Efficient Brain Tumor Classification with a Hybrid CNN-SVM Approach in MRI

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***Abstract*—Brain Magnetic Resonance Imaging (MRI) is a crucial diagnostic tool in neuroimaging that provides valuable insights into various neurological disorders. Accurate classification of brain MRI images is vital in aiding medical professionals in diagnosis and treatment planning. The multiclass classification of brain MRI images has significant implications in clinical practice. Accurate classification can aid in detecting and characterizing various brain abnormalities, including tumors, haemorrhages, and neurological disorders. Our suggested strategy can help doctors make prompt and accurate diagnoses by automating the classification process and improving patient care and results. This study uses the two standard datasets, Brats and Sartaj, to propose a thorough method for multiclass classification of brain MRI utilizing Convolutional Neural Network (CNN), VGG19, and the Convolutional Neural Network-Support Vector Machines (CNN-SVM) algorithm. The proposed approach leverages the power of deep learning for feature extraction and the versatility of Support Vector Machines (SVM) for classification. Firstly, the CNN model is trained to extract discriminative features from brain MRI images. The VGG19 architecture, a widely used pre-trained CNN, is employed as a feature extractor. By utilizing the pre-trained weights of VGG19, the model can effectively capture high-level representations of the input images. The results demonstrate the efficacy of this method in accurately classifying brain MRI images. Further research can explore the application of this approach in larger datasets and investigate other deep learning architectures for feature extraction, providing further advancements in medical image analysis and diagnosis.**

***Keywords*—brain tumor, Magnetic Resonance Imaging (MRL), Convolutional Neural Network-Support Vector Machines (CNN-SVM) algorithm, Convolutional Neural Networks (CNNs), VGG19 architecture**

I. INTRODUCTION

Brain tumors are one of the most complex medical disorders to treat, impacting millions worldwide [1]. The diagnosis of brain tumor at an early stage and their correct categorization are necessary for developing successful treatment plans and improving patient outcomes. In recent years, significant progress has been made in developing automated brain tumor detection and classification methods, particularly in the multiclass scenario. Multiclass brain tumor detection refers to accurately identifying and distinguishing between different types of brain tumors, including gliomas, meningiomas, pituitary adenomas, and others. This classification is crucial as different tumor types require specific treatment approaches and have varying prognoses.

The examination of brain tumor has undergone a sea change due to the introduction of cutting-edge medical imaging technology like Magnetic Resonance Imaging (MRI) [2]. These imaging modalities generate high-resolution and detailed images that can be leveraged for accurate detection and classification. However, analyzing brain tumor images poses significant challenges due to the complexity of tumor characteristics, tumor appearance variability, and various anatomical structures. This exhaustive study provides an in-depth examination of the current state-of-the-art techniques and methodology used in detecting and classifying multiclass brain tumor by providing an overview of such techniques and processes. It encompasses a range of elements, such as dataset attributes, preprocessing procedures, techniques for extracting features, classification algorithms, and metrics for assessment [3].

Comprehending the attributes of existing data sets is essential when training and assessing models. Furthermore, preprocessing methods like image noise reduction, standardization, and partitioning cannot be overstated, as they significantly contribute to improving the quality of brain tumor images and extracting pertinent data [4]. Feature extraction methods, including traditional handcrafted features and deep learning-based approaches, extract discriminative features from the images to aid in accurate classification. Classification algorithms, ranging from traditional machine learning techniques to deep learning architectures, classify brain tumors. These algorithms utilize the extracted features to differentiate between different tumor types. The performance of brain

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tumor detection and classification systems relies significantly on the assessment criteria they employ. Commonly utilized metrics such as the Area under the Curve (AUC) and measures like accuracy, sensitivity, and specificity are often employed to assess the effectiveness of these systems [5].

The proposed approach combines Support Vector Machines (SVM) for categorization with deep learning to extract features. Initially, a Convolutional Neural Network (CNN) is trained to extract distinctive characteristics from brain MRI pictures. To perform this feature extraction, the established VGG19 CNN architecture, which is widely recognized, is employed. Leveraging the pre-trained parameters of VGG19 allows the model to capture the input images' higher-level features adeptly.

Traditional methods of brain MRI classification often rely on manual feature extraction and handcrafted feature engineering techniques. However, these approaches have certain limitations regarding their capacity to capture the intricate patterns and minor variances that may be seen in brain imaging. The application of Convolutional Neural Networks (CNNs) for classifying brain MRI images has demonstrated promising outcomes, especially given the recent advancements in deep learning and the extensive utilization of CNNs for addressing challenges in computer vision [6].

CNNs have shown excellent performance in image classification tasks, autonomously learning hierarchical features from the raw input data. CNNs have also been used in other applications. They can effectively capture local patterns and global contextual information in an image, making them well-suited for analyzing complex medical images such as brain MRI. Moreover, pre-trained CNN models, such as VGG19, have been trained on large-scale image datasets and can be utilized as powerful feature extractors for transfer learning in medical imaging tasks [7].

Besides Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) have gained significant popularity in addressing classification problems thanks to their ability to handle complex feature spaces with high dimensions and perform well in multiclass classification tasks. Support Vector Machines (SVMs) aim to locate an ideal hyperplane in the feature space that can maximally separate the various classes. By merging the feature extraction capabilities of CNNs with the classification prowess of SVMs, we can achieve precise and resilient brain MRI classification, leveraging the advantages of both methods. This will allow us to take advantage of the strengths of both approaches. This research uses a CNN, VGG19, and the CNN-SVM algorithm to offer a technique for multiclass categorization of brain MRI images.

The contributions of this study include:

- Presenting an innovative approach for the multiclass categorization of brain MRI pictures involving the utilization of CNN, VGG19, and the CNN-SVM technique.
- Illustrating the efficacy of utilizing pre-trained CNN models, particularly VGG19, to extract features for the classification of brain MRI scans.
- Evaluating the proposed method's performance on a brain MRI image dataset and comparing it with traditional classification approaches.
- Providing insights into the potential applications and benefits of automated brain MRI classification in clinical practice, including improved diagnosis and treatment planning.

The rest of the paper follows this organization: Section II reviews pertinent research on brain MRI classification using both deep learning and traditional methods. Section III elaborates on the deep learning architectures, including the CNN model, VGG19, and the CNN-SVM algorithm. Section IV outlines the proposed approach. Section V presents the results and their analysis. Lastly, Section VI concludes the paper with future directions.

II. Literature Survey

Aggarwal *et al*. [8] have introduced a practical approach for brain tumor segmentation using an Enhanced Residual Network. This method addresses the inherent gradient issue in deep neural networks, specifically ResNet. Two potential improvements can be implemented to enhance the existing ResNet. One is to maintain the specific characteristics of all available connection links, and the other is to improve the projection shortcuts. These particulars are then passed on to the following phases, which is how enhanced ResNet can reach greater precision and accelerate the learning process. The upgraded version of ResNet that has been offered addresses all three of the most critical aspects of the current version of ResNet. These characteristics encompass the transmission of information through network layers, the residual building block, and the projection shortcut. This methodology minimizes computational time and effort, resulting in an accelerated process.

