JCEC
THE JOURNAL OF ENGINEERING AND EXACT SCIENCES

OPEN ACCESS

The Journal of Engineering and Exact Sciences – jCEC, Vol. 09 N. 08 (2023)
journal homepage: https://periodicos.ufv.br/jcec
eISSN: 2527-1075
ISSN: 2446-9416

An efficient hybrid model of CNNs and different kernels of SVM for brain tumor classification

Article Info:
Article history: Received 2023-06-15 / Accepted 2023-10-20 / Available online 2023-10-30
doi: 10.18540/jcecvl9iss8pp16739-01e

Mohammed Bourennane
ORCID: https://orcid.org/0009-0000-1420-4467
Laboratory of Modeling Simulation and Optimization of Systems Complexes,
University of Djelfa, Djelfa 17000, Algeria
E-mail: bourennane@univ-djelfa.dz
Hilal Naimi
ORCID: https://orcid.org/0009-0004-7571-9420
Laboratory of Modeling Simulation and Optimization of Systems Complexes,
University of Djelfa, Djelfa 17000, Algeria
E-mail: h.naimi@univ-djelfa.dz

Abstract
Technological advancements have had a profound impact on various aspects of human existence. The realm of medicine is one major area where technology has made important advances. We will talk specifically about the role technology has had in treating brain tumors, a serious and widespread condition. A large number of people pass away from brain tumors every year. Patients with BTs have a worse likelihood of survival when they receive subpar care and a false diagnosis. The most widely employed technique for detecting brain tumors is magnetic resonance imaging (MRI). Moreover, MRI is extensively utilized in medical imaging and image processing to identify variations in various regions of the body. A convolutional neural network (CNN)-based model was developed in this study to classify brain tumor. Using nine pre-trained CNN models (efficientnetb0, mobilenetv2, nasnetlarge, resnet50, resnet10, googlenet, vgg16, vgg19, and shufflenet), deep features were extracted from the acquired images. Then use a Support Vector Machines (SVM) classifier to classify the deep features. The classification accuracy results obtained from the various kernel functions, namely linear, gaussian, cubic, and quadratic—was then compared. The deep features retrieved from the efficientnetb0 model allowed accurate classification of brain tumors. The classification accuracy achieved using the Gaussian kernel function of SVM was recorded at an impressive 99.78%.
Keywords: Convolutional neural network; Support Vector Machines; Brain tumors; Efficientnetb0; Gaussian kernel function.

1. Introduction

Brain tumors are now regarded as one of the most dangerous diseases (Shahin *et al.,* 2023). Brain tumor is known as an abnormal growth of a mass of brain tissues through which cells start to multiply intractably and gets unchecked by the cell growth controlling mechanism (Bockaert and Marin 2015). According to World Health Organization (WHO) every year, approximately 9 million people die from various types of malignancies. There are generic basic signs of brain tumor such as: headaches, mood changes and depression, lack of feeling, lack of attention. To demonstrate the brain tumor injury, medical imaging or biopsy is the key two approaches of it. However, treatment may comprise radiotherapy, chemotherapy, surgery, or a mix of other treatments might be performed (Le Rhun and Weller 2020). The most recent advances in imaging technology have shown to be extremely useful in the field of medical imaging (Larbi *et al.,* 2023), notably in the identification and diagnosis of serious human disorders such as brain tumors. There are numerous imaging techniques and modules utilized for diagnosis purpose.

The most diagnostic imaging modalities for brain imaging are Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and Ultrasound (US). The main notion of these instruments is the electromagnetic waves emission through body except for ultrasound which exploits the sound waves propagation. Other common imaging techniques are X-Ray (Smith-Bindman *et al.,* 2012). MRI is employed in cancer diagnosis, future monitoring of brain tumor, and therapy planning. This imaging method is a non-invasive radiation that leverages the magnetization of water protons of the body which characterizes brain tissues. MRI gives greater soft tissues contrast and visibility over the cross-sectional imaging modalities (e.g., CT, PET) which in turn enable better visualization for the infiltrated malignant parenchyma. MRIs leverage the hydrogen magnetic characteristics to generate the output image. MRI has the feature of creating several kinds of pictures to accentuate specific tissues features in the brain. These different images “scans” are called frequently modalities, channels, or sequences (Jena *et al.,* 2022).

