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Brain tumor detection and classification from MRI images based on hybrid deep learning approaches

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Abstract
Cancer stands out as among the most relentless and ruinous illnesses, curtailing the typical lifespans of those afflicted. When brain tumours are misdiagnosed, it results in unwarranted medical interventions, thereby diminishing the likelihood of patient survival. Precise and timely early diagnoses of brain tumours constitute a pivotal starting point for devising treatment strategies that enhance the chances of survival for individuals grappling with such tumours. The domain of computer-aided diagnosis systems has witnessed a series of breakthroughs, enabling medical experts to achieve precise diagnoses with the assistance of these systems, as evident in the advancements in deep learning and machine learning communities. Specifically, deep convolutional layers can capture informative discriminative features at points of interest, outperforming conventional extraction approaches. In this work, we present a series of tests for the diagnosis and detection of brain tumors by combining deep as well as traditional machine learning. The method uses AlexNet and ResNet-18, in combination with SVM methodology, which helps to correctly classify/diagnose brain tumors from MRI images. The Average filter approach was adopted to improve the MRI brain tumor images. Subsequently, the powerful and semantic descriptors of the images are learned by deep learning frameworks via the deep convolutional layers. The deep and the machine learning techniques integration begins at feature extraction extracted based on AlexNet & ResNet-18. These selected features are further applied to classification by both SoftMax and SVM methods. The study's dataset consists of 3110 MRI images classified into four classes, which include three forms of tumours and one class representing the normal images. The results obtained across all systems are notably outstanding. Remarkably, the hybrid technique combining AlexNet and SVM achieves the highest performance, with an accuracy of 94.60%, a sensitivity of 94.75%, and a specificity of 98%.

Keywords: Deep learning, CNN, brain tumor, segmentation, classification, MRI images

I. Introduction

The human brain is a vital body organ participating in regulatory activities and decision-making. As the superior center of the nervous system, it is very essential to protect this vital part from injury and disease. The central nervous system (CNS), which includes the brain and spinal cord, has a central role in the human body [1]. Its main part, the brain conducts innumerable body activities, such as investigation, integration, decision-making, and commanding other body activities. Anatomically, the human brain is a very complex organ [2]. The CNS is subjected to variety of disastrous conditions, which present major medical challenges in their identification, analysis, and the development of suitable treatment methods [3]. These include stroke, infections, brain tumors, and headaches. Among these diseases, brain tumors are one of the most important, which result from the abnormal growth of cells within the rigid cranial enclosure [4-6]. Growth in such a limited space invites complications, as any type of tumor arising within the skull leads to brain damage and thus is a serious threat to this important organ [7, 8]. Brain tumors are the 10th major cause of death in adults and children [9].

The high resolution, contrast, and marked differentiation of soft tissues are some of the factors that enable doctors to precisely identify certain illnesses [10]. The application of automated segmentation methods has proven useful for dealing with different levels of uncertainty in delineating boundaries between heterogeneous regions of tissue. These techniques allow the volumetric analysis of pathologic MRI signals automatically, which is used for effective management [11]. Brain tumors affect approximately a quarter of a million people throughout the world every year, and malignant growths manifest in about 2%

such cases [12]. Brain tumors were projected to affect approximately 23, 890 adults in the United States in the year 2020. This included 13, 610 men and 10, 295 women. About 1, 879 new cases of brain cancer have been estimated to be diagnosed in Australia during the same year. Approximately 14.1% of new cases among Americans annually involve primary brain tumors, where children account for approximately 70% of new cases. However, there are no early treatments for primary brain tumors, although they do result in long-lasting negative effects [13, 14]. Cases of brain tumors have remarkably increased by about almost 10% to 15% globally between the years 2004 and 2020 [15].

A review of the existing literature reveals that different machine learning approaches have been tried for the classification of MRI images [16, 17]. Later, in the advancement the several deep learning approaches are commonly employed in the healthcare sector to perform tasks such as analysis, categorization, and identification [18-20]. Convolutional Neural Networks, commonly referred to as CNNs, were first used in 1980 [21, 22, 49]. Taking inspiration from the human brain that recognizes and identifies an object by its external features, CNN follow a similar procedure, although CNNs are known for their capabilities of handling images. Important CNN architectures include "ResNet (148 layers), GoogLeNet (26 layers), AlexNet (8 layers), and VGG (17-20) [23-26].

In this research, we investigate and evaluate the efficiency of various deep learning architectures, like AlexNet and ResNet-18, for the detection of brain tumors at an early stage. To evaluate the efficiency of both deep learning techniques, namely AlexNet and ResNet-18 and a machine learning approach, namely SVM, integrated as AlexNet+SVM and ResNet-18+SVM, respectively in the context of early brain tumor recognition from MRI images. The key contributions of this study can be outlined as follows:

- Hybrid approaches are used, including both deep learning and machine learning methodologies. The approach mainly focuses on the pre-processing of images to enhance clarity by reducing noise. Once refined, the images are fed into deep learning methods to capture crucial discriminative features. Additionally, the procedures for classification include the use of CNN with SoftMax activation, while the machine learning utilizes the technique of SVM.
- Different architectures of CNNs for both AlexNet and ResNet-18 methods, along with their implementation, were investigated to employ a transfer learning method for the detection of brain tumor MRI images.
- The hyper column technique employed by the proposed hybrid approaches maintains crucial local distinguishing attributes. It accomplishes this by transferring features inherent in the earlier layer. This transfer learning improves the classification performance of the models.

The developed approaches also offer a potentially effective and highly sensitive diagnostic approach for the classification of brain tumors in MRI images, aiding experts and radiologists in their decision-making process.