Malla *et al*. [9] have undertaken a study to categorize different types of brain cancers, including meningioma, glioma, and pituitary tumor. Their research employs a pre-trained Deep Convolutional Neural Network (DCNN) architecture known as VGG16, utilizing transfer learning. This approach effectively overcomes a limitation in training DCNN architectures associated with data samples and yields more precise classification results. The suggested framework addresses overfitting and vanishing gradients by incorporating a Global Average Pooling (GAP) layer at the output stage. On the Figshare dataset, this method achieves an impressive classification accuracy of 98.93%, surpassing state-of-the-art learning-based techniques. These findings hold promise for aiding medical professionals in making more precise diagnoses of brain tumor types. As a result, it may lessen the number of diagnostic errors that occur. Even though the transfer learning-based DCNN framework that was suggested has demonstrated remarkable outcomes, there is still a need for specific enhancements. In the future, a more extensive dataset may be utilized for instructional reasons. In addition, it is possible to solve the problems with feature dimensionality that crop up while transferring weights and parameters.

Krishnapriya *et al.* [10] conducted research to explore the effectiveness of pre-trained Deep Convolutional Neural Network (DCNN) models, including VGG19, VGG16, ResNet50, and Inception V3, for categorizing brain MR images. Their study assessed vital performance metrics, including accuracy, recall, precision, and F1-score, revealing that the pre-trained VGG19 model, utilizing transfer learning, displayed the most impressive overall performance. Furthermore, these algorithms facilitated the end-to-end categorization of raw images without requiring manual feature extraction. The research involved classifying 305 brain MRI images, differentiating between those with and without malignancies. Raw MR images underwent preprocessing to streamline the training process, involving brain tissue boundary determination, cropping, and scaling. Data augmentation techniques were employed to balance class distribution in the dataset. Evaluation of the classification process using four different models revealed that the VGG19 model achieved the highest success, boasting an accuracy score of 99.48%, recall of 98.76%, precision of 100%, and F1-score of 99.17%. The VGG16 model followed closely with an accuracy score of 99%, recall of 98.18%, precision of 100%, and F1-score of 99.08%. Meanwhile, the ResNet50 and Inception V3 models demonstrated 97.92% and 81.25% accuracy, respectively.

Sarkar *et al*. [11] have introduced a novel and efficient technique for categorizing brain tumors in MRI scans. Their method utilizes the AlexNet Convolutional Neural Network (CNN) to split the dataset into training and test sets and to extract features. The primary goal of this approach is to identify different types of brain tumors within MRI images, namely, no tumor, glioma, meningioma, or pituitary tumor. To achieve this, they employ four different classifiers: BayesNet, Sequential Minimal Optimization (SMO), Naive Bayes (NB), and Random Forest (RF). Among these classifiers, BayesNet exhibits the highest accuracy. To evaluate the performance of their method, the researchers employed a publicly available Kaggle dataset. They present the classification results using various assessment metrics, including ROC curves, Precision-Recall Curves (PRC), and cost curves. These metrics include accuracy, sensitivity, specificity, false positive rate, false negative rate, precision, F-measure, kappa statistics, Matthews Correlation Coefficient (MCC), ROC area, and PRC area.

Kulkarni *et al.* [12] present a way to identify brain tumors and a categorization system for them. Diagnosing a brain tumor begins with preprocessing, then moves on to skull stripping, and finally, tumor segmentation. It utilizes a thresholding approach and then proceeds to carry out morphological procedures. The amount of training images affects the features the CNN retrieves; nonetheless, CNN models become overfit beyond a particular epoch. As a result, a deep learning CNN that utilizes transfer learning techniques has been developed. The CNN-based AlexNet architecture is used to classify the tumorous MRI of the patient's brain. In addition, the malignant brain tumor is categorized with the help of the GooLeNet transfer learning architecture. Precision, recall, F-measure, and accuracy evaluate this technique's success. It is advised that tumorous MRIs be categorized as benign or malignant and that meningioma or glioma be assigned to malignant brain MRIs. The process of detecting brain tumors involves several stages. Initially, preprocessing techniques are employed to prepare the data. Subsequently, the removal of the skull is performed, followed by the segmentation of the brain tumor. This segmentation technique effectively separates the tumor from the MRI images. Next, utilizing transfer learning algorithms based on the Convolutional Neural Network (CNN) architecture, specifically the AlexNet model, the tumor images are categorized into benign and malignant groups. This approach's results show an accuracy of 0.9375, a recall of 1, and an F-measure of 0.9677. Additionally, the malignant MRI images are further classified into glioma and meningioma by employing the same CNN-based transfer learning system, specifically utilizing the GoogleNet model. The performance metrics for the GoogleNet model include an accuracy of 0.9750, a precision of 0.95, a recall of 1, and an F-measure of 0.9743.

Sowrirajan *et al.* [13] used deep learning models to interpret Magnetic Resonance Imaging (MRI) data, which is currently the approach to early cancer diagnosis with the highest prevalence and accuracy. In this context, a distinctive hybrid model (NADE) is created by merging the Neural Autoregressive Distribution Estimation (NADE) with the VGG16 Convolutional Neural Network (CNN). 3,064 MRI scans of brain tumor were used in the investigation, and they were split into three groups. A hybrid VGG16-NADE model was utilized to categorize the T1-weighted contrast-enhanced MRI images, and this classification was then contrasted with alternative methods. Based on the results, the hybrid model, VGG16-NADE, outperforms other models across various metrics such as classification accuracy, specificity, sensitivity, and the F1-score. The proposed VGG16-NADE hybrid achieves a prediction accuracy of 96.01%, precision of 95.72%, recall of 95.64%, F-measure of 95.68%, Receiver Operating Characteristic (ROC) score of 0.91, an error rate of 0.075, and a Matthews Correlation Coefficient (MCC) of 0.3564. Additionally, the hybrid model demonstrates an overall accuracy of 95.68%.

Khairandish *et al.* [14] explained how brain tumors behave. With the aid of many methodologies and the analysis of research studies using various criteria, it offers a clear image of this stage. The examination is conducted with the dataset, proposed model, proposed model performance, and type of method used in each paper. Between 79% and 97.7% of the publications under study had accurate results. They employed Convolutional Neural Network, K-Nearest Neighbour, K-Means, and Random Forest algorithms in that sequence (highest frequency of use to lowest). Here, the CNN-SVM gave highest accuracy of 98.4959%.

Someswararao *et al*. [15] introduced an innovative approach for identifying tumors in MR images by employing machine learning methods, specifically the CNN model. Their research encompassed two key aspects: firstly, a CNN model was applied to address the classification task of identifying the presence of a brain tumor in an individual, and secondly, a computer vision challenge was tackled to extract the brain region from MRI scans automatically. The primary objective of this investigation was to ascertain the existence of a brain tumor in patients. The study also employed Convolutional Neural Networks and K-means clustering as additional techniques. The Convolutional Neural Network achieved the highest accuracy, reaching approximately 90%.