Image processing was the initial strategy that encourages later streams of applications to extract meaningful information from images. Such methodologies use picture interpretation lead to numerous applications in different domains like medical imaging applications (Krig 2014; Wang *et al.,* 2021; Iqbal *et al.,* 2023). Machine Learning (ML), it is considered as the core field of artificial intelligence, concerned with making computers able to perform actions without explicit programming. The major aspects of machine learning is the data and observations which makes computers able to learn and get rid of traditional rule-based programming (Taye 2023). There are common machine learning algorithms based on parametric models which mean that machine should learn its own parameters (weights) through the training phase before being generalized for un-seen data and produce output. There are also multiple aspects that involve in machine learning pathology such as loss functions and optimization techniques. Several common and fundamental algorithms have been utilized for the complex tasks of brain tumors classification.

Moreover, researchers have suggested modifications and amalgamations of various techniques to address this challenge. For instance, the K-NN algorithm, which is a widely used and fundamental machine learning algorithm, has been employed for classification purposes. Additionally, the Support Vector Machine (SVM) is a non-parametric model that can be used effectively with intricate datasets to yield acceptable accuracy (Unlersen *et al.,* 2022). The SVM algorithm is commonly used for classification in supervised machine learning. It generates a decision border that successfully separates data points in a multi-dimensional space, ensuring new data points are assigned to the correct class. SVM identifies support vectors, which are data points that maximize the margin of classifiers. These support vectors are vital in establishing the ideal hyper plane. Additionally, kernel functions play a key role in SVM classification (Shanishchara and Patel, 2022). The purpose of this research is to develop an automated and efficient method for identification brain tumor in MR images, allowing doctors to make more informed decisions. In this study, nine different CNN architectures with four different kernels (Gaussian, Linear, Quadratic, and Gaussian) of SVM are studied. The findings supplied by specified classification structures have good accuracy. The acquired results compared with prior studies in the literature.

The most notable contributions of this study are the high accuracy in classification, the combination of state-of-the art CNN models and 4 different SVM architectures. In this study we use The Br35H dataset: Brain Tumor detection 2020 dataset (Hamada, 2020), is divided into two different groups, the labels "Tumor" and the labels "No Tumor". in the next section, discusses the literature review. In section (3), outlines methodology followed in designing the featured work and deep feature extraction technique and SVM is given. Then findings and comments are presented and performance criteria are discussed in “Results and discussion”. Finally, in “Conclusions”, the full study is analyzed and concluded.