II. Materials and Method

Most of the previous studies depended on manually extracting patterns of tumor behaviors before categorizing them. Nonetheless, complete automation is hindered by this approach. When the dataset in a limited size, only a handful of research endeavors have shown the ability to generate automated solutions. Numerous experiments were carried out to measure the efficacy of AlexNet and ResNet in incorporation with SVM for the aim of brain tumor classification. The overall architecture of the brain tumor recognition system utilized in this research is depicted in Fig. 1."

A. Preprocessing

Preprocessing plays a crucial role and serves as a fundamental component within the MRI image processing mechanism. The main purpose of pre-processing is to improve the quality of MRI images and prepare them for subsequent human or computer-based analysis by enhancing their suitability for visual interpretation. During the MRI pre-processing phase, noise elimination is achieved using an average and a Laplacian filter. These filters work by smoothing images and minimizing contrast disparities among neighboring pixels. Exactly, we included bias field correction through the N4ITK methods to address low-frequency intensity inhomogeneities across scans. Furthermore, skull stripping is done by BET (Brain Extraction Tool) to segment out the brain tissues and remove the irrelevant regions. For improving the consistency between MRI modalities, intensity normalization is done through scaling of voxel intensities to zero mean and unit variance. Lastly, for slice selection, the central slices covering visible tumor areas are preferred with the help of segmentation masks to ensure reliable representation of relevant structures. These steps cooperatively enhance the robustness and generalization capability of the developed detection system.

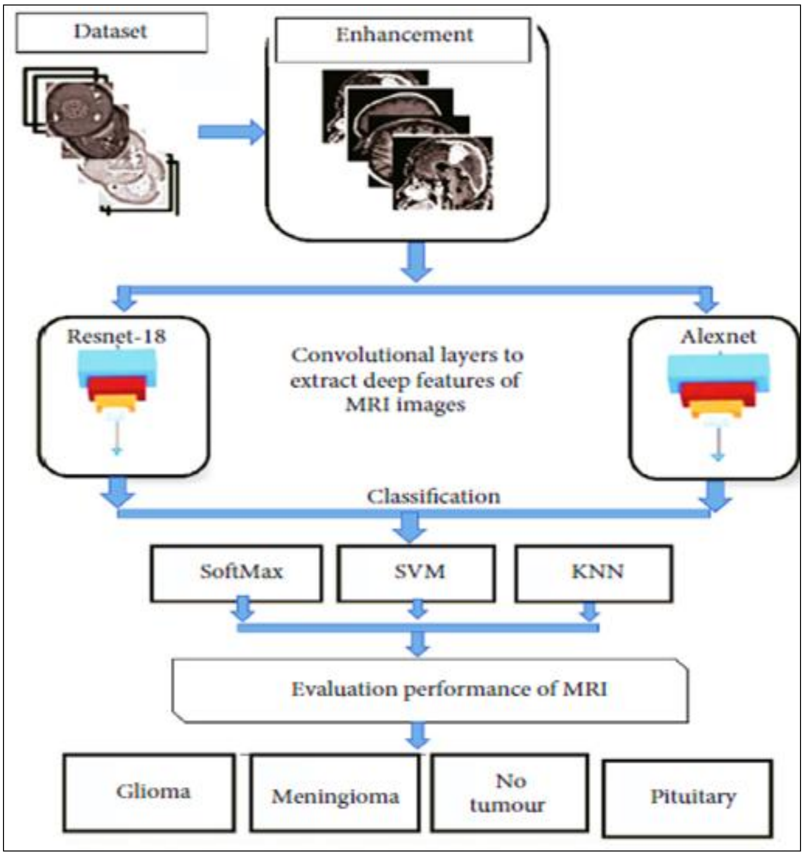

Fig 1: Overall framework by integrating deep and machine learning methodologies

made using both deep learning algorithms, namely AlexNet and ResNet-18 with SoftMax, and machine learning by SVM. Each of the classifiers was evaluated on metrics including accuracy, sensitivity, and specificity.

B. Dataset Description

The assessment of model effectiveness is conducted through the brain tumor dataset, sourced from Nanfang Hospital in Guangzhou, China, and Tianjin Medical University General Hospital, China. This compilation was carried out between 2005 and 2010 [27]. The dataset comprises 3, 110 MRI images, categorized into four groups: 837 images of glioma, 945 images of meningioma, 416 images of no tumor, and 912 images of pituitary tumors. All the MRI images have dimensions of 512 × 512 pixels." Additionally, Fig. 2 displays MRI images representing the three brain tumor types, along with the normal fourth type.

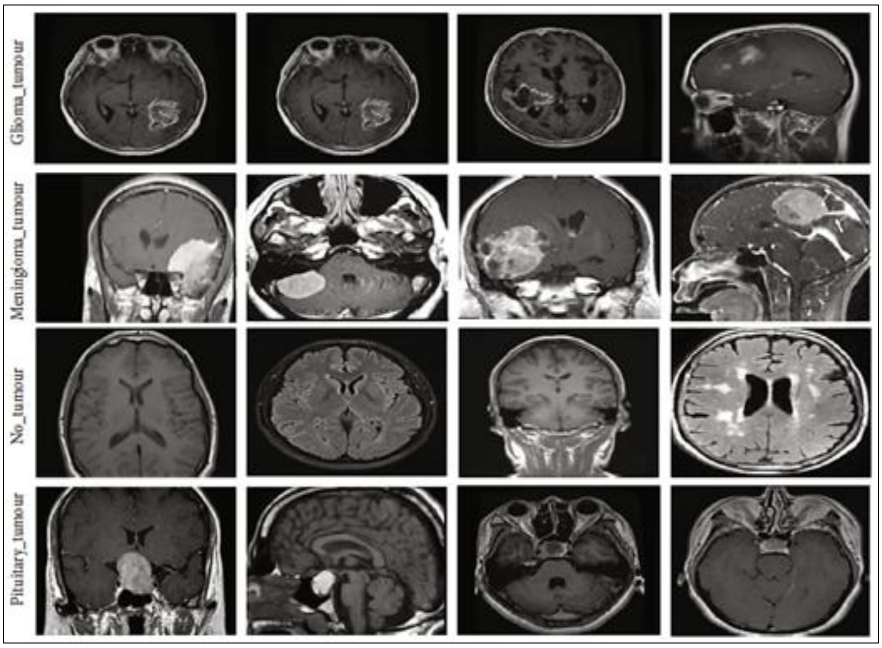

Fig 2: Examples of Instances from a brain tumor MRI dataset are provided. The dataset source can be found at: https://www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri.