Choudhury *et al*. [16] suggested a new CNN-based method that can differentiate between various MRIs of the brain and categorize them as having or not having tumor. The F-score of the model was 97.3%, while the model's accuracy was 96.08%. To generate results in 35 epochs, the model employs a CNN consisting of three layers and takes just a few preprocessing steps. The importance of predictive therapeutic and diagnostic machine-learning applications is emphasized in this work. Support Vector Machine, Convolutional Neural Network, k-nearest Neighbor, Boosted trees, Random Forest, and Decision Trees were other methods utilized. The suggested approaches will be efficient and accurate in detecting, categorizing, and segmenting brain tumor. Automatic or semi-automatic precision

In Ref. [17], this study identifies the MRI images with the help of a Recurrent Neural Network (RNN). The BP NN activation function was first used to scale up and down the network's nodes. The number of nodes in the hidden layer was set to 270 and then brought back down to 230 using the log sigmoid function. Finally, we have reached the optimal performance for RNN thanks to a bump in the node count to 300. For optimal efficiency, we use an Elman network. When the number of nodes increases, so does the amount of performance mistakes. When used in the recognition process, Elman networks were shown to be quick and accurate compared to other ANN systems. When compared to Elman's 88.14%, our ratio was 76.47%.

Table I provides an overview of the findings from the literature review.

TABLE I. SUMMARY OF LITERATURE SURVEY

Authors	Methodology	Results	Research Gap
Aggarwal *et al.* [8]	Improved Residual Network for brain tumor segmentation, addressing gradient issues in DNN (ResNet).	Accuracy = 0.854%	Require more complex architectures to enhance the overall efficiency of segmentation results.
Malla *et al.* [9]	VGG16-based transfer learning for classifying meningioma, glioma, and pituitary brain tumors.	Accuracy with Data pre-processing = 98.93% Accuracy with Data pre-processing = 97.82%	The problems related to feature dimensionality that emerge during the transfer of weights and parameters can be effectively dealt with.
Krishnapriya *et al.* [10]	Evaluation of pre-trained DCNN models (VGG19, VGG16, ResNet50, Inception V3) for brain MR image categorization.	VGG19 with Transfer Learning = 99.48% VGG16 with Transfer Learning = 99% ResNet50 with Transfer Learning = 97.92% Inception V3 with Transfer Learning = 81.25%	The challenges related to feature dimensionality encountered when transferring weights and parameters can be effectively dealt with.
Sarkar *et al*. [11]	Utilizing AlexNet CNN for brain tumor classification with classifiers (BayesNet, SMO, Naive Bayes, Random Forest).	AlexNet CNN+BayesNet = 88.75% AlexNet CNN+SMO = 98.15% AlexNet CNN+NB = 86.25% AlexNet CNN+RF = 100%	The suggested model underwent assessment using a dataset of moderate size, representing a limitation in the present study. Therefore, it is crucial to conduct future evaluations of the model using larger datasets to assess its performance more comprehensively.
Kulkarni *et al.* [12]	CNN-based AlexNet and GoogleNet for categorizing benign/malignant tumors and distinguishing meningioma/glioma.	AlexNet = 90.47% VGG16 = 66.67% ResNet18 = 85% ResNet50 = 85% GoogLeNet = 97.50%	Deep neural networks, specifically CNNs, are not commonly employed in the context of boundary detection challenges. Consequently, they hold potential as a forthcoming avenue for addressing brain tumor segmentation and detection issues.
Sowrirajan *et al.* [13]	Combination of Neural Autoregressive Distribution Estimation (NADE) and VGG16 CNN for MRI-based brain tumor classification.	MRI Brain Tumor Classification Using a Hybrid VGG16-NADE Model = 96.01%	VGG16's capacity to train the dataset is hampered by its sluggish training process, primarily stemming from the extensive storage and bandwidth requirements associated with the input size, rendering it ineffective.
Khairandish *et al.* [14]	Comprehensive analysis of brain tumor detection methodologies using Convolutional Neural Networks and other algorithms.	hybrid CNN-SVM = 98.495%	To improve decision-making, use a faster CNN with SVM and optimization techniques like bio-inspired algorithms. Also, consider tumor size and precise location when detecting tumors.
Someswararao *et al.* [15]	Novel CNN-based method for detecting brain tumors in MR images.	The accuracy of testing data is 100% on 31 images.	This method could be increased by more train images or model hyperparameter tuning.
Choudhury *et al.* [16]	CNN-based approach for differentiating MRI images of brain tumors.	Accuracy of 96.08%, with an f-score of 97.3%	The accuracy could be increased by more train images or through model hyperparameter tuning.

III. Deep Learning Algorithms

In the proposed approach, three distinguished deep learning algorithms are used. This section presents a detailed explanation of CNN, VGG19 and hybrid SVM-CNN architectures.

A. CNN

CNNs are a specific neural network with exceptional performance in various image processing and classification tasks. CNN is a multi-layered feed-forward neural network. CNNs are built using programmable weights, parameters, and biases for their filters, kernels, or neurons, which make up the CNN. Every filter receives specific inputs, conducts convolution, and may or may not perform non-linearity. Convolutional layers, Rectified Linear Unit (ReLU), Fully Connected, Pooling, and makeup CNN's structure [17].

The architecture of the CNN algorithm is shown in Fig. 1.

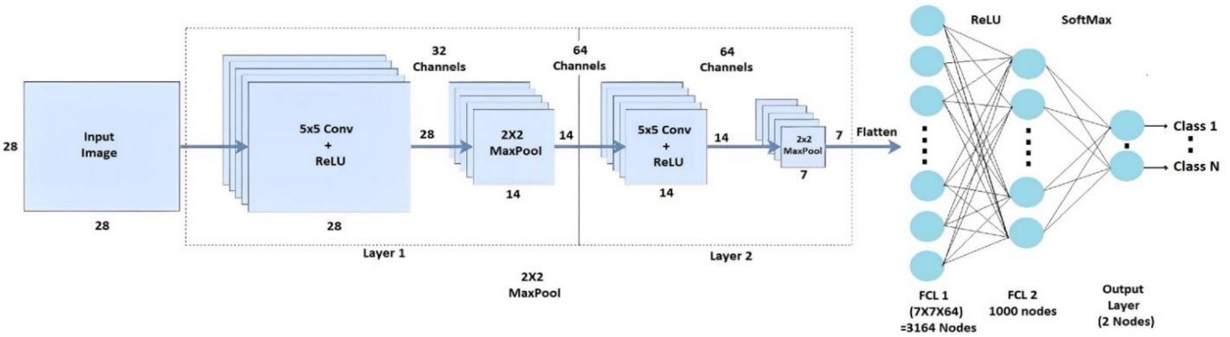


Fig. 1. Architecture of CNN.

Each block of CNN architecture is explained below.