2. Related works

One of the cancer forms that can be the deadliest is a malignant brain tumor. Because the human brain is a sophisticated device, any interference with its major neuronal motor might have a wide-ranging influence (Hanif *et al.,* 2017). Finding strategies to diagnose brain tumors early or to warn of their probable existence is thus of the highest priority. Its importance originates from the fact that earlier diagnosis increases treatment outcomes and, eventually, patient survival. Significant improvements in cancer treatment have been made recently, especially for people who are suffering from the disease's early stages (Walker *et al.,* 2013). Convolutional neural networks (CNNs), a type of deep learning architecture, have grown in popularity in recent years due to its capacity to carry out complex tasks utilizing convolution filters (Nazir *et al.,* 2021). A major research endeavor in the subject was carried out by Hinton, who focused on picture categorization using convolutional neural networks (Krizhevsky *et al.,* 2012). In the research work of A. Rehman *et al.,* (2021) it has been reported that a convolutional neural network may be used for the identification and classification of brain cancers. There are many databases that have been used, including Kaggle-Br35H dataset (Br35H: Brain Tumor Detection 2020 dataset) (Hamada 2020) , in many works (Kang *et al.,* 2021; Naseer *et al.,* 2021; Amran *et al.,* 2022; Bansal and Jindal 2022; Çınar *et al.,* 2022; Mondal and Shrivastava 2022; Garg *et al.,* 2023; Islam *et al.,* 2023). Several pre-trained CNN models have been used in brain tumor recognition such as fficientNetB0 (C *et al.,* 2022; Khan *et al.,* 2023; Zulfiqar *et al.,* 2023; Soundarya *et al.,* 2023), VGG-19 (Saba *et al.,* 2020; C *et al.,* 2022; Soundarya *et al.,* 2023), VGG-16 (Belaid and Loudini 2020; Amran *et al.,* 2022; Younis *et al.,* 2022), ResNet (Amran *et al.,* 2022; C *et al.,* 2022; Soundarya *et al.,* 2023), AlexNet (Lu *et al.,* 2021; Amran *et al.,* 2022; Sarkar *et al.,* 2023), SqeezNet (Amran *et al.,* 2022), MobileNet (Amran *et al.,* 2022), GoogleNet (Dang *et al.,* 2022; Sekhar *et al.,* 2022). Nandpuru *et al.* (2014.), They used grayscale, isotropic, and texture features to extract features from MRI images. and they used SVM with various kernel functions to divide them into the normal and abnormal categories, their model achieved an overall accuracy of 74% using Linear, 84% using Quadratic, and 76% using Polynomial Kernel Function. Islam *et al., 2023*, used three models of CNN and this to identify cancer cells in the Kaggle (Br35H) dataset, and they achieved an accuracy of 97% with VGG16 , 94.5% with ResNet50, 99% with MobileNet (Islam *et al.,* 2023). Chattopadhyay and Maitra, They implement SVM on CNN, and They changed the final layer parameter to softmax and optimizer to RMSProp, They got the output accuracy to 99.74% (Chattopadhyay and Maitra, 2022).

3. Methodology

In this section, we discuss the proposed method for separating the Kaggle (Br35H) image dataset into two classes: the tumor class and the non-tumor class, and the training strategy utilized to accomplish those classification findings. On the other hand, utilizing key performance indicators, we analyze the performance of the suggested model. Deep features are derived using pre-trained CNN. The classifier that needs to be trained makes use of the deep characteristics of the fully connected layer. Deep features can be obtained from a variety of CNN designs. The SVM classifier uses them after that. The performance metrics for each model are then gathered after categorization. Figure 1 displays a deep feature-based brain tumor detection model using an SVM classifier. In this work, deep features were extracted using pre-trained models (efficientnetb0, mobilenetv2, nasnetlarge, resnet50, resnet10, googlenet, vgg16, vgg19, and shufflenet). We employ a variety of kernel functions, including linear, gaussian, cubic, and quadratic with deep features, to train the SVM classifier. Deep features are extracted from a particular layer of the CNN models to produce a feature vector. The SVM classifier separates the input photos into normal and abnormal categories using the attributes it has gathered. Each layer of the CNN network has its own output. The layers create the fundamental components of the image, which are then sent to the following layer. Table 1 for the various pre-trained CNN models used displays the size of the input image, the name of the feature layer, and the number of features in the output.

