

## 2D Brain Tumor Classification Using CNN and SVM

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### Abstract

In the contemporary era, the doctor-to-patient ratio is notably insufficient. In the year 2020, an approximate 251,329 individuals globally succumbed to primary cancerous brain and central nervous system tumors. Analyzing the vast array of magnetic resonance imaging (MRI) images and manually identifying a brain tumor is an arduous and error-prone endeavor. Timely detection of tumors holds paramount significance in preserving a patient's life. However, this becomes a time-consuming process when dealing with extensive datasets. The visual resemblance between normal tissue and brain tumor cells complicates the segmentation of tumor regions, posing a formidable challenge. Consequently, there arises a crucial need for a highly accurate automatic tumor detection method.

In this study, we introduce a novel algorithm designed for the classification of brain tumors using 2D Magnetic Resonance Imaging (MRI) scans. Our approach involves the utilization of a convolutional neural network (CNN) in conjunction with a support vector machine (SVM). To ensure the robustness of our model, we curated a diverse dataset encompassing MRI images featuring varying tumor sizes, locations, shapes, and intensity levels. The classification process involves the application of the CNN model, followed by classification using the SVM classifier. The implementation of our proposed method is carried out using the "TensorFlow" and "Keras" libraries in the "Python" programming language, chosen for its efficiency in facilitating rapid and effective computational tasks.

During our research endeavors, the model achieved an impressive training accuracy of 99.55% and a commendable testing accuracy of 98.47%. These results surpass the previously achieved state-of-the-art outcomes in this field. Our system enables doctors to precisely identify brain tumors in MRI images, significantly reducing the time required for diagnosis. This, in turn, accelerates the treatment process, ensuring a faster response to medical needs.

**Keywords**— CNN, SVM, Medical Image, MRI, Deep learning, Machine learning

### Introduction

Medical imaging encompasses various non-invasive techniques aimed at visualizing the internal structures of the body for diagnostic and treatment purposes [1]. Its pivotal role in enhancing healthcare and facilitating accurate diagnoses cannot be overstated. Image segmentation, a fundamental step in image processing, holds particular importance as it significantly influences the success of subsequent processing stages [2]. In the context of medical image processing, the objective of image segmentation is often the detection of tumors, promoting efficient vision and achieving satisfactory outcomes for diagnostic procedures.

CAD systems leverage computational algorithms to assist healthcare professionals in interpreting medical images accurately. Enhancing the precision of these

systems is crucial for early and accurate diagnosis, ultimately contributing to improved patient outcomes.

According to available data [3], it is estimated that in 2020, approximately 308,102 peoples worldwide received a diagnosis of a primary brain or spinal cord tumor. In the year of 2023, it is expected that around 24,810 adults in the United States will be diagnosed with primary cancerous tumors affecting the brain and spinal cord. This estimate comprises 14,280 cases in men and 10,530 cases in women. The reported lifetime risk of developing such tumors stands at less than 1%.

A significant proportion of diagnosed cases involves brain tumors, constituting 85% to 90% of all primary tumors. In the United States, an estimated Under the age of 20, 5230 children are expected to be diagnosed with a CNS tumor in 2023. These statistics highlight the global and national

impact of primary brain and spinal cord tumors, underscoring the importance of ongoing research and medical advancements in addressing these health challenges.

Over the past few decades, there has been a transformative evolution in the field of diagnosing and characterizing brain tumors, thanks to notable progress in medical imaging techniques. An assortment of imaging modalities has surfaced, including Electroencephalography (EEG), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), Magnetic Resonance Imaging (MRI),

Ultrasonography, X-ray, Magnetoencephalography (MEG), Computed Tomography (CT). These modalities go beyond offering intricate and all-encompassing perspectives of brain tumors; they also play a pivotal role in ensuring precise diagnosis and guiding the formulation of appropriate treatment strategies [4].

Among these imaging techniques, Magnetic Resonance Imaging (MRI) stands out as most popular and widely utilized methods for detecting and characterizing brain tumors [5]. MRI offers exceptional resolution and contrast, allowing healthcare professionals to visualize the intricate details of brain structures and abnormalities. Its non-invasive nature, coupled with the absence of ionizing radiation, makes MRI a preferred choice for imaging the brain and its associated pathologies.