C. Data Augmentation

Data augmentation methods are valuable for addressing the imbalance and expanding datasets for classes when dealing with limited and skewed data. This approach proves useful in equilibrating the quantity of images across different categories of brain tumor classes in MRI scans, thereby also augmenting the overall number of images available. During the training process, a data augmentation method was employed to enhance model generalization and address class imbalance. Augmentation was accomplished on-the-fly during training, utilizing the Keras *ImageDataGenerator* to ensure variety across training batches. The subsequent alterations were employed with their particular parameter ranges and probabilities: rotation (±15° with probability 0.5), horizontal and vertical flips (0.5), width and height shifts (±10%), zoom (0.9-1.1 range with probability 0.3), and brightness variation (range 0.8-1.2). Class balancing was confirmed through implementing augmentation more commonly to the minority class (tumor images) until both classes reached parity. This augmentation process enhances the robustness to orientation, scale, and illumination disparities, thereby reducing overfitting and improving the reproducibility of model training.

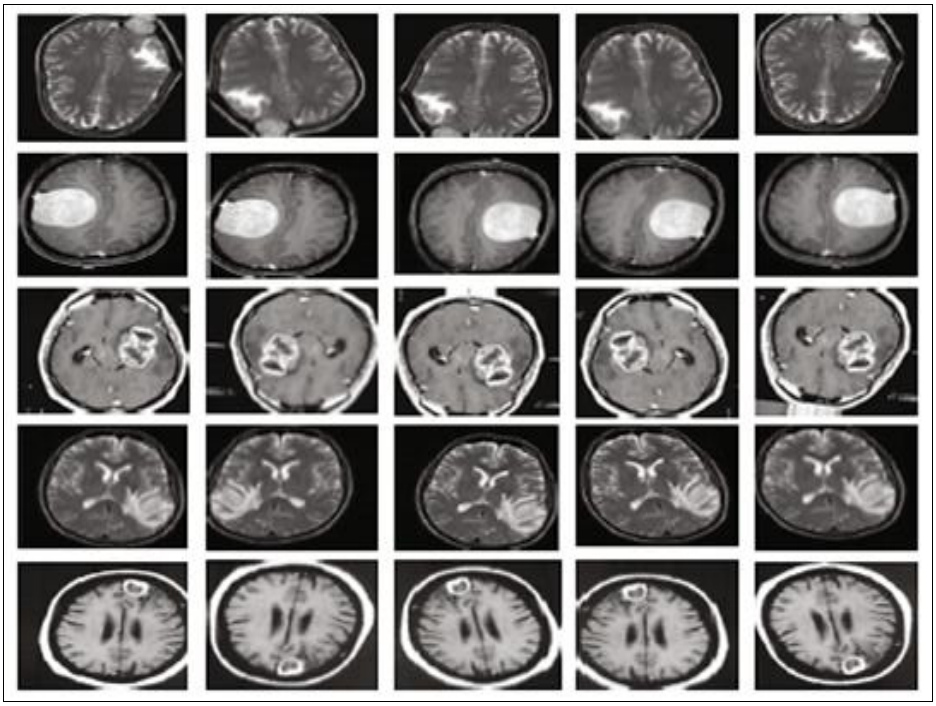

Fig 3: A collection of image samples after utilizing the data augmentation process

We used data augmentation to boost the model's learning by creating mirrored versions of the MRI and introducing variations such as rotation, changes in width and height, cutting, changing, and zooming. The datasets were validated using the holdout validation method. Fig. 3 shows a sample of images from the brain tumor dataset after applying the data augmentation technique.

D. Deep Learning Approaches

Transfer learning is a dominating approach to machine learning, which involves the usage of previously trained neural networks [29, 30]. Among these, some of the transfer learning architectures such as AlexNet and ResNet-18 are commonly used in applications dealing with image categorization and detection [31, 32]. The most considerable advantages of transfer learning are its cost and time efficiency, as reported in many works [33, 34].

1) AlexNet CNN: In 2012, the AlexNet method remained considered by Alex Krizhevsky. Comprising a total of 25 layers, the architecture includes five convolutional layers that play a crucial role in extracting in-depth features. Moreover, there are three max-pooling layers designed to decrease the dimensions of these features. To counter overfitting, two dropout layers are employed; these deactivate 50% of neurons during each iteration, albeit at the cost of doubling training time.