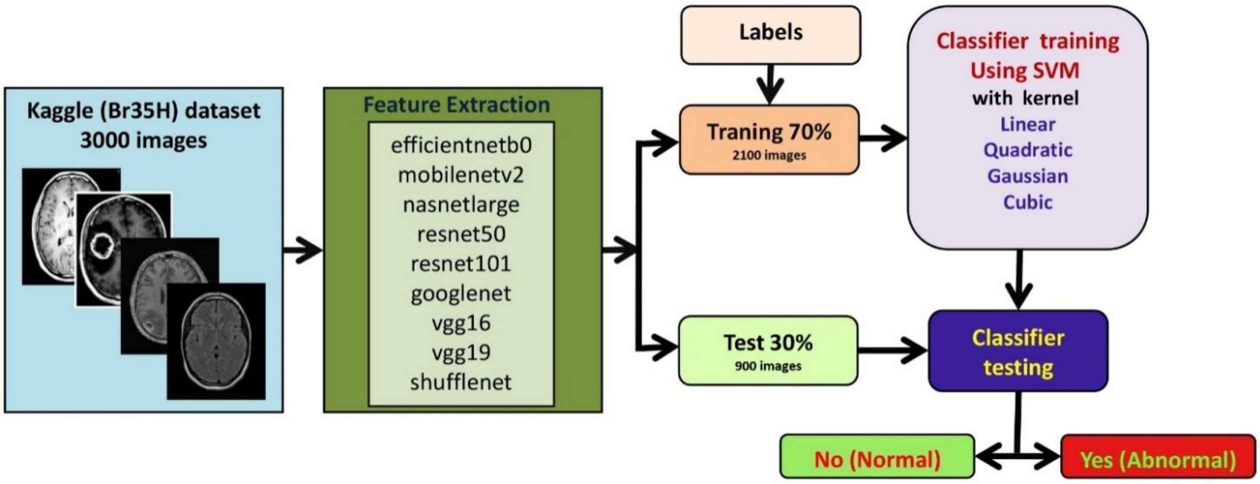


Figure 1 - Main stages of the proposed technique for brain tumor classification

According to Table 1, a model used has a same input size (224 × 224), hence the image size must be changed for each model. Each input images undergoes convolution, rectified linear unit (ReLU), pooling, etc.; after are applied to the pre-trained models. The aforementioned steps are repeated until the pre-trained model reaches the feature layer.

Table 1 – CNN models characteristics.

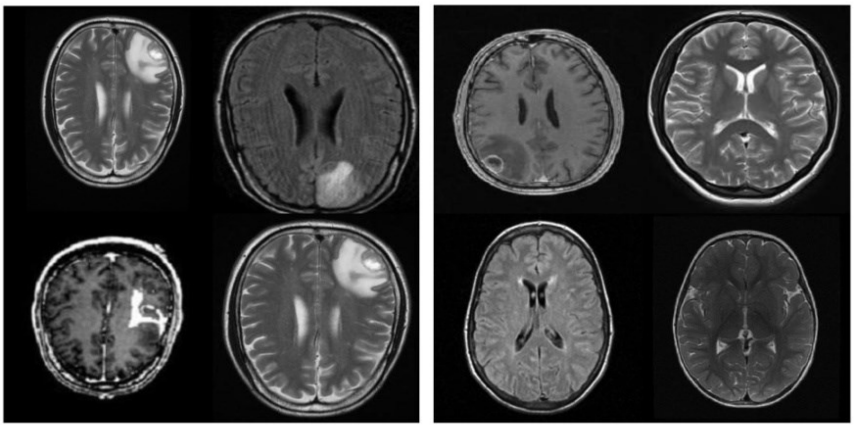
CNN models	Input size	Feature layer	Feature vector
efficientnetb0		MatMul	
`mobilenetv2		Logits	
nasnetlarge		predictions	
resnet50; resnet101	**224 × 224**	fc1000	**1000**
shufflenet		'node_202'	
googlenet		loss3-classifier	
vgg16; vgg19		'fc8'	

The suggested transfer learning approach for classifying brain tumors is shown in Figure 1. In the ImageNet assignment, all of the pre-trained models are taught to recognize 1000 classes. All of the deep learning models are trained using various source datasets that can identify at least a thousand different types of photos. As a result, the output completely linked layer has 1000 neurons in it. In the suggested approach we use 1000 neurons in the fully connected layer extracted from the pre-trained models (efficientnetb0, mobilenetv2, nasnetlarge, resnet50, resnet10, googlenet, vgg16, vgg19, and shufflenet) instead of using the original images taken from the database, and in order to classify them into only two categories, we use SVM Classifier with the variety of kernel functions, including Linear, Gaussian, Cubic, and Quadratic.

The experiments reported in this paper were carried out using a dataset obtained from a Kaggle (Br35H) that was made public. This dataset consisted of 1500 MRI scans of the brain with tumors and 1500 scans without tumors. Each image was 256 × 256 pixels in height and breadth, making them all two-dimensional. Every image had its cranium peeled off, and if it showed a tumor, it was labeled yes; otherwise, it was labeled no. Images with and without tumors are labeled yes and no in the dataset. Table 2 lists the training and testing datasets. Figures 2 shows examples of "normal" and "malignant" data from the dataset.