There are 3 basic types of tumours:[6].

- 1) Benign tumour: Benign tumours are non-cancerous growths of cells. It is typically slow-growing and Well-differentiated cells (resemble normal cells). Typically, these growths tend to remain localized and refrain from infiltrating nearby tissues or disseminating to distant body regions (metastasis). In most cases, they do not pose a serious threat to life. However, complications may arise if they exert pressure on essential structures or organs.
- 2) Pre-Malignant tumour: Pre-malignant tumours, also known as pre-cancerous tumours or lesions, are characterized by the presence of abnormal cells that have not yet developed into cancer but have the potential to do so. These cells may show certain changes that make them more likely to progress to a malignant (cancerous) state over time.
- 3) Malignant tumour: Malignant tumors are cancerous growths characterized by uncontrolled and abnormal cell proliferation. Malignant cells are often poorly differentiated or undifferentiated, meaning they do not resemble normal cells. The rapid cell division contributes to the aggressive nature of these cancers.

These effects are often a result of the body's response to the presence of cancer.

Detecting brain tumors early is beneficial for improving treatment options and increasing the chances of recovery. However, manually segmenting tumors or lesions from medical images, particularly the very high amount of MRI (Magnetic Resonance Imaging) images generated. For manually detection, this is a very time-consuming, challenging task. MRI is a widely used imaging modality for brain tumor detection.

The process of brain tumor detection and segmentation from MRI images is a difficult task in medical image processing, given the substantial amount of data involved. Additionally, brain tumors often have ill-defined boundaries with soft tissue, making the accurate detection of tumors from the brain a highly complex and extensive task.

Automated or computer-assisted methods for tumor segmentation in MRI images have been developed to alleviate the challenges associated with manual segmentation. These methods leverage advanced image processing, machine learning and deep learning techniques to assist in the accurate identification and delineation of tumor regions. Implementing such automated approaches for segmentation so they reduces the time and effort, but also enhances the precision of tumor delineation, contributing to more effective diagnosis and treatment planning.

## Literature Review

Classifying images is a highly challenging and demanding task that has captivated researchers worldwide. The pursuit of optimal training and testing accuracy in this field is relentless. Presently, there is a notable emphasis on utilizing Neural Network-based segmentation models, which have demonstrated remarkable outcomes. The adoption of these models is on the rise, with researchers continually refining and expanding their applications. The evolution of Neural Network-based segmentation represents a significant advancement in image classification, contributing to the development of increasingly sophisticated and effective approaches in this dynamic and evolving field.

Arkapravo Chattopadhyay et al.[7] proposed a methodology for binary classification of brain tumour. It used 128x128x3 as input image. It is used 9 layer CNN with Softmax activation function for classification. It used RMSprop optimizer for backpropagation and updating the weight. It used BRATS2020 dataset for training the model in this dataset total 2742 images. The training accuracy 99.74% and validation accuracy 93.78%. Training Accuracy of this

model is good. The problem of this model is validation accuracy is not good, gap between validation and training accuracy is high, complexity of this model is very high because it consumes 1 sec per step size, for model training it consumes 871 sec (14 min 31 sec).

Tonmoy Hossain et al. [8] proposed a methodology for binary classification of tumor. It used 64x64x3 as input image. It used 5 layer CNN with Sigmoid activation function for classification. It used Adam optimizer for backpropagation and it used binary cross-entropy as a loss function. It used BRATS dataset for training the model in this dataset total 217 images. The number of images are very low then it used data augmentation for creating more images. The training accuracy 98.47% and validation accuracy 97.87%. Testing Accuracy of this model is good and complexity also low but we require more accuracy and low complexity. In this paper they used very low size of dataset so it is not robust of all type of tumors images.

J. Seetha et al. [9] introduced a binary tumor classification methodology, leveraging a pre-trained model. Their approach focused on training only the final layer, resulting in a simplified model with low complexity. The feature extraction process was carried out using Convolutional Neural Networks (CNN), and a Gradient Descent-based loss function was employed. The BRATS (2015) dataset served as the foundation for training the model, achieving a training accuracy level of 97.5% and a testing accuracy level in a similar range. Despite the advantageous low complexity attributed to training only the final layer, the model's accuracy remained relatively modest. As a response to this, there is a recognized need for an enhanced model to achieve improved accuracy levels.

