images trained with GoogleNet [33]. In whole fully connected layer, prevention of adaptation on training data is gained for minimizing overfitting. The rectified linear activation function was accessed in the whole fully connected layer [34].

NasNet-Mobile: NasNet-Mobile is a per-trained convolutional neural network developed by Google Brain in 2018. The optimization of the NasNet-mobile is by using a different architecture was consist of two functions Normal cell and Reduction cell. The normal cell determined the feature map size while the reduction cell resorted the reduction feature map dimension. The Recurrent Neural network (RNN) consider as control architecture in NasNet- mobile by anticipate whole structure of the network. The research of NasNet is considered to be the best network of convolutional neutrality through which CNNs can be optimized for different sizes. The model used in this study is “NasNet-Mobile” which is the smaller one of the types [35].

ShuffleNet: ShuffleNet can be defined as a network of convolutional neutrality basically designed for mobiles, and limitedly for computing. With the object of minimizing costs of computing while maintaining accuracy, two new operations (convolution “point wise group”, and channel shuffle) are utilized by the architecture. A ShuffleNet, an architecture of CNN with high efficiency of computation, and barely noted computing power. ShuffleNet superior performance over other structures is demonstrated by the Image Net Classification experiments and object detection [21].

Table I. Features of CNN model

Title	Size of input Image	Feature of Layer	Feature of Vector
ShuffleNet	224*224*3	node_200	544
NasNet-Mobile	224*224*3	global_average_pooling2d_1	1056
GoogleNet	224*224*3	Pool5-7x7_s1	1024

As a matter of fact, the dataset, with the object of achieving higher results, has undergone to preprocessing techniques to be appropriate for pre-trained deep networks, and since the dimensions of images are diversified and we need to feed the per-trained models with 224*224*3, we resize all dataset to be fit with per-trained models. And then, we applied the dataset to the models. We select the last layers to deduce the features, due to it can reduce the number of features and make it more appropriate to apply to the various kind of machine learning classifiers. As shown in Table 1, we summarize the parameters used for each mode to extract features. As well as our methodology used in this study is illustrated in Figure 5.

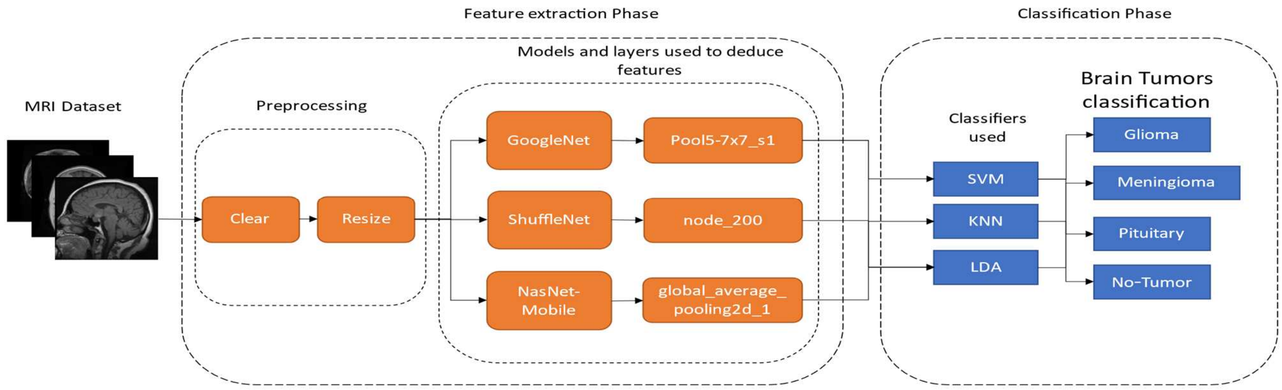

Fig. 2. Overview of the methodology

KNN: It can be defined as a classification type in which the approximation of the function is done locally, and the computation is delayed till the evaluation of the function. The fact that this algorithm depends on distance for classification turns normalizing the data of training able to have its accuracy improved dramatically if different physical units are represented by the unites or come in vastly different scales. Assigning weights to the neighbors contribution, both for classification and regression, can be done by adopting a useful technique the result of which more contribution from the nearer neighbors than the distant ones [36].