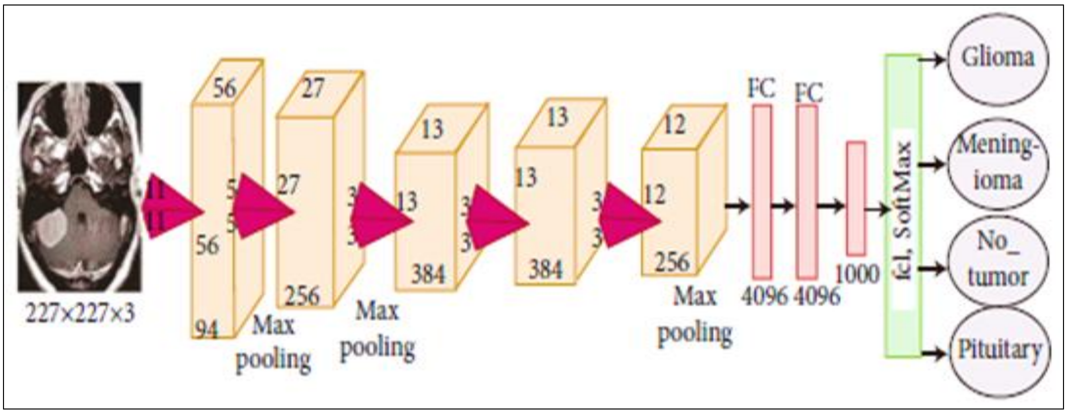

Fig 4: Architecture of AlexNet model

as visually depicted in Fig. 4. Remarkably, AlexNet is comprised of through 6 million trainable parameters [35].

2) ResNet-18 CNN: Numerous ResNet variations have been created, utilizing varying depths and layer configurations, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. These architectures have shown great performance and efficiency. For illustration, ResNet-18 consists of five convolution layers for deep feature extraction, an average pooling layer for reducing the dimension, a fully connected layer, and a SoftMax layer that outputs four classes, as shown in Fig. 5. The ResNet-18 model has over 11.5 million parameters. Detailed information about the layers of ResNet-18 is provided in Table 1. The training process of the ResNet-18 method is shown in Fig. 6, which includes the training accuracy and the loss function. Both methods' parameters, such as frequency, repetitions per period, maximum repetitions thru training, and the execution setting, have been changed accordingly.

Table 1: Detailed configuration of the ResNet-18 model

Layer	Conv 1	Conv2.x	Conv3.x	Conv4.x	Conv5.x	Pooling
Output size	112 × 112 × 64	56 × 56 × 64	28 × 28 × 128	14 × 14 × 256	07 × 07 × 512	01 × 01 × 512
Filter	8 × 8, 64 strides 2	4 × 4 × 64 4 × 4 × 64	4 × 4 128 4 × 4 128	4 × 4 256 4 × 4 256	4 × 4 512 4 × 4 512	Average