- Convolutional Layers: These layers are responsible for acquiring knowledge from the input data and discerning its characteristics. To perform convolution operations, they employ a set of adaptable filters or kernels on the input picture, moving them across it and calculating dot products at every location. This process yields a collection of feature maps encompassing various patterns and configurations within the image [18].
- Activation Function: After each convolutional operation, a layer-by-layer activation function is applied in the network to give it a non-linear quality. In CNNs, the activation function known as Rectified Linear Unit (ReLU) is utilized most of the time. This activation function keeps all positive values unaltered while putting all negative values to zero [19].
- Pooling Layers: The spatial dimensions of the feature maps can be reduced by the combination of layers. These maps still have their essential information content. In a typical pooling process called max pooling, the feature map is divided into non-overlapping areas, and the most significant value inside each zone is kept while the other values are discarded. This facilitates a decrease in parameters and limits overfitting [18].
- Fully Connected Layers: Following multiple convolutional and pooling operations, the feature maps' spatial dimensions are transformed into a vector inputted into one or more fully connected layers. These layers resemble those in a conventional neural network and play a crucial role in generating predictions using the acquired features [18].
- Softmax Layer: In classification tasks, including a softmax layer after the network is common. This softmax layer produces probability scores for every class by transforming the outputs from the previous layer into a probability distribution [19].
- Loss Function: The loss function quantifies the difference between the predicted results and the actual labels. It measures the network's performance during training and guides the learning process. Standard loss functions for classification tasks include cross-entropy loss [20].
- Optimization Algorithm: CNNs are trained using optimization algorithms that update the network's parameters based on the gradients of the loss function [17].

B. VGG19

The VGG19 model consists of nineteen layers and is a modified version of the VGG model. It comprises 16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and 1 SoftMax layer. VGG19 was trained on a vast dataset of over a million images from the ImageNet collection. Essentially, VGG is a deep convolutional neural network designed for image classification. You can see the architecture of VGG19 in Fig. 2.

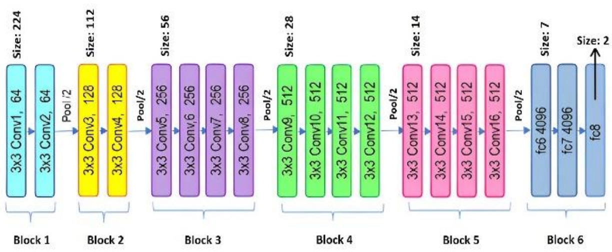


Fig. 2. Architecture of VGG19.

The following is a list of the layers that make up the VGG19 model: The 19-layer neural network can identify more than a thousand distinct objects, including keyboards, mice, pencils, and numerous others. Consequently, this network can produce extensive feature representations for various images.

- The RGB picture with a predetermined size (224, 224) served as the input for this network, which exemplified the matrix's structure (224,224,3).
- The only step that needed to be preprocessed was figuring out the average RGB value for each pixel throughout the training set. The value was subtracted from each pixel in its entirety independently.
- They employed kernels of three by three and a stride size of one pixel to cover the whole picture.
- Utilizing spatial padding is one method that would allow the image's original spatial resolution to be preserved.
- To do maximum pooling across a 2×2 pixel frame, Stride 2 was utilized.
- After that, the Rectified Linear Unit (ReLu), which adds non-linearity to the model to extend the time required for classification and calculating, was introduced. This model performed far better than previous ones using tanh or sigmoid functions.

The outcome involved creating three fully interconnected layers. The initial two layers had a total size of 4,096, whereas the third layer, which employed a SoftMax function, comprised 1,000 channels for classification and was utilized in a 1000-category ILSVRC. Adding a third layer was referred to as "layering,"

C. *Hybrid CNN-SVM*

CNNs and Support Vector Machines (SVMs) are two methods that are frequently employed in the process of image classification. The CNN-SVM technique combines these two methods. The CNN component of the algorithm is responsible for extracting features from the pictures, whilst the SVM component of the algorithm is responsible for classifying the images based on those features. Fig. 3 depicts the overall layout of the CNN-SVM algorithm's workings.

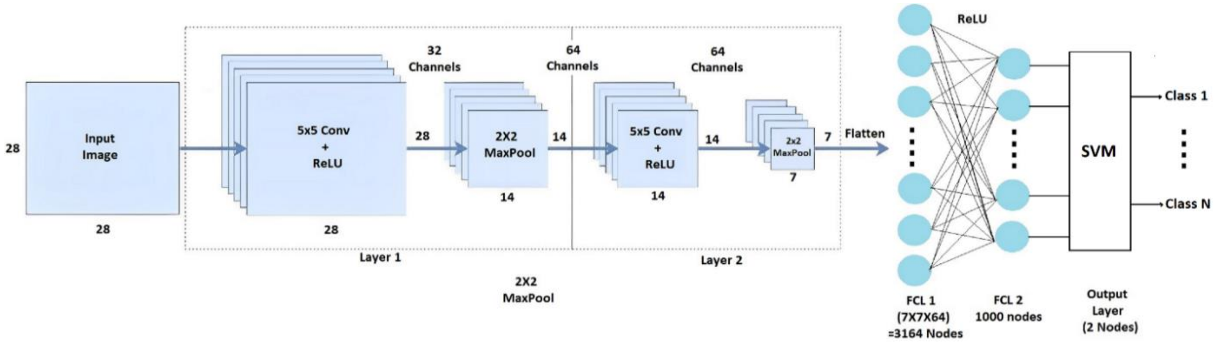


Fig. 3. CNN-SVM architecture for brain MRI classification.

Step-by-step guide on how to implement the CNN-SVM algorithm for image classification:

- **Data preparation:** Collect a dataset of images and divide it into training and testing sets. Ensure that the images are in a suitable format, such as JPEG or PNG, and are the same size.
- **Feature extraction using CNNs:** Train a convolutional neural network (CNN) using the training dataset to capture image features. This process entails passing the images through the CNN and retrieving the output from one of the intermediate layers, usually before the fully connected layers. The result from this specific layer forms a feature vector, serving as a representation for each image.
- **SVM classification:** Use the feature vectors from the CNN to train an SVM on the training set. The SVM can be trained using the sci-kit-learn library in Python, with the feature vectors as input and the corresponding labels as output.
- **Testing and evaluation:** Utilize the SVM to predict the labels of the images included in the testing set. Then, assess the algorithm's effectiveness based on accuracy, precision, recall, and F1-score.

Here are some additional considerations when using the CNN-SVM algorithm for image classification:

- **Preprocessing:** It is often beneficial to preprocess the images before feeding them into the CNN by normalizing the pixel values and data augmentation to increase the data samples.
- **CNN architecture:** The choice of CNN architecture can significantly impact the algorithm's performance. It is often a good idea to start with a pre-trained CNN, such as VGG or ResNet, and fine-tune it on the specific dataset.
- **SVM hyperparameters:** The performance of the SVM can be influenced by its hyperparameters, such as the kernel type, regularization parameter, and gamma parameter. The optimal performance can be achieved by fine-tuning these parameters through cross-validation on the training dataset.
- **Class imbalance:** If the dataset has a class imbalance, with some classes having fewer examples than others, it may be necessary to use techniques such as oversampling or under sampling to balance the classes. Alternatively, one can use techniques such as weighted loss or focal loss during training to give more weight to the underrepresented classes.