Table 2 – Description of Kaggle-Br35H dataset

Tumor Class	Image	Training	Testing	Class Labels
Malignant	1500	1050	450	1 (Yes)
Normal	1500	1050	450	0 (No)
Total	**3000**	**2100**	**900**	



(a) (b)

Figure 2 - MRI Kaggle-Br35H dataset: (a) Malignant, (b)Normal

3.1 Data set preparation

The publicly accessible Kaggle dataset (Br35H) has 3,000 images in total, 1,500 of which are images of brain tumors and 1,500 of which are images of healthy people without brain tumors. To make the dataset compatible with the suggested processes, pre-processing is done on it. According to the input image sizes required by our suggested deep learning models, each image must first be changed its size using the built-in resize function of MATLAB to 224 × 224 pixels.

A training group, of 2100 images, which makes up 70% of the dataset, and a test group, which makes up 30% of the dataset (900 images), were created from the photos in the dataset. Additionally, the image data was labeled as (0) for normal instances and (1) for input data for the suggested model's brain tumor identification.

3.2 Classification Performance metrics

When testing a classifier, there are several methods for measuring its performance. All performance metrics are based on four numbers derived from applying the classifier to the test set for supervised learning with two classes. The titles of such numbers are True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) (Unlersen *et al.,* 2022; Garg *et al.,* 2023; Larbi *et al.,* 2023)

TP : When there is a disease present, a true positive test result indicates it.
TN : When a test does not detect a disease when there is none, it is said to be True Negative.
FP : A test result that detects a disease when none exists is referred to as a false positive.

FN : When a test results in a false negative, the illness has not been detected even though there is one.

Assessed the performance of the image-based classification based on sensitivity / recall, specificity, precision, F1-score and accuracy. Some terms were presented in the previous paragraph to determine these metrics and then the following mathematical expressions are defined.

Accuracy: Accuracy gives the total number of predictions that are correct and is given by:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

Sensitivity / Recall: Sensitivity is the measure of the capacity to test the positive samples and is given by:

$$\text{Sensitivity /Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

Specificity: Specificity is the measure of capacity to test the negative samples and is given by:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (3)$$

Precision / PPV: Precision/PPV is the proportion of predicted positives that are correct and is given by:

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

F1-Score: F-Score expresses the weighing scale between the precision/PPV and the recall and is a measure of tests accuracy. It is given by:

$$\text{F1} - \text{Score} = 2 * \frac{\text{PPV}\times\text{Recall}}{\text{PPV+Recall}} \quad (5)$$

4. Results and discussion

This section addresses the proposed brain MRI image categorization process's outcome analysis. This compares the expected result and actual data with a standard dataset to validate the performance of suggested algorithms and prediction quality based on statistical factors. The suggested work's findings are compared to numerous current image classification approaches for the characteristics of sensitivity and accuracy-related statistical value.

To convey the prediction rate of the proposed ensemble model of classification process in the brain MRI image dataset, the results are provided in the form of a comparison table and bar charts. on R2023a, the procedure is implemented on the MATLAB scripting tool platform. This is done to simulate and estimate the error rate in order to validate the entire work's outcomes. To generate deep features for the classification step, different pre-trained CNN structures such as efficientnetb0, mobilenetv2, nasnetlarge, resnet50, resnet10, googlenet, vgg16, vgg19, and shufflenet are utilized. Furthermore, these deep characteristics are identified using SVM with four distinct kernels: Cubic, Gaussian, Linear, and Quadratic. The PC utilized in the experiments is equipped with Intel Core i7-8750H CPU @ 2.20GHZ, 16 GB RAM, and an NVIDIA GeForce GTX1060 6 GB graphics card.

The detection of each class is measured by a confusion matrix, a performance assessment indicator. Table 3 shows the metric values obtained based on the architecture and SVM kernel function employed. all models tested on the Br35H dataset. As demonstrated in Table 3, the structure with the deep feature produced by Efficientnetb0 and a Gaussian SVM kernel has the greatest performance across all measures.

This structure has a classification accuracy of 99.78%. The Efficientnetb0 CNN structure, like the best structure, is used in the second-best performing structure, but the SVM kernel is quadratic, and the success rate is 99.67%. Efficientnetb0 with Cubic SVM kernel is ranked third with a success rating of 99.56%.