LDA: It is a technique for decreasing of dimension. LDA is a step of preprocessing in applications of machine learning model classification. With the object of avoiding the dimensionality curse, reducing dimensional costs and resources, LDA aims at projecting the features in higher dimensional space onto a lower dimensional space. It is used in crafting competitive models of machine learning. Images recognition and market predicative analysis are some of the areas in which such a dimensionality reduction category is used [37].

SVM: Compared to other supervised classifiers, SVM, in machine learning, is considered to be a classifier of high popularity. It is used within two kinds of problems; classification and regression, and when used, an excellent solution and high performance are provided. A hyperplane is the core idea of SVM. By checking the space between the edge and the point, it classifies features into different kinds of classes. Radial Basis Function (RBF), Gaussian kernel, Linear, and Polynomial are types of use in SVM, and to each one of those types a special mechanism for classifying of the data [38].

Statistical Measurement of Classification Performance

Evaluating SVM, LDA, and KNN classification was conducted using the four types (accuracy, precision, recall, and F1 score) which are considered to be a kind of measurement that has the most popularity. Where the Recall (or Sensitivity) showed in the Eq1.

$$Recall\ or\ Sensitivity = \frac{TP}{TP+FN} \qquad Eq1$$

Here, true positive (TP) refers to people with positively have a brain tumor, false negative (FN) refers to those who are misclassified as people with no brain tumor, and true negative (TN) refers to people who have been identified as having no brain tumor from the very beginning, false positive (FP) denotes people misclassified as having the tumor. Classification total accuracy (ACC) can be measured by this connection which as Eq2.

$$Accuracy \frac{TP+TN}{TP+FP+TN+FN} \qquad Eq2$$

Precision refers to the actual value that can identified as positive people who have tumor to the total number of both true and false positives, it refers shown in Eq3:

$$Precision\ (PPV) \frac{TP}{TP+FP} \qquad Eq3$$

The scale between precision and recall (true positive divided by true positive and false positive) is referred to as F1-score Classification total accuracy (ACC) can be calculated as Eq4:

$$F1-score \frac{2*TP}{2*TP+FP+FN} \qquad Eq4$$

IV. RESULT

Initially, deep learning was used for feature extraction of MRI datasets, while machine learning was used for classification of extracted features. These steps are crucial for diagnosis of brain tumors. The result that attained from (SVM, KNN, and LDA) classifiers by implementing four types of MRI image features deduced from CNN models namely GoogleNet, NasNet-Mobile, and ShuffleNet. show amazing results with Cross-validation used with the k=5 to get rid of overfitting. The results of classifiers by GoogleNet are presented in Table (2). Whereas the results of classifiers namely (SVM, KNN, and LDA) with features extracted from NasNet-Mobile. Finally, the results of classifiers (SVM, KNN, and LDA) with ShuffleNet. Also, for each classifier, we calculated four evaluation metrics Accuracy, Precision, F1 Score, and Recall. The highest result which was 98.40% that obtained by using ShuffleNet. While the lowest value was 95.05% accuracy by using NasNet-Mobile.

Table II. Confusion matrix of the results for each model and classifier

Model Name	Classifier	Acc	Pre	Recall	F1 Score
GoogleNet	SVM	97.86	95.5	95.5	95.5
	KNN	96.93	93.75	93.75	93.5
	LDA	96.11	91.75	92	92
Model Name	**Classifier**	**Acc**	**Pre**	**Recall**	**F1 Score**
NasNet-Mobile	SVM	96.77	93	93.25	93.5
	KNN	95.15	89.75	90.25	89.75
	LDA	95.05	89.5	90	89.75
Model Name	**Classifier**	**Acc**	**Pre**	**Recall**	**F1 Score**
ShuffleNet	SVM	98.40	97	96.75	96.75
	KNN	97.81	95.5	95.25	95.25
	LDA	96.21	92.25	92.25	92

V. DISCUSSION

This research procedure a hybrid method that combines deep convolutional neural networks models namely (GoogleNet, ShuffleNet, and NasNet-Mobile) to deduce the important features particularly and implemented to machine learning classifiers namely (SVM, KNN, and LDA) to be classified four kinds of brain tumors. We utilized MRI images dataset which is an open-source Kaggle. That includes four types of classes namely Glioma, Meningioma, pituitary, and no tumor people.