IV. PROPOSED SYSTEM

The block diagram of the proposed system is shown in Fig. 4. It consists of an input dataset, preprocessing, dataset splitting, training and classification.

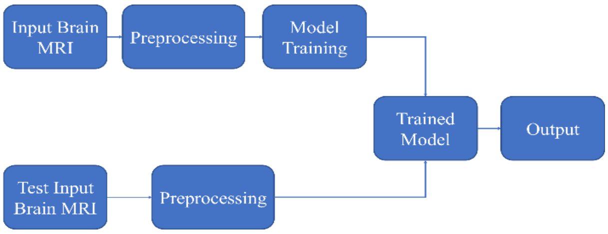
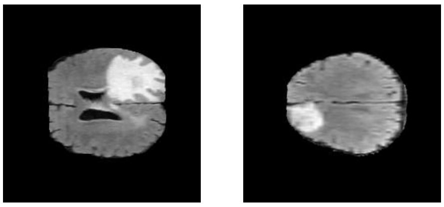


Fig. 4. Block diagram of the proposed system.

A. Dataset Preparation

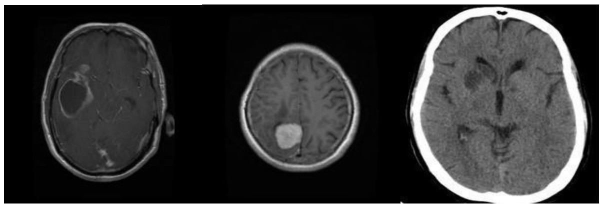
This strategy uses two datasets for assessment: The Brain Tumor Segmentation (BTATS) and the Sartaj datasets [21–24]. The BRATS dataset is a widely utilized benchmark dataset in brain MRI analysis and classification, primarily designed to segment brain tumors. It contains multiple multimodal brain MRI scans, including T1-weighted, T1-weighted contrast-enhanced, T2-weighted, and Fluid-Attenuated Inversion Recovery (FLAIR) images. Moreover, it includes accurate tumor segmentation labels corresponding to each image within the dataset. The MRI scans used to compile the BraTS dataset came from hospitals and medical centres. There are 285 instances in the 2018 edition of the BraTS dataset, comprising a training set and a validation set. Each instance comprises four different MRI modalities and their matching tumor segmentation masks. The training dataset is divided into two categories, High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG), to accurately represent the range of tumor grades. Fig. 5 shows an example image from the Brats dataset.



(a) (b)

Fig. 5. Dataset samples of brats 2018 dataset. (a) HGG (b) LGG.

The SARTAJ dataset includes Magnetic Resonance Imaging (MR) of three different kinds of brain cancers (glioma, meningioma, and pituitary), as well as images of normal brain tissue (no tumor) [25]. The collection includes 3264 photos that are in RGB JPG format. The dataset has two problems: the first is an uneven distribution of classes, and the second is random splitting ratios. The number of photographs with "no tumor" is relatively low when compared to the number of images with tumors, which are as follows: There are 500 images depicting a lack of tumors, while 937 images display meningioma tumors, 901 images depict pituitary tumors, and 926 images showcase glioma tumors. As a result, this distinction leads to classification challenges that lead to an imbalance, where the classifier may have a bias toward tumor scans. In addition, the train-test splitting ratio of the pictures associated with "Pituitary Tumor" is unequal to that of the other images. Therefore, the dataset discards the pituitary class from this approach. The dataset sample image of the SARTAJ dataset is shown in Fig. 6.



(a) (b) (c)

Fig. 6. Dataset samples of sartaj dataset. (a) Glioma (b) Meningioma (c) No tumor.

A training dataset makes up 80% of the whole dataset, while a validation dataset makes up the remaining 20%. Table II summarizes the image dataset distribution of Brats 1,018 and the SARTAJ dataset used for the proposed system.

TABLE II. DATASET DISTRIBUTION

Dataset	Classes	Training	Validation
Brats	HGG	7,148	1,786
	LGG	4,623	1,155
SARTAJ	Glioma	1,321	300
	Meningioma	1,339	306
	No tumor	1,595	405

B. Data Preprocessing

This image has been preprocessed to make it easier to work with. Filtering is an essential part of the preprocessing procedure. The median filter is non-linear to eliminate noise and smooth out a picture. As a result of its ability to reduce noise while preserving edges, it has found widespread use. It does an outstanding job of escaping noise like salt and pepper. The median filter iteratively applies itself to an image, replacing each value with its neighborhood median value as it moves from pixel to pixel. Calculating the median involves first sorting all the pixel values in the window using a numerical order and then replacing the center pixel in the window with the pixel value representing the median.

C. Training and Classification

In this approach, CNN, VGG19 and a hybrid CNN-SVM algorithm are for classifying Brain MRI into HGG and LGG, while in another approach, classifying into glioma, meningioma and no tumor classes.

The model summary of CNN, VGG19 and CNN-SVM algorithm for HGG and LGG classification of brain MRI of Brats 2018 and SARTAJ dataset is shown in Tables III–V, respectively.

The Param column represents the number of parameters in each layer, indicating the capacity and complexity of the model. The value displayed in the Total params column corresponds to the total number of trainable parameters across the model. Tables III–V show that the parameter required for the transfer learning algorithm (VGG19) is much less than the CNN and hybrid CNN-SVM algorithm.

TABLE III. MODEL SUMMARY OF CNN ALGORITHM ON BRATS DATASET

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 98, 98, 256)	7,168
activation (Activation)	None, 98, 98, 256)	0
max_pooling2d (MaxPooling2D)	(None, 49, 49, 256)	0
conv2d_1 (Conv2D)	(None, 47, 47, 128)	295,040
activation_1 (Activation)	(None, 47, 47, 128)	0
max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 128)	0
flatten (Flatten)	(None, 67712)	0
dense (Dense)	(None, 64)	4,333,632
activation_2 (Activation)	(None, 64)	0
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 2)	130
Total params		**4,635,970**
Trainable params		**4,635,970**
Non-trainable params		**0**

TABLE IV. MODEL SUMMARY OF VGG19 ALGORITHM ON BRATS DATASET

Layer (type)	Output Shape	Param
input_1 (InputLayer)	(None, 200, 200, 3)	0
block1_conv1 (Conv2D)	(None, 200, 200, 64)	1,792
block1_conv2 (Conv2D)	(None, 200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None, 100, 100, 64)	0
block2_conv1 (Conv2D)	(None, 100, 100, 128)	73,856
block2_conv2 (Conv2D)	(None, 100, 100, 128)	147,584
block2_pool (MaxPooling2D)	(None, 50, 50, 128)	0
conv2d_11 (Conv2D)	(None, 48, 48, 256)	36,896
max_pooling2d_11 (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_1_12 (Conv2D)	(None, 22, 22, 64)	18,496
conv2d_13 (Conv2D)	(None, 9, 9, 128)	0
max_pooling2d_13 (MaxPoolin g2D)	(None, 4, 4, 128)	0
Flatten_4 (Flatten)	(None, 2048)	0
batch_normalization (BatchNormalization)	(None, 2048)	8,192
dense_8 (Dense)	(None, 256)	524,544
dropout_4 (Dropout)	(None, 256)	0
dense_9 (Dense)	(None, 2)	514
Total params		**922,658**
Trainable params		**805,986**
Non-trainable params		**116,672**