Shenbagarajan Anantharajan et al. [10] The EDN-SVM method was successfully implemented for image classification, establishing a direct link between all levels and promoting seamless data sharing among them. The effectiveness and viability of the proposed model were rigorously tested through extensive simulations. Notably, the model exhibited a high accuracy rate of 97.93% in correctly identifying tumor images. The EDN-SVM model seamlessly integrated the best features of support vector machines (SVM) and deep neural networks enhancing its overall performance in image classification.

Suraj Patil et al. [11] In this methodology, the weights from two distinctively crafted deep learning models is employed. Through this approach, achieving 97.77% prediction accuracy The model's accuracy is compared with various performance metrics such as sensitivity, recall, precision and specificity. The outcomes of this research underscore that leveraging features derived from a shallow Convolutional Neural Network

contributes valuable information about tumors, aiding in their location within the brain. Combining the surface-level features obtained from a Convolutional Neural Network (CNN) with the deeper features derived from a complex model such as VGG16 produces a blend of hybrid features.

## Proposed methodology

An advanced computational approach Convolutional Neural Network (CNN) is specifically crafted for the intricate tasks of processing and interpreting visual data, such as images and videos. CNNs have showcased remarkable prowess across a spectrum of machine vision applications, notably excelling in tasks like facial recognition and object detection, and image classification. They are inspired by the visual mechanism of the human brain and particularly well-suited for tasks where the spatial arrangement of features in the input data matters.

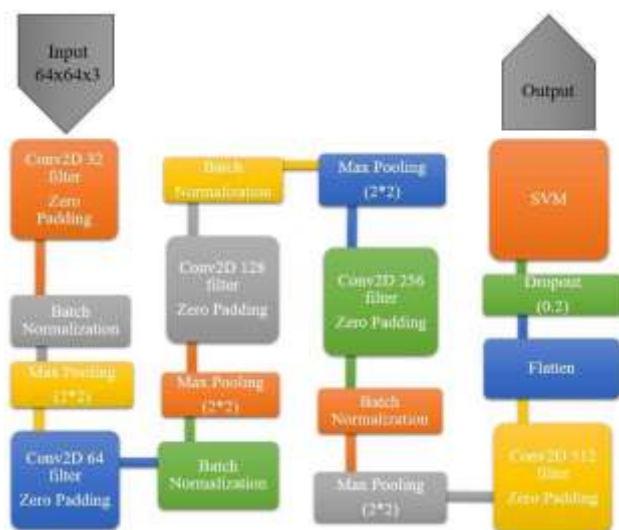
Convolutional Neural Networks (CNNs) have established themselves as a potent and extensively utilized tool. Researchers have dedicated significant efforts to crafting models that can bolster the effectiveness of tumor detection. Our specific focus revolves around the development of an exemplary model tailored to precisely classify tumors within 2D Brain MRI images, with a keen eye on minimizing complexity.

While a densely connected neural network possesses the capacity to identify tumors, we made a strategic choice in favor of a Convolutional Neural Network (CNN) in our model. This decision was driven by the advantages conferred by parameter sharing and the exploitation of connection sparsity. What sets our work apart is the transformation of the foundational CNN model; we introduce a substantially improved iteration that not only demonstrates superior performance but also incorporates advanced capabilities.

Our contribution takes the form of a 16-Layer Convolutional Neural Network (CNN) designed explicitly for tumor detection. Figure 1 visually encapsulates the projected methodology, complemented by a concise narrative that provides insight into our innovative approach.

In our innovative approach, we begin by taking a diverse set of tumor images as input. These images are then standardized by resizing them all to a consistent dimension of 64\*64\*3, ensuring uniformity in their

sizes. To analyze these images, we use convolves the input layer with convolutional kernel that, utilizing



thirty two (32) 3x3 convolutional filters for each channel tensor. The activation function Rectified Linear Unit (ReLU) is employed. The Rectified Linear Unit (ReLU) is a function characterized by a linear output for positive inputs, directly reflecting the input values. However, for negative inputs, the function outputs zero. To preserve the correspondence between the input and output, zero padding is integrated. Furthermore, we introduce batch normalization, a technique proposed by Sergey Ioffe et al. in 2015 [12].