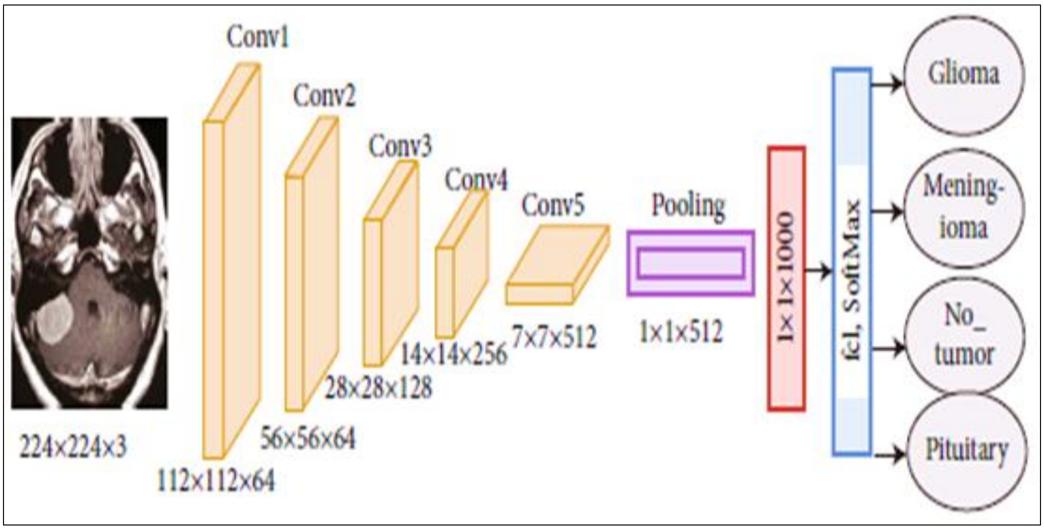

Fig 5: Architecture of the ResNet-18 model

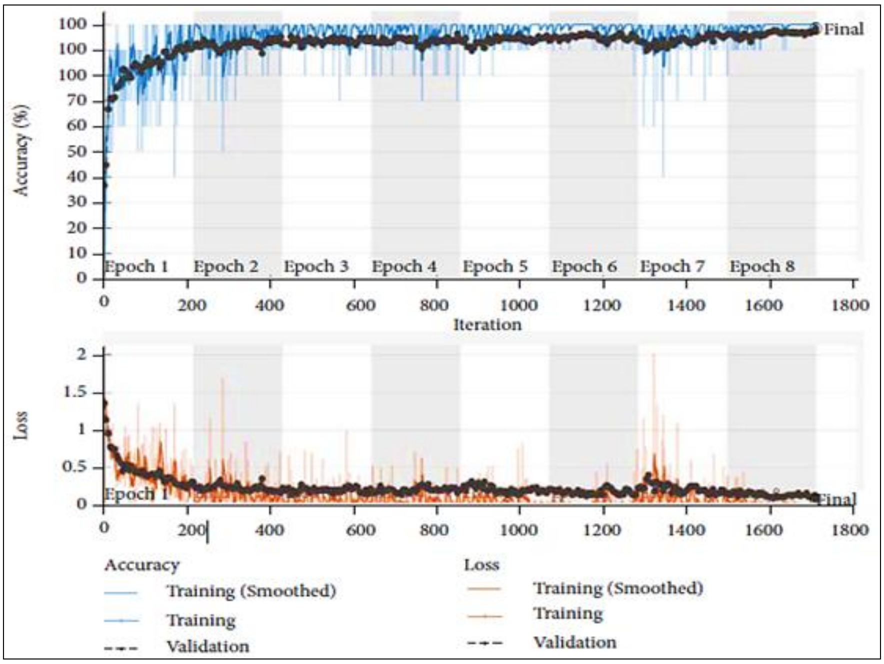

Fig 6: The process of training and loss for the ResNet-18 model

3) Hybrid Deep and Machine Learning Approaches: In this work, we apply a hybrid deep and machine learning approach for the efficient detection of brain tumors. Addressing the computational costs, time, and hardware requirements required for training the deep learning-based approaches on datasets, combined approaches provide solutions to these challenges. This approach enables for solving computational challenges and their implementations at higher speeds by utilizing resources at a moderate cost. The proposed methodology has two significant parts. First, it has the CNN methods, which are responsible for extracting deep feature maps, exactly 9366 features per image. Second, the SVM machine learning approach provides the potential for quickly and accurately classifying 3110 × 9366 deep feature plots. The dataset collected has been divided into two parts: 80% is used for training and validation, while the remaining 20% is reserved for testing. The hybrid approaches, denoted as AlexNet+SVM and ResNet-18+SVM, which combine the CNN approach with the SVM technique, are illustrated in Figures 7 and 8.

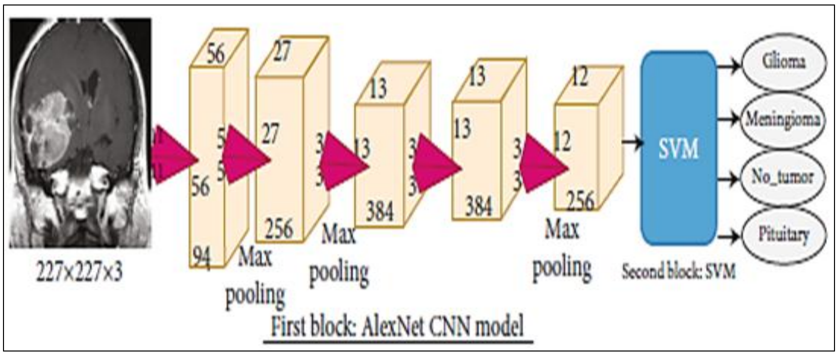

Fig 7: AlexNet CNN and SVM hybrid architecture these developed hybrid approaches are applied to the classification of a brain tumor dataset

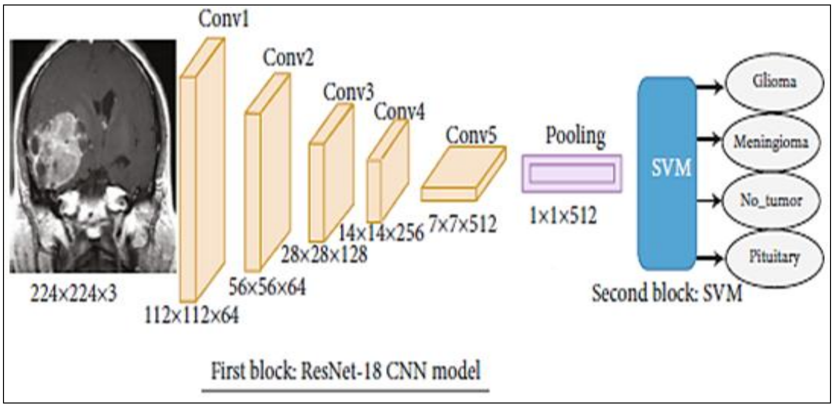

Fig 8: ResNet-18 CNN and SVM hybrid architecture

E. Implementation Setup

In this section, the intended setup for the experiment is detailed, focusing on classification. The hybrid model was created utilizing Python 3.11 and selected due to its harmony with widely used machine learning and neural network libraries. Specifically, the TensorFlow and Keras libraries were employed. The model is designed to execute on both the Central Processing Unit (CPU) on Microsoft Windows 10 as the operating system and the Graphical Processing Unit (GPU). The implementation of the model was performed using Google Colaboratory (Colab). Colab, which extends Jupyter Notebooks, is a free cloud-based service for sharing machine learning code, concepts, and results in education and research [28]. This sharing environment provides generous resources: 16 GB of RAM, a 500 GB hard disk, and free access to powerful GPUs. Moreover, we have used the Adam optimizer with a specific learning rate of 0.0001 for the optimization of this model. This model was evaluated based on binary accuracy, and the loss function that was picked was the binary cross-entropy.

F. Evaluation Measure

To assess the effectiveness of the developed approach, we conducted an inclusive analysis based on various metrics, including accuracy, sensitivity, and specificity, defined in Equations 1, 2, and 3, respectively.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100 \quad (1)$$

$$Sensitivity = Recall = \frac{TP}{(TP+FN)} \times 100 \quad (2)$$

$$Specificity = \frac{TN}{(TN+FP)} \times 100 \quad (3)$$

III. Results and Discussion

This section illustrates details about the results of the various experiments that were conducted on the brain tumor MRI image datasets for the hybrid deep and machine learning approaches. The effectiveness of deep learning methods, such as “AlexNet, ResNet-18, AlexNet+SVM, and ResNet-18+SVM, was explored using brain tumor MR image datasets. The performance of the established approaches was tested with a set of assessment measures.

A. Results Analysis of CNN Approach

The challenge of an imbalanced dataset was addressed, and the issue of overfitting was overcome by utilizing a data augmentation method. In the convolutional layers, for each image, depth feature maps were obtained, while the pooling layers were used to reduce the dimensions of each image. Thereafter,” fully connected layers were used to evaluate the deep feature maps for both AlexNet and ResNet-18 models, which allowed the detection of brain tumor-related patterns within MRI images. These two models performed excellently for the diagnosis of brain tumors into four different classes and reported outstanding outcomes.