Table 3 – SVM-based performance metrics for CNN models

Pre-trained model	SVM Kernel function	Accuracy (%)	Specificity (%)	Precision (%)	Sensitivity (%)	F1-Score (%)
Efficientnetb0	Linear	97.44	97.13	97.11	97.76	97.44
	Quadratic	99.67	**99.78**	**99.78**	99.56	99.67
	Gaussian	**99.78**	**99.78**	**99.78**	**99.78**	**99.78**
	Cubic	99.56	**99.78**	**99.78**	99.34	99.56
Mobilenetv2	Linear	95.89	97.25	97.33	94.60	95.95
	Quadratic	98.33	98.44	98.44	98.23	98.34
	Gaussian	98.67	98.45	98.44	98.88	98.66
	Cubic	99.11	99.55	99.56	98.68	99.12
Nasnetlarge	Linear	95.33	94.93	94.89	95.74	95.31
	Quadratic	98.11	98.00	98.00	98.22	98.11
	Gaussian	97.78	97.57	97.56	97.99	97.77
	Cubic	98.67	98.45	98.44	98.88	98.66
Resnet50	Linear	96.33	96.23	96.22	96.44	96.33
	Quadratic	98.67	98.88	98.89	98.45	98.67
	Gaussian	99	98.68	98.67	99.33	99
	Cubic	99.33	99.33	99.33	99.33	99.33
Resnet101	Linear	96.11	96.21	96.22	96.01	96.12
	Quadratic	99	98.89	98.89	99.11	99
	Gaussian	99	98.89	98.89	99.11	99
	Cubic	99.11	99.11	99.11	99.11	99.11
Googlenet	Linear	92.11	93.97	94.22	90.41	92.27
	Quadratic	96.78	96.88	96.89	96.67	96.78
	Gaussian	96.56	96.45	96.44	96.66	96.55
	Cubic	97.89	98.43	98.44	97.36	97.9
Vgg16	Linear	94.33	94.24	94.22	94.43	94.33
	Quadratic	97.78	97.99	98.00	97.57	97.78
	Gaussian	98	97.37	97.33	98.65	97.99
	Cubic	98.56	98.66	98.67	98.45	98.56
Vgg19	Linear	93.22	93.51	93.56	92.94	93.24
	Quadratic	98.44	98.23	98.22	98.66	98.44
	Gaussian	98.44	98.02	98.00	98.88	98.44
	Cubic	98.78	98.24	98.22	99.33	98.77
Shufflenet	Linear	95.78	95.78	95.78	95.78	95.78
	Quadratic	98.22	98.44	98.44	98.01	98.23
	Gaussian	98.22	98.44	98.44	98.01	98.23
	Cubic	98.89	98.89	98.89	98.89	98.89

Table 3 shows that googlenet and linear kernel SVM structure have the poorest performance, with an accomplishment score of 92.11%. By studying the findings, it is feasible to observe that the kernel function with the best average accuracy score is the Gaussian kernel function with 99.78% success rate. By studying the findings, it can be observed that the CNN structure with the best average accuracy score is the Efficientnetb0 with a success rate of 99.13%.

On the other hand, it is feasible to observe that the kernel function with the best average accuracy score is the Gaussian kernel function with 98.88% success rate. The Gaussian kernel function comes in second place in terms of accuracy, with 98.38% accuracy. The accuracy scores for the Quadratic kernel function and linear kernel function are 98.33% and 95.17%, respectively. On the other hand, Figure 3 displays the confusion matrix for proposed method using feature extraction of Efficientnetb0 and a Gaussian SVM kernel.