The extracted features used as input to the (KNN, SVM, and LDA) for classification features. By employment SVM classifier regard to the features extracted from ShuffleNet, accuracy was 98.40%, which consider the topmost result obtained. By implantation features of ShuffleNet again to the KNN classifier the accuracy was 97.81%, by using LDA classifier the accuracy was 96.21%. While accuracies for other CNNs models GoogleNet by using SVM, KNN, and LDA classifier 97.86, 96.93%, and 96.11% respectively. And accuracies for NasNet-Mobile by using SVM, KNN, and LDA classifier 96.77, 95.15%, and 95.05% respectively.

The highest value of classification was ShuffleNet with SVM because we used a ShuffleNet, and it has less feature vectors (544) that can deduce best features from the images and reduce the number of bias features that can make an effect of the final results. Moreover, the lightweight of the number of parameters also play a critical role on the features. While high Feature Vector of NasNet-Mobile (1056) and GoogleNet (1024) render the accuracies less than ShuffleNet.

The published studies of classification of brain tumor by deep learning and machine learning when compared with our proposed result show less accuracy as shown in Table 3 which appear there are different studies used only 3 classes [39], they obtained results it were less of ours. Furthermore, many of them used transfer learning to classify brain tumors or modified deep learning as in [9] which obtain 99.67 accuracy due to using GoogleLeNet, which is higher than our results achieved but they classify only three classes. While both studies [40] and [41] used only two classes and reached less accuracy. In addition, other studies [42]and [43] used four classes of brain tumor classification (no tumor, pituitary, meningioma, glioma) with the same dataset that we used, and again our proposed method outperformed of them.

Table III. Comparison result with the published paper using MRI images

Ref.	Year	Classes Number	Acc	Sen	Pre	F1-Score
[25]	2021	3	94.6	94	94.6	NA
			92	96.3	87.3	
[7]	2022	3	99.67	100	99.6	99.66
[40]	2022	2	98.97	98.86		97.14
[44]	2020	3	95.56	NA	NA	NA
[41]	2020	2	96.08	NA	NA	97.3
[45]	2021	3	98.91	98.28	99.75	99
[46]	2019	3	94.39	93%	93.33	NA
[47]	2020	3	98.71	NA	NA	NA
[48]	2021	3	98.54	NA	NA	NA
[49]	2019	3	99	98.52	NA	NA
[29]	2022	3	98.70	NA	NA	NA
[43]	2022	4	89.55	NA	NA	NA
Our method	**2020**	**4**	**98.40**	**97**	**96.75**	**96.75**

VI. CONCLUSION

Brain tumor diagnosis efficiently is fundamental for early therapy of patients. Tumor analysis is difficult due to the size, texture, location, and heterogeneous form appearance of tumors in medical images. In this respect, deep learning used for detecting and categorizing tumors of the brain in magnetic resonance imaging is proposed (MRIs). Feature of MRI images extracted by three types of convolutional neural networks (CNN) models which are (GoogleNet, ShuffleNet, and NasNet-Mobile) of datasets of MRI collected from Kaggle source. Furthermore, a hybrid method is used by combining a set of deep learning models which is a convolutional neural network with a set of machine learning classifiers which are k-Nearest Neighbor (KNN), Supporting Vector Machines (SVM), and Linear Discriminant Analysis (LDA). In the deep learning side, the highest result showed by using features extracted by Shuffle-Net. While, in the machine learning side, the SVM yielded better results than other classifiers whether using the same feature or other features extracted by other models, the results obtained were accuracy (98.40%), recall (97.00%), precision (96.75%), and F1-Score (96.75%) compared to other classifiers. Deep learning and machine learning play a crucial role for diagnosis and classification of brain tumors that aid doctors and radiologists in rapidly detect of a huge amount of MRI images without consuming time. for future work, we plan to develop a convolutional neural network that has new structures with fewer layers that can reduce the time consuming to classify brain tumors and increase the accuracy further.

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