Batch normalization, often denoted as batch norm [13], accelerates The neural networks undergo training, thereby augmenting their stability by normalizing inputs at each layer through re-centering and rescaling. Utilizing this technique contributed to the increased speed of our algorithm.

Following that, the pooling operation entails traversing a 2D filter through every channel of the feature map, merging the features within the region covered by the filter. The resultant output dimensions after applying a pooling layer to a feature map with dimensions  $nh \times nw \times nc$  is

$(nw + 1 - f) / s \times (nh + 1 - f) / s \times nc$  where,

“nh - height of feature map” “nw - width of feature map”

“nc - no. of channels in the feature map” “f - size of filter”

“s - stride length”

A typical configuration for a CNN model involves stacking numerous convolutional and pooling layers sequentially. In convolutional neural networks (CNNs), pooling layers play a vital role by downsampling The dimensional aspects of feature maps generated by convolutional layers in terms of spatial propertie. These pooling layers serve a key function in diminishing the computational intricacies of the network and enhancing its resilience to input variations, all the while preserving the essential features. Max-pooling stands out as the most prevalent form of pooling employed in this context.

In this context, a 2x2 Max pooling operation [14] has been applied, which involves identifying the max element within the filter's across the feature map. Consequently, After the maxpooling layer, a condensed feature map is generated, capturing crucial information from the preceding layer. Refer to Fig. 3 for visualization.

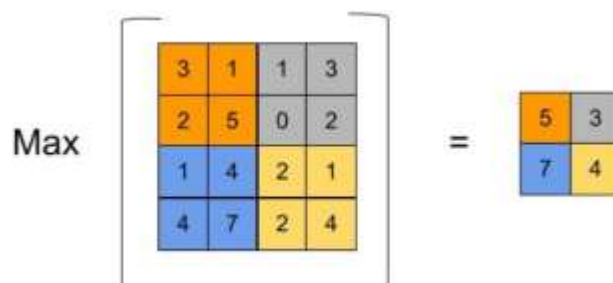


Fig 3. Max pooling

After that, agian we applied a series of convolutional operations, starting with 64 filters and incorporating zero padding, batch normalization, and max-pooling. Following this, we repeated the process with 128, 256, and 512 filters, respectively, before proceeding to flatten the resulting feature maps in the Convolutional Neural Network (CNN), we used Dropout layer to prevent overfitting. Dropout is a simple but effective method for reducing overfitting in neural networks. After that we used SVM for binary classification. we employed the "hinge" as our chosen loss function, complemented by RMSProp as the optimizer. RMSProp, an Adaptive Gradient Algorithm known as Root Mean Squared Propagation, refines gradient descent principles by adjusting step sizes for individual parameters through a decaying average of partial gradients. It offers enhanced adaptability in optimization. The operational workflow of our proposed CNN model is illustrated in Figure 4, while Figure 5 provides a visual representation of the architecture we have devised for our model.