TABLE V. MODEL SUMMARY OF CNN-SVM ALGORITHM ON BRATS DATASET

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 98, 98, 16)	3,328
activation (Activation)	(None, 98, 98, 16)	0
max_pooling2d (MaxPooling2D)	(None, 49, 49, 16)	0
conv2d_1 (Conv2D)	(None, 47, 47, 32)	131,200
activation_1 (Activation)	(None, 47, 47, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 32)	0
conv2d_2 (Conv2D)	(None, 21, 21, 64)	18,496
activation_2 (Activation)	(None, 21, 21, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 64)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 128)	819,328
activation_3 (Activation)	(None, 128)	0
dropout (Dropout)	(None, 128)	
dense_1 (Dense)	(None, 2)	258
Total params		**843,170**
Trainable params		**843,170**
Non-trainable params		**0**

V. RESULTS AND DISCUSSION

The proposed method for classifying brain MRI results is assessed using several key evaluation metrics, including sensitivity, specificity, accuracy, precision, recall, and F1-score. Below, we will explain each of these evaluation criteria.

- **Sensitivity or recall:** Sensitivity, which is also referred to as the True Positive Rate or Recall, measures the model's capacity to accurately detect positive instances, like the detection of a brain tumor. Its calculation method is as follows.

$$Sensitivity = \frac{TP}{TP+FN} \tag{1}$$

- **Specificity:** On the other hand, specificity assesses the model's proficiency in correctly recognizing negative cases or instances where there is no brain tumor. The formula for specificity is given by:

$$Specificity = \frac{TN}{TN+FP} \tag{2}$$

- **Accuracy:** Accuracy provides a comprehensive measure of overall correctness in predictions and is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

- **Precision:** Precision, often referred to as the Positive Predictive Value, gauges the accuracy of positive predictions made by the model, which is particularly important when minimizing false positives is a concern. Its equation is as follows:

$$Precision\ (P) = \frac{TP}{TP+FP} \tag{4}$$

- **F1-score:** The F1-score merges precision and recall into a unified measurement, which is particularly beneficial when working with datasets with uneven class distribution. Its definition is as follows:

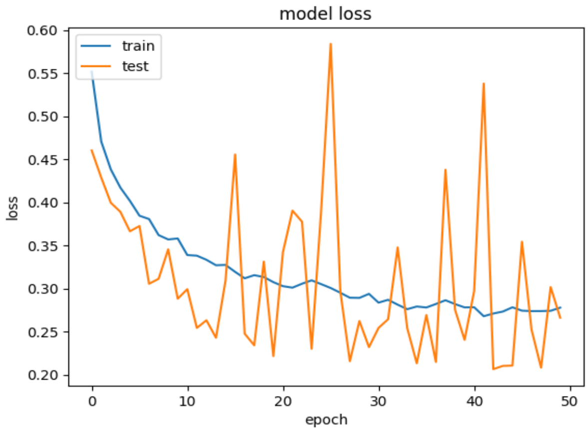
$$F1 - Score = 2\times\frac{P \times R}{P+R} \tag{5}$$

Evaluating a model's performance involves various metrics such as Sensitivity (or recall), Specificity, Accuracy, Precision, and F1-score. These metrics are employed when dealing with classification problems, where samples are categorized as True Positive (TP), False Positive (FP), True Negative, and False Negative (FN) based on the alignment between the actual and predicted class labels.

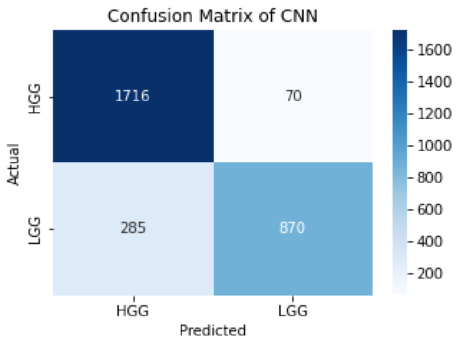
A. Result of Deep Learning Algorithm on Brats Dataset

The results of the CNN algorithm for brain MRI classified into HGG and LGG classification are presented below. The training progress graph and confusion matrix for CNN classification for the Brats dataset are shown in Fig. 7.

(a)

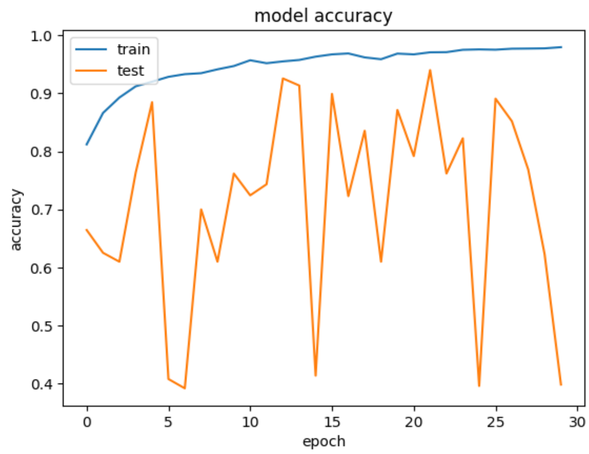


(b)

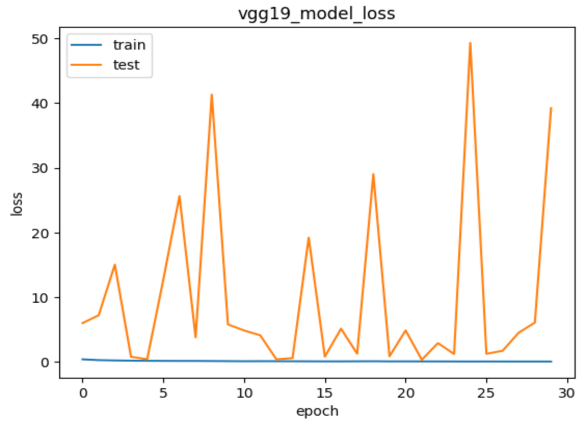


(c)

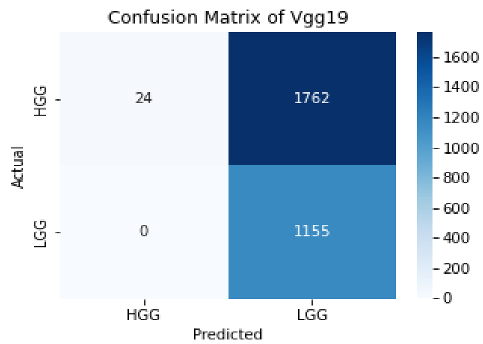
Fig. 7. Training performance of CNN. (a) Accuracy (b) Loss (c) Confusion matrix.