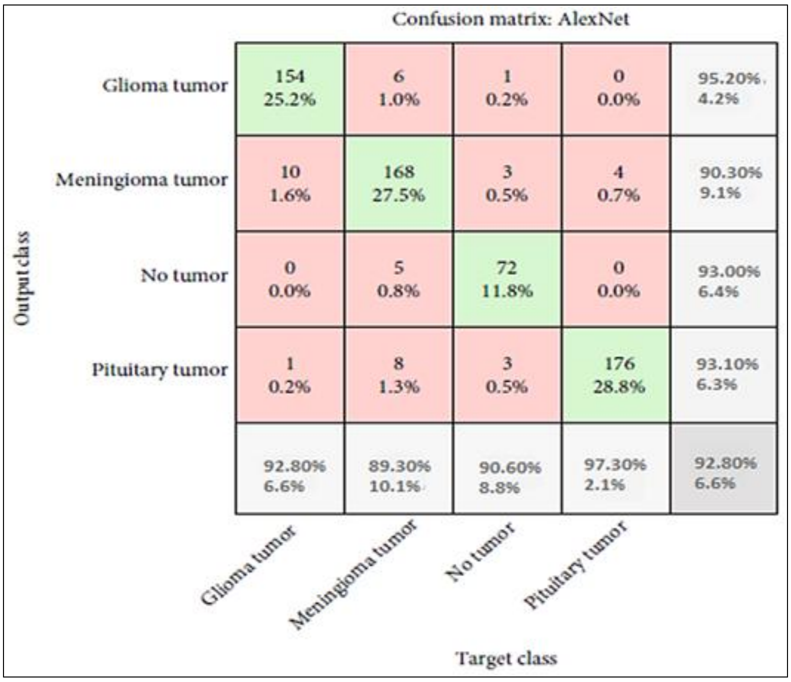

Fig 9: Confusion matrix to assess MRI brain tumor data using AlexNet model

Fig 10: Confusion matrix to assess MRI brain tumor data using the Resnet-18 model

In Fig. 9, the confusion matrix displays the results for the AlexNet model, achieving an accuracy of 92.80%, with a sensitivity of 92.50% and a specificity of 97.10%. The model effectively identified glioma with 92.80% accuracy, meningioma with 89.30% accuracy, cases without tumors (no_tumour) with 90.60% accuracy, and pituitary tumors with 97.30% accuracy. On the other hand, in Figure 10, the confusion matrix represents outcomes for the ResNet-18 network," attaining an accuracy of 93.30%. Sensitivity was noted at 93.20%, while specificity reached 97.10%. The ResNet-18 model demonstrated precision in diagnosing glioma with 92.80% accuracy, meningioma with 93.10% accuracy, instances without tumors with 86.80% accuracy, and pituitary tumors with 96.70% accuracy.

B. Results Analysis of Hybrid CNN Approaches with SVM

In this section, we applied two AI methods, specifically deep learning and machine learning, to accomplish two tasks: the extraction of profound feature maps and the subsequent classification of these derived features using deep learning. However, due to the computational complexities of deep learning methods, requiring high-performance computers, longer training time, and complex computations in their classification layers (fully connected layers), we decided to use SVM to classify the features extracted through deep learning. This consisted of two separate experiments: one with AlexNet and SVM, and another with ResNet-18 and SVM. The result for the AlexNet+SVM is represented using a confusion matrix in Fig. 11. In this regard, that approach realized very impressive results, having an accuracy of 94.60%, with a sensitivity of 94.75% and a specificity of 98%. The AlexNet+SVM configuration realized the diagnostic accuracy for different tumor types as follows: 93.40% for glioma, 93.10% for meningioma, 94.40% for no tumor, and 97.30% for pituitary adenoma. In contrast, the ResNet-18+SVM model achieved an overall accuracy of 90.70%, along with a sensitivity of 91% and a specificity of 96.50%, as depicted in Fig. 12.

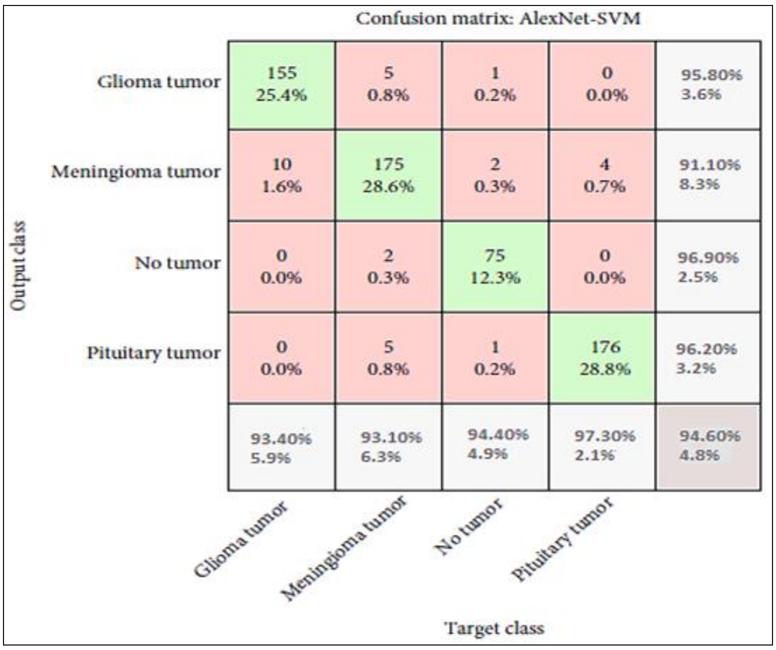

Fig 11: Confusion matrix to assess MRI brain tumor using a hybrid AlexNet+SVM model