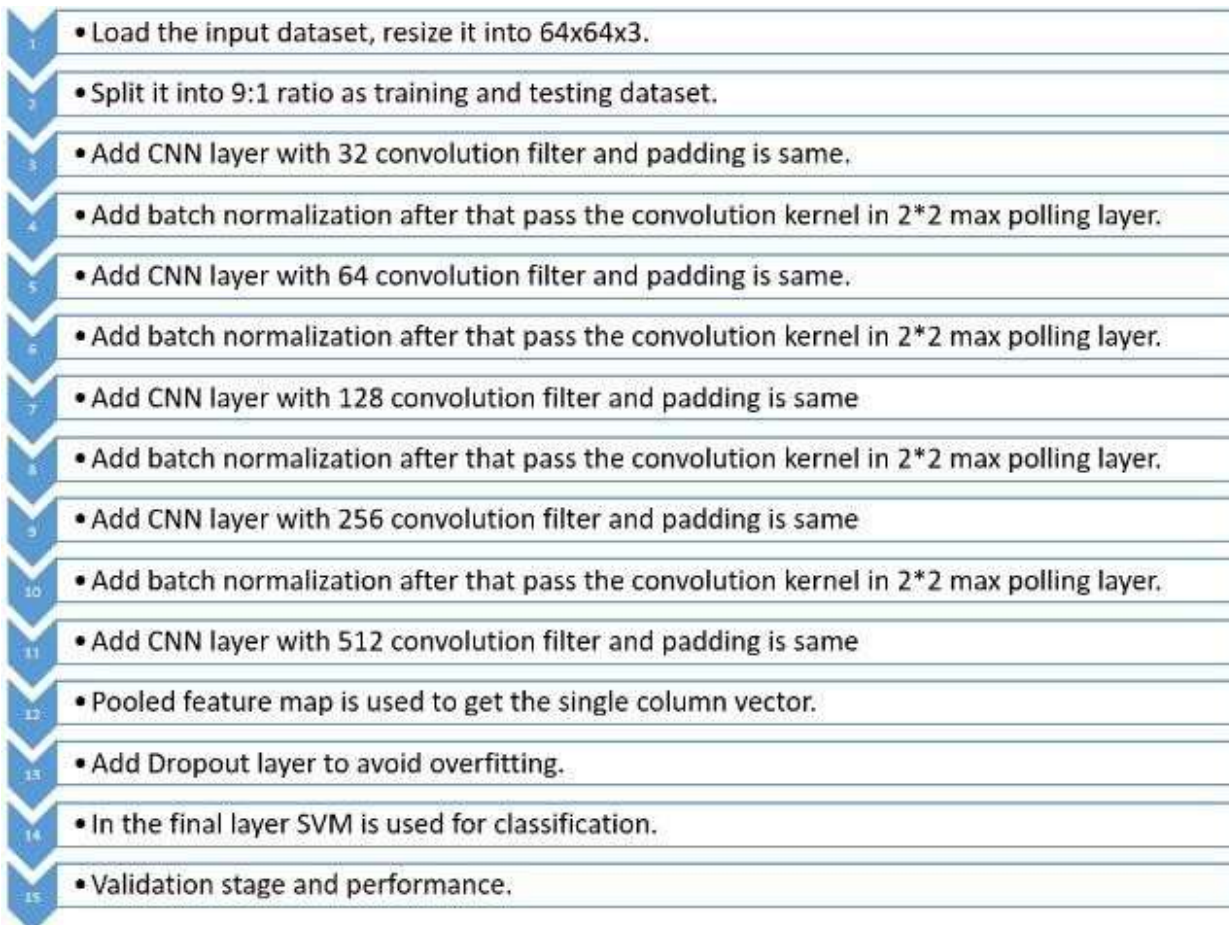


Fig 4. operational sequence of our proposed Convolutional Neural Network (CNN) model