(a)



(b)



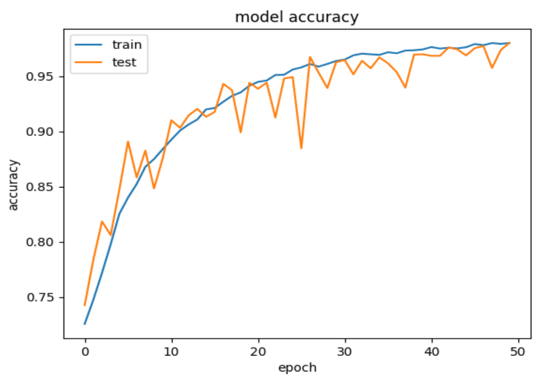
(c)

Fig. 8. Training performance of VGG19. (a) Accuracy (b) Loss (c) Confusion matrix.

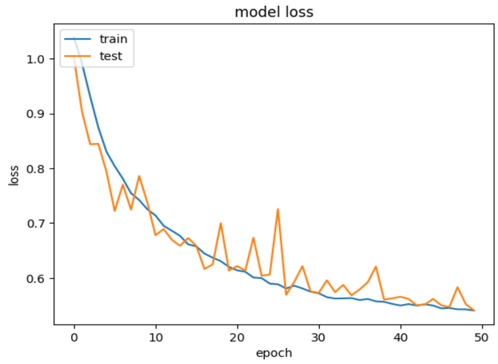
The Convolutional Neural Network (CNN) is trained using the rmsprop optimizer for 50 epochs, employing a learning rate set at 0.001.

Furthermore, this section presents the results using the VGG19 algorithm to categorize brain MRI scans into HGG and LGG categories. Fig. 8 depicts the training progress graph and the confusion matrix for the VGG19 classification. The VGG19 model is trained for 30 epochs with a rmsprop optimizer and a learning rate of 0.00001.

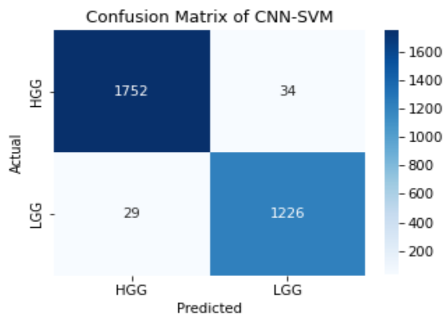
Fig. 9 displays the hybrid CNN-SVM classification's confusion matrix and training progress graph for the classification of brain MRI into HGG and LGG.



(a)



(b)



(c)

Fig. 9. Training performance of CNN-SVM. (a) Accuracy (b) Loss (c) Confusion Matrix.

The CNN-SVM model is trained for 50 epochs with adam optimizer, kernel regularizer L2 of 0.001 and hinge loss.

Table VI displays a side-by-side evaluation of the performance of CNN, VGG19, and the combined CNN-SVM algorithm, considering precision, recall, F1-score, and accuracy as metrics.

Table VI presents a comparative analysis of various classifiers' performance on the Brats Dataset, a medical imaging dataset commonly used for brain tumor classification. The table evaluates four different algorithms: Convolutional Neural Network (CNN), VGG19 (a specific CNN architecture), and CNN-SVM (CNN combined with a Support Vector Machine). Each algorithm is assessed based on several key metrics. CNN demonstrates a relatively high sensitivity/recall of 0.8575, specificity of 0.9255, precision of 0.9608, the accuracy of 0.8792, and F1-score of 0.9062, indicating a robust overall performance in brain tumor classification. VGG19, on the other hand, has perfect sensitivity but very low specificity and precision, resulting in a much lower F1-score, which signifies its limitations in distinguishing tumor cases. Finally, CNN-SVM performs exceptionally well regarding sensitivity, specificity, precision, accuracy, and F1-score, showcasing its robustness in brain tumor classification on the Brats Dataset.

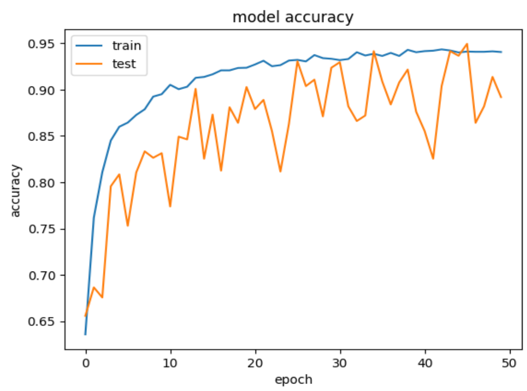
TABLE VI. COMPARATIVE ANALYSIS OF DIFFERENT CLASSIFIERS ON BRATS DATASET

Algorithm	Sensitivity/Recall	Specificity	Precision	Accuracy	F1-score
CNN	0.8575	0.9255	0.9608	0.8792	0.9062
VGG19	1	0.3959	0.0134	0.4008	0.0265
CNN-SVM	0.9853	0.9730	0.9809	0.9802	0.9831

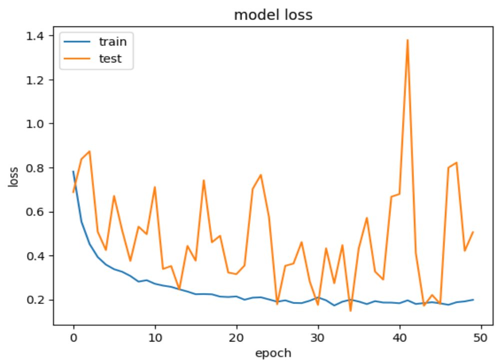
B. *Result of Deep Learning Algorithm on SARTAJ Dataset*

The results of the CNN algorithm for brain MRI classified into glioma, meningioma and no tumor classification are presented below. The training progress graph and confusion matrix for CNN classification for the Brats dataset are shown in Fig. 10.

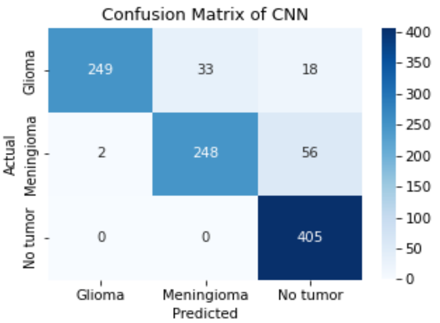
The Convolutional Neural Network (CNN) is subjected to 50 training epochs using rmsprop optimizer and a learning rate set at 0.001.