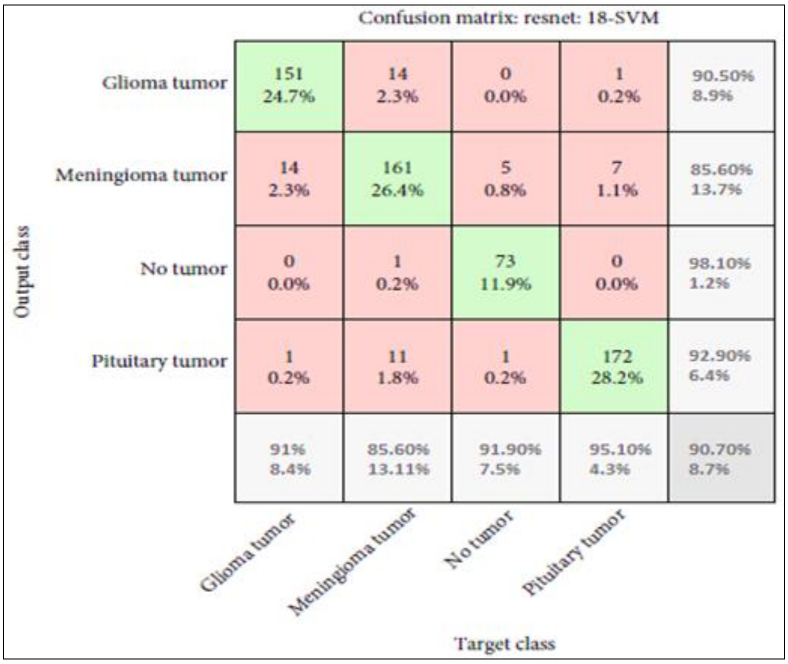

Fig 12: Confusion matrix to assess MRI brain tumor using a hybrid ResNet-18+SVM model

Specifically, when considering specific tumor types, the ResNet-18+SVM network accomplished an accuracy of 91% for glioma, 85.60% for meningioma, 91.60% for cases without tumors, and 95.10% for pituitary adenoma.

C. Comparison Study

In this study, the MRI images from a brain tumor dataset were subjected to diagnosis through a pair of CNN approaches: specifically, AlexNet and ResNet-18. Additionally, the same dataset underwent examination through hybrid methodologies that combined deep and machine learning approaches, such as AlexNet and ResNet-18 captured deep features, which were subsequently utilized as inputs for a machine learning algorithm (SVM) responsible for the final diagnosis. Pre-processing steps were necessary to ensure the quality of the dataset before feeding it into the models, and such involved the use of two filters, the average filter and the Laplacian filter, which removed the noise and other artifacts. Moreover, bias correction, skull stripping, intensity normalization, and slice selection strategy are some of the techniques used in the pre-processing of the dataset.

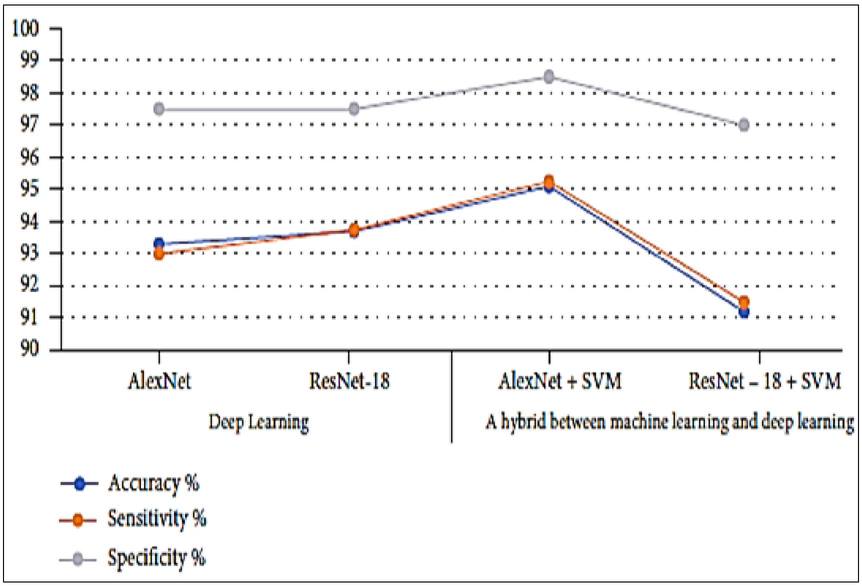

Fig 13: Evaluation of the effectiveness of the proposed models on the brain tumor dataset

learning and hybrid models using the brain tumor dataset. These models attained accuracy rates of 92.80%, 93.30%, 94.60%, and 90.70%, as well as sensitivity rates of 92.50%, 93.20%, 94.75%, and 91.00%, and specificity rates of 97.10%, 97.10%, 98.00%, and 96.50% for AlexNet, ResNet-18, AlexNet+SVM, and ResNet-18+SVM, respectively. Among these experiments, the AlexNet+SVM hybrid model demonstrated the most exceptional performance.