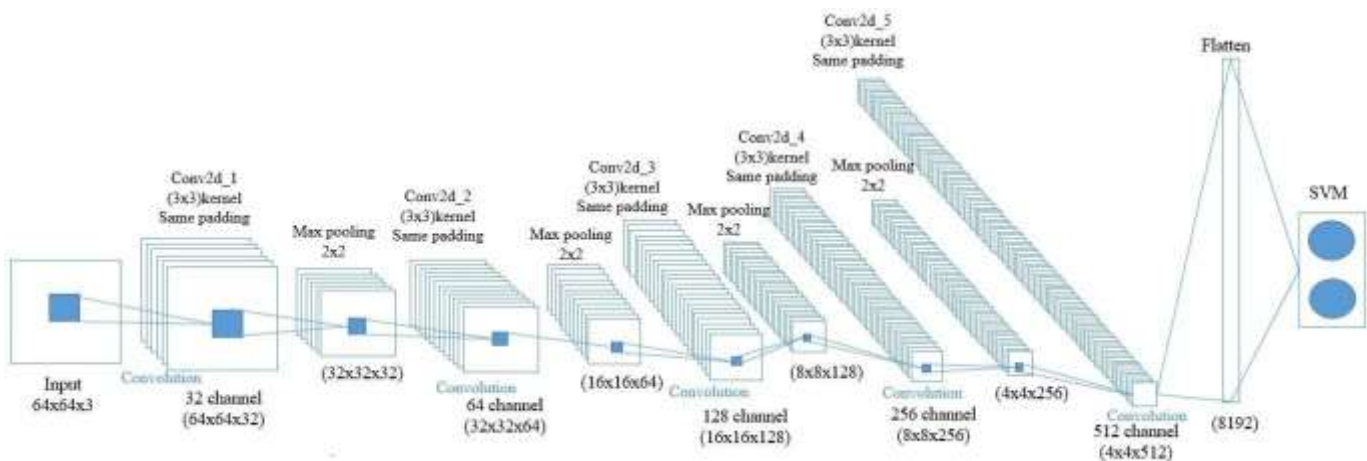


Fig 5. Architecture of our proposed model

## Result and discussion

### Experimental Dataset

We used Brain Tumour Classification (MRI) Dataset [15]. It consists of 3264 images. The Training and Testing folders contain categorized images, each classified into one of four subfolders. Within these subfolders, you will find MRIs depicting Glioma tumors, Meningioma tumors, No tumors, and Pituitary tumors.

### Experimental Result

To performing the operation, we used Jupiter notebook. About Laptop Specification we used Hp pavilion Ryzen 5, 8 Gb RAM 512 Gb SSD. We tried various experiments and analysed the problems, after changes of different parameter in the model we finally came to our proposed methodology. We got 99.40% of training accuracy and 98.46% of testing accuracy. The comparison of our proposed methodologies with other three model is given in the below table, and we have even compared it with other proposed methodologies in different research papers we went through during our research at the end of our result section.

We will now discuss each experiment in chronological order and all the problem that occurred in each experiment following the result of our experiment below-

Table 1

#### A. CNN using SVM classifier and ADAM optimizer

Improved model using Adam optimizer for backpropagation and weight updating.

Attained a training accuracy level of 99.51%, accompanied by a validation accuracy rate of 97.62%, and a testing accuracy score reaching 97.55%.

Aimed to address overfitting.

#### B. CNN using SVM classifier and RMSProp optimizer

Continued optimization with RMSProp optimizer.

Achieved a training accuracy level of 99.55%, with validation and testing accuracies reaching 97.28% and 97.30%, respectively.

#### C. CNN using SVM classifier and RMSProp optimizer using Zero padding

We Further adjustments included the addition of zero padding to prevent image size reduction.

Achieved training accuracy level of 99.55 with validation and testing accuracies reaching 98.30% and 98.47%, respectively. It used RMSProp optimizer for backpropagation.

Trained on 2937 images with 327 images for testing with 20 epoch.

Performance comparison of all the models we tried during our research

| S.L. no | Final Layer | Optimizer | Training Accuracy | Testing Accuracy | problems             |
|---------|-------------|-----------|-------------------|------------------|----------------------|
| 01      | SVM         | ADAM      | 99.51%            | 97.55%           | Low testing accuracy |
| 02      | SVM         | RMSProp   | 99.55%            | 97.30%           | Low testing accuracy |
| 03      | SVM         | RMSProp   | 99.55%            | 98.47%           | -----                |

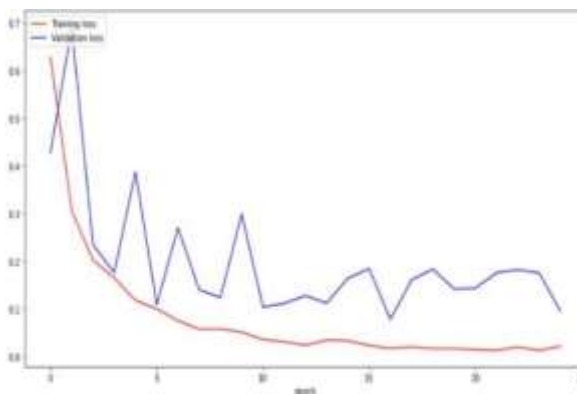
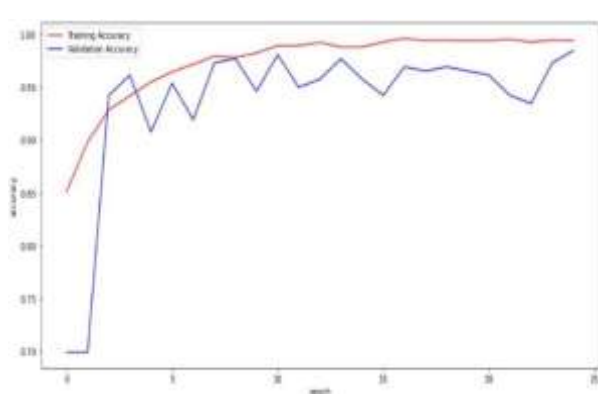