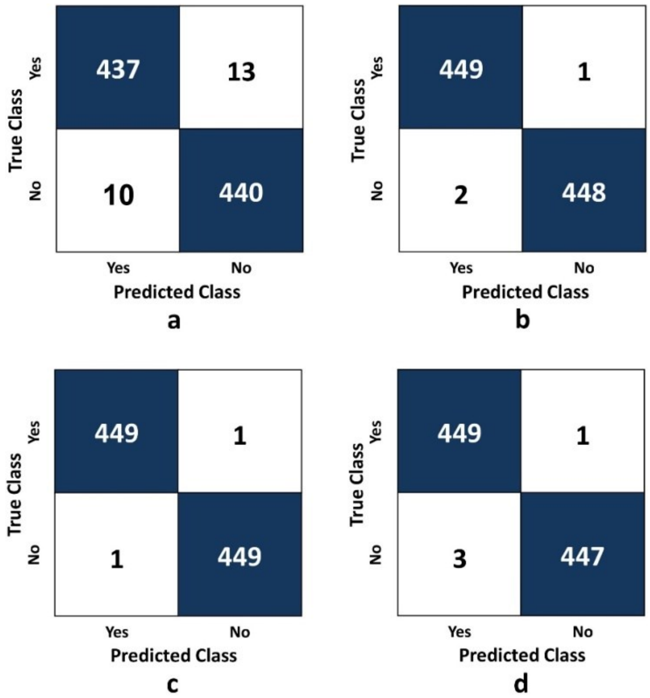


Figure 3 - Confusion matrices obtained with efficientnetb0 model and SVM. (a) Linear, (b) Quadratic, (c) Gaussian, (d) Cubic

This confusion matrix successfully detected binary tumors in this investigation and correctly identified each type of brain tumor. As a result, 898 out of 900 photos were properly identified, giving the accuracy a score of 99.78%, Precision of 99.78%, specificity of 99.78%, Recall of 99.78%, and F1-Score of 99.78%.

On the other hand, we compare our proposed method with several other basic methods from the existing literature, as shown in Table 4.

As demonstrated in Table 4, we contrasted the suggested deep tumor network with other top-notch benchmark techniques. The performance of our suggested model in binary tumor classification is astounding when compared to other benchmark techniques from the published literature.

Table 4 – Presents the comparison study of suggested model with recent models

Author (year)	Validation Method	Overall Accuracy (%)	Average Precision (%)	Average Specificity (%)	Average Sensitivity (%)	Average F1-score (%)
Islam *et al.,* 2023	Hold-out (80:20)	98.5	98	NA	98	98
Garg *et al.,* 2023	Hold-out (80:20)	98.66	97.27	NA	98.83	98.83
Bansal and Jindal, 2022	Hold-out (80:20)	99	NA	NA	NA	NA
Amran *et al.,* 2022	5-fold cross validation-Test (90:10)	99.1	98.9	NA	98.6	98
Çınar *et al.,* 2022	Hold-out (80:20)	98.6	98.4	NA	98.6	97.9
Mondal and Shrivastava, 2022	Hold-out (70:30)	99	99	99	99	98.99
	5-fold cross validation	98.33	98.34	98.33	98.33	98.33
Naseer *et al.,* 2021	Hold-out (90:10)	98.8	NA	NA	NA	NA
Kang *et al.,* 2021	Hold-out (80:20)	98.67	NA	NA	NA	NA
This work	**Hold-out (70:30)**	**99.78**	**99.78**	**99.78**	**99.78**	**99.78**

5. Conclusions

This research presents promising results for brain tumor detection. Nine models of CNN are used only to extract features. They do not serve as categorization tools. With a ratio of 70% to 30%, the retrieved deep features are split into two groups: training and testing. The four different kernels of the SVM machine learning approach receive the produced deep features. The trained SVM classifies the test data in order to assess performance. The features obtained from several CNN models are correctly classified using four SVM kernels as a result. 99.78% of the classes are correctly classified while using the Efficientnetb0-SVM Gaussian kernel structure for the Kaggle (Br35H) image dataset. The findings demonstrate that the suggested study is effective in identifying a brain tumor using images. This study's contribution is that it offers good classification performance for identifying brain tumors and suggests combining popular CNN models with SVM kernels. Finally, we hope that our research will aid people in receiving an earlier warning regarding their health status. More research is needed, however, to improve the model's accuracy and to work on leveraging multi-classification datasets. Furthermore, we want to see how well the technique performs with other types of data in biomedical imaging domains such as asthma detection, lung disease, etc.

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