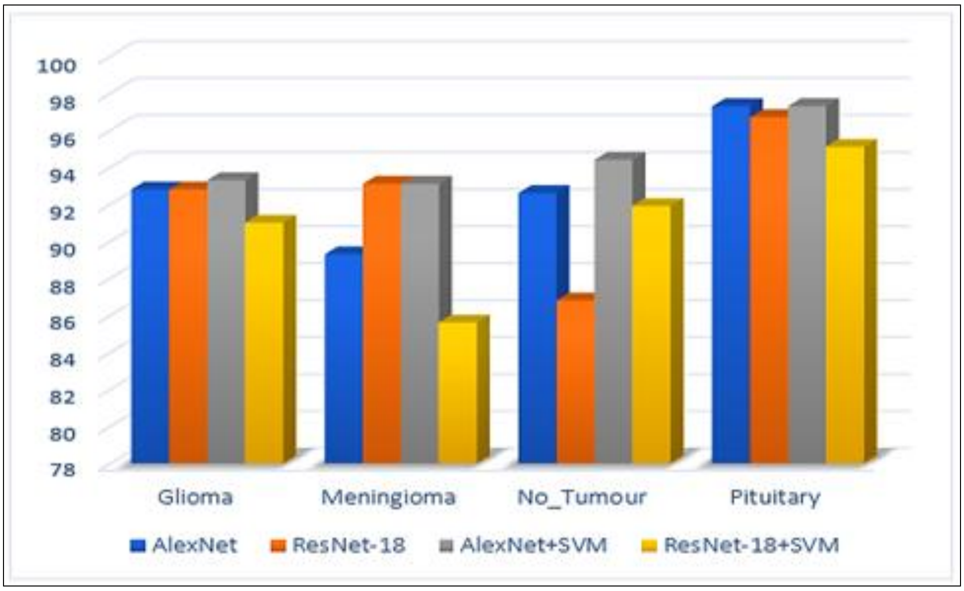

Fig 14: The detection performance of each brain tumor by the four models

Table 2 presents the diagnostic performance in terms of accuracy for the four methodologies in classifying each type of tumor. "The AlexNet+SVM hybrid method demonstrates the highest accuracy among the systems. Specifically, this model achieves a diagnostic accuracy of 93.40% for glioma classification, while for meningioma classification, the same model attains a diagnostic accuracy of 93.10%. Furthermore, the AlexNet+SVM hybrid model performs with a diagnostic accuracy of 94.40% for nontumour image classification, and for pituitary tumor classification, it achieves the highest accuracy of 97.30%. Fig. 14 depicts the performance of four models regarding diagnosis accuracy across each class for the MRI dataset. Table 3 demonstrates the performance of the developed models and state-of-the-art traditional studies," assessed through various techniques outlined in the literature review [8, 36-48]. Multiple relevant studies were also examined in this context. Accuracy levels in previous research varied from "85% to 94.12%, in contrast to our system achieved an accuracy of 94.60%. Similarly, the range of sensitivity observed in previous investigations spanned from 84.36% to 92.38%, whereas our system demonstrated a sensitivity of 94.75%. Specificity reported in previous works falls between 79% to 95.80%, while our system was able to achieve a specificity of 98.00%. These results highlight the fact that the developed approach offers balanced improvement across all metrics, especially in its robustness towards specificity important metric for assured diagnosis. This development suggests the effective resolution of the previous limitations, as highlighted in the methodology, such as overlapping cell segmentation and feature optimization.

Table 2: Performance of the four models in terms of diagnostic accuracy for each type of tumor class

Models	Glioma	Meningioma	No_tumour	Pituitary
AlexNet	92.80	89.30	90.60	97.30
ResNet-18	92.80	93.10	86.80	96.70
AlexNet+SVM	93.40	93.10	94.40	97.30
ResNet-18+SVM	91.00	85.60	91.90	95.10

Table 3: Performance comparison of the proposed model with state-of-the-art studies

Previous Studies	Accuracy (%)	Sensitivity (%)	Specificity (%)
Togacar *et al.* [36]	87.93	84.36	92.31
Bahadure *et al* [37]	92.03	92.36	91.42
Kumar *et al.* [38]	92.63	92.38	93.33
Afshar *et al.* [39]	92.45	9.36	91.98
Kaur *et al.* [40]	91.51	90.65	95.80
Dandu *et al.* [41]	90.20	--	--
Sharif *et al.* [42]	92.50	--	--
David *et al.* [43]	85.00	87.00	79.00
Ghassemi *et al.* [44]	91.70	90.16	95.58
Amin *et al.* [8]	87.00	92.00	80.00
Cho *et al.* [45]	89.80	88.90	90.74
Huang *et al.* [46]	94.12	--	--
Virupakshappa [47]	89.00	85.00	91.00
AlexNet	92.80	92.50	97.10
ResNet-18	93.30	93.20	97.10
Proposed Models AlexNet+SVM	94.60	94.75	98.00
ResNet-18+SVM	90.70	91.00	96.50

Conclusion
This study integrates deep learning methods with a machine learning technique to perform multi-class tumor identification, categorization, and explanation concurrently in a unified architecture. The automated categorization of initial-stage brain tumors is very important through deep learning methods. These systems enable timely diagnoses, improving patients' survival prospects. We conducted four series of experiments to diagnose various types of MRI images of brain tumors, such as meningioma, glioma, and pituitary tumors, in addition to a class containing healthy images. This work proposes a novel approach that combines the strengths of deep learning models (AlexNet and ResNet-18") with machine learning techniques (SVM) to achieve superior accuracy in the detection of brain tumors. To filter and enhance the images, both average and Laplacian filters have been applied, after which the filtered images were fed into the DL approaches for meaningful and distinctive feature extraction. To classify images, both CNN classifiers, such as SoftMax, and machine learning classifiers in the form of SVM algorithms, have been used, which enable diagnosing the images with high precision. Surprisingly, all the proposed models showed promising results in the diagnosis of brain tumor MRI images, with minimal differences between the accuracy of the approaches. Among those, the hybrid model that combined AlexNet and SVM presented the most exceptional performance. Considering some limitations regarding our study, since the CNN network was complex, with several layers, and since our computer setup did not feature a powerful GPU, the training procedure took a lot of time. This time would increase if the dataset were extensive, with more than one thousand images in each group of tumors. There is also room for further studies to develop the accuracy of brain cancer detection by including personalized data of patients gathered from various sources.

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