Fig 6. Accuracy in Training and Validation

Fig 7. Loss in Training and Validation

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Epoch 1/20
83/83 [=====] - 25s 285ms/step - loss: 0.8106 - accuracy: 0.8441 - val_loss: 0.6713 - val_accuracy: 0.4966
Epoch 2/20
83/83 [=====] - 24s 289ms/step - loss: 0.2614 - accuracy: 0.9809 - val_loss: 1.8568 - val_accuracy: 0.3435
Epoch 3/20
83/83 [=====] - 25s 299ms/step - loss: 0.1857 - accuracy: 0.9296 - val_loss: 0.3133 - val_accuracy: 0.7959
Epoch 4/20
83/83 [=====] - 23s 283ms/step - loss: 0.1366 - accuracy: 0.9508 - val_loss: 0.1350 - val_accuracy: 0.9286
Epoch 5/20
83/83 [=====] - 23s 275ms/step - loss: 0.0894 - accuracy: 0.9663 - val_loss: 0.2457 - val_accuracy: 0.8776
Epoch 6/20
83/83 [=====] - 25s 302ms/step - loss: 0.0687 - accuracy: 0.9747 - val_loss: 0.1286 - val_accuracy: 0.9422
Epoch 7/20
83/83 [=====] - 25s 298ms/step - loss: 0.0521 - accuracy: 0.9830 - val_loss: 0.1899 - val_accuracy: 0.9660
Epoch 8/20
83/83 [=====] - 25s 306ms/step - loss: 0.0450 - accuracy: 0.9845 - val_loss: 0.0705 - val_accuracy: 0.9864
Epoch 9/20
83/83 [=====] - 25s 297ms/step - loss: 0.0357 - accuracy: 0.9871 - val_loss: 0.0724 - val_accuracy: 0.9796
Epoch 10/20
83/83 [=====] - 24s 295ms/step - loss: 0.0377 - accuracy: 0.9875 - val_loss: 0.1465 - val_accuracy: 0.9762
Epoch 11/20
83/83 [=====] - 25s 301ms/step - loss: 0.0298 - accuracy: 0.9913 - val_loss: 0.0739 - val_accuracy: 0.9694
Epoch 12/20
83/83 [=====] - 25s 302ms/step - loss: 0.0210 - accuracy: 0.9920 - val_loss: 0.1114 - val_accuracy: 0.9728
Epoch 13/20
83/83 [=====] - 25s 296ms/step - loss: 0.0268 - accuracy: 0.9924 - val_loss: 0.1108 - val_accuracy: 0.9728
Epoch 14/20
83/83 [=====] - 25s 296ms/step - loss: 0.0197 - accuracy: 0.9928 - val_loss: 0.0873 - val_accuracy: 0.9762
Epoch 15/20
83/83 [=====] - 24s 283ms/step - loss: 0.0177 - accuracy: 0.9947 - val_loss: 0.1152 - val_accuracy: 0.9694
Epoch 16/20
83/83 [=====] - 23s 276ms/step - loss: 0.0175 - accuracy: 0.9951 - val_loss: 0.0848 - val_accuracy: 0.9796
Epoch 17/20
83/83 [=====] - 23s 273ms/step - loss: 0.0148 - accuracy: 0.9951 - val_loss: 0.0726 - val_accuracy: 0.9864
Epoch 18/20
83/83 [=====] - 22s 271ms/step - loss: 0.0114 - accuracy: 0.9962 - val_loss: 0.0527 - val_accuracy: 0.9864
Epoch 19/20
83/83 [=====] - 23s 274ms/step - loss: 0.0199 - accuracy: 0.9932 - val_loss: 0.0569 - val_accuracy: 0.9762
Epoch 20/20
83/83 [=====] - 23s 273ms/step - loss: 0.0137 - accuracy: 0.9955 - val_loss: 0.0586 - val_accuracy: 0.9830
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Fig 8. The end result achieved through our proposed method

Table 2.