(a)



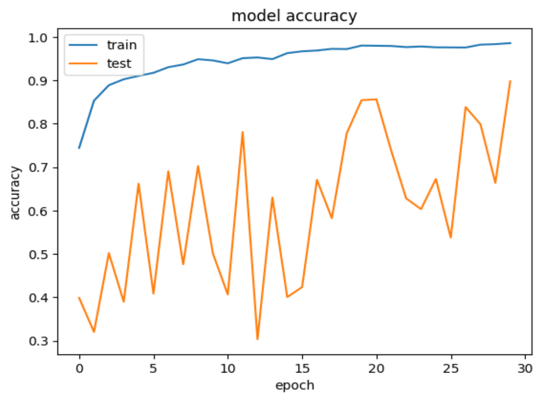
(b)



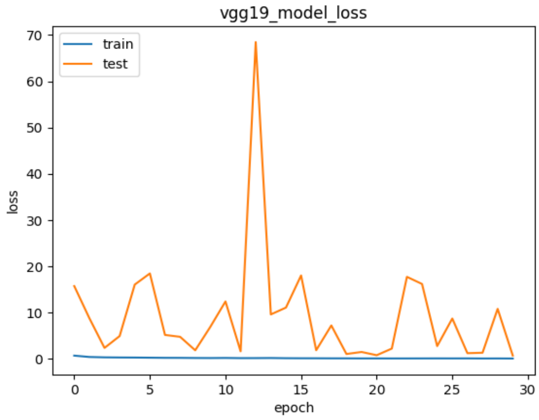
(c)

Fig. 10. Raining performance of CNN. (a) accuracy (b) Loss (c) Confusion Matrix.

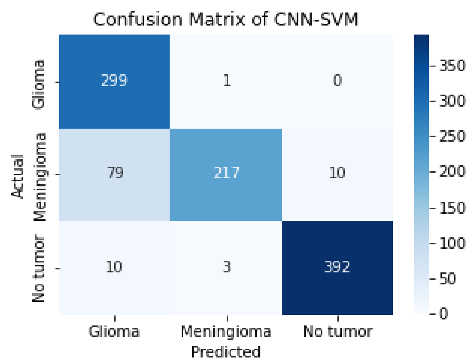
The results of the VGG19 algorithm brain MRI classification into glioma, meningioma and no tumor are presented below. The training progress graph and confusion matrix for the VGG19 classification are shown in Fig. 11.



(a)



(b)

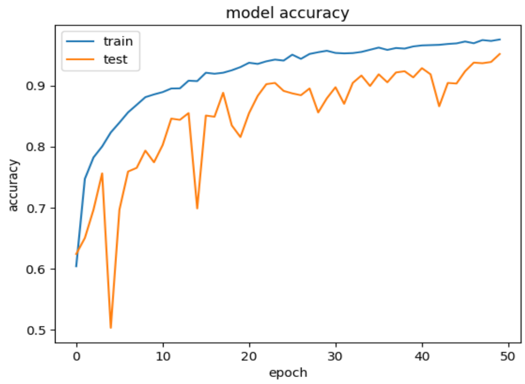


(c)

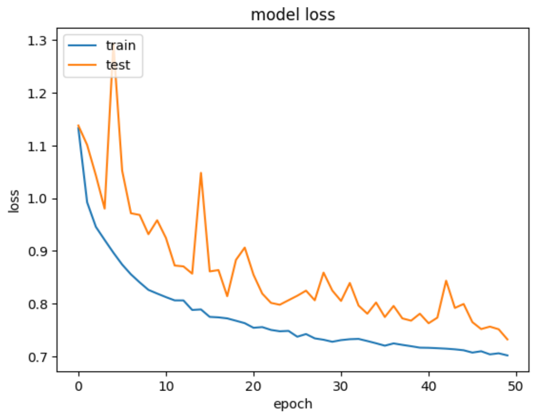
Fig. 11. Training performance of VGG19. (a) accuracy (b) Loss (c) Confusion Matrix.

The VGG19 model is trained for 30 epochs with a rmsprop optimizer and a learning rate 0.00001. Below are the outcomes of the hybrid CNN-SVM algorithm's classification for distinguishing between glioma, meningioma, and No tumors. Fig. 12 displays the training progress graph and the confusion matrix related to the hybrid CNN-SVM classification.

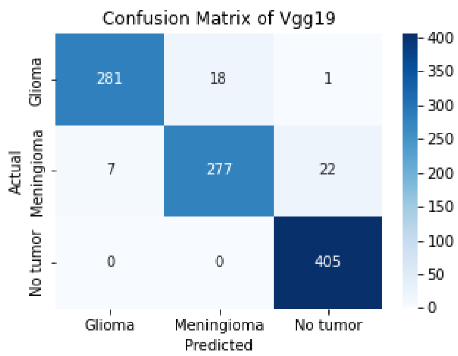
The CNN-SVM model is trained for 50 epochs with adam optimizer, kernel regularizer L2 of 0.001 and hinge loss.



(a)



(b)



(c)

Fig. 12. Training performance of CNN-SVM. (a) accuracy (b) Loss (c) Confusion Matrix.

Table VII compares the precision, recall, F1-score, and accuracy of the CNN, VGG19, and hybrid CNN-SVM algorithms for classifying brain MRI scans into glioma, meningioma, and no tumor. Table VII presents a comparative analysis of various classifiers' performance on the Sartaj Dataset, evaluating their ability to classify data correctly. The table includes five algorithms: CNN, VGG19, and CNN-SVM, and corresponding metrics for each algorithm's performance. Sensitivity, or recall, evaluates how well positive cases are correctly identified, while specificity measures the accuracy in identifying negative cases. Accuracy indicates correct classification, precision assesses the accuracy of positive predictions, and the F1-score combines precision and recall for a balanced performance measure. Among the algorithms, CNN-SVM stands out as the top performer, showing the highest sensitivity, specificity, accuracy, precision, and F1-score, indicating its superior performance in classifying the dataset. Additionally, CNN and VGG19 also exhibit strong performance across these evaluation metrics.

TABLE VII. COMPARATIVE ANALYSIS OF DIFFERENT CLASSIFIERS ON THE SARTAJ DATASET

Algorithm	Sensitivity/recall	Specificity	Accuracy	Precision	F1-score
CNN	0.8802	0.9428	0.9281	0.9067	0.8884
VGG19	0.8912	0.9509	0.9321	0.9092	0.8881
CNN-SVM	0.9473	0.9756	0.9683	0.9536	0.95

The depiction in Fig. 13 illustrates the qualitative assessment of the proposed system when applied to the Brats dataset, specifically for distinguishing between HGG and LGG. Meanwhile, Fig. 14 displays the system's performance in categorizing brain MRI scans into glioma, meningioma, and no tumor.

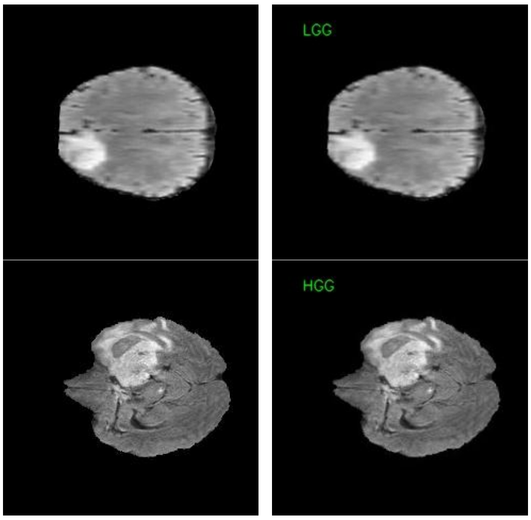


Fig. 13. Testing results of the proposed system on the Brats dataset.