Evaluating the performance across various research papers.

| Author                   | Training Accuracy | Testing Accuracy |
|--------------------------|-------------------|------------------|
| Seetha et al.[7]         | 97.50%            | ----             |
| Tonmoy Hossain et al.[8] | 98.47%            | 97.87%           |

|                                       |        |        |
|---------------------------------------|--------|--------|
| Arkapravo Chattopadhyay et al.[9]     | 99.74% | 93.78% |
| Shenbagarajan Anantharajan et al.[10] | 97.93% | ---    |
| Suraj Patil et al. [11]               | 97.77% | ---    |
| Our proposed Model                    | 99.40% | 98.46% |

In the presented model, impressive accuracy metrics were achieved during training, validation, and testing phases.

Specifically, the model demonstrated a remarkable 99.40% accuracy on the training dataset, an accuracy in validation of 98.30%, and a testing accuracy of 98.46%.

These results surpass the state-of-the-art outcomes reported by Arkapravo Chattopadhyay et al. [7], Seetha et al. [8], and Tonmoy Hossain et al. [9], Shenbagarajan Anantharajan et al. [10], Suraj Patil et al. [11] as outlined in Table 3. This high level of accuracy indicates the effectiveness of the proposed model in its classification task, potentially outperforming existing approaches in the field.

## Conclusion

The main objective is to devise a highly efficient and selfoperating brain tumor classification system characterized by elevated training and testing accuracy, a robust resistance to overfitting, and low computational complexity. Our model has successfully met all of these conditions. In our approach, Convolutional Neural Networks (CNNs) are employed for feature extraction, while Support Vector Machines (SVMs) are utilized for the classification task. By combining MRI and CT scan images, our model gains increased resilience. CNNs, specifically, excel in independently acquiring complex features from multimodal MRI images, capturing details from both normal brain tissues and tumor tissues for a comprehensive analysis. This methodology aims to contribute to the advancement of accurate and efficient brain tumor classification systems, ensuring optimal performance across various metrics.

In our work, first we use CNN for feature extraction then we use SVM for classification in this model we are not using optimizer so the weights are not updated. Here we got the training accuracy 100% and testing accuracy 95.11%. The problem of this model is overfitting. Further for better result and remove the problem we use Adam optimizer for back propagation and updating the weight. Here we got the output training accuracy to 99.51%, validation accuracy 97.62 and testing accuracy 97.55. Further for better result we use RMSProp optimizer and we got the output training accuracy to 99.55%, validation accuracy 97.28 and testing accuracy 97.30.

We required more accuracy so we further change some parameter, in previous model we are not using any padding so by apply convolution filter image size is reduced, in the previous model we used 32,64,128,256 convolution filter. In the final model we used 32, 64, 128, 256 and 512 convolution filter and all of the convolution filter we used zero padding then image size is not reduced. We employed the RMSProp optimizer for

backpropagation, achieving significant success in training our model. With a dataset consisting of 2937 images for training and 327 images for testing, and employing a 20-epoch training procedure with a runtime of 285

milliseconds per step, we attained impressive results. Our model demonstrated exceptional performance with a accuracy in training is 99.55%, accuracy in validation is 98.30%, and accuracy in testing is 98.47%.

Looking ahead, our future endeavors involve transitioning to 3D brain images, aiming to enhance the efficiency of brain tumor classification and segmentation. We aim to go beyond merely detecting tumors, striving to precisely outline their boundaries and forecast their dimensions for enhanced accuracy. Undoubtedly, delving into this ambitious endeavor will enhance our grasp of brain pathologies and elevate diagnostic capacities within the realm of medical imaging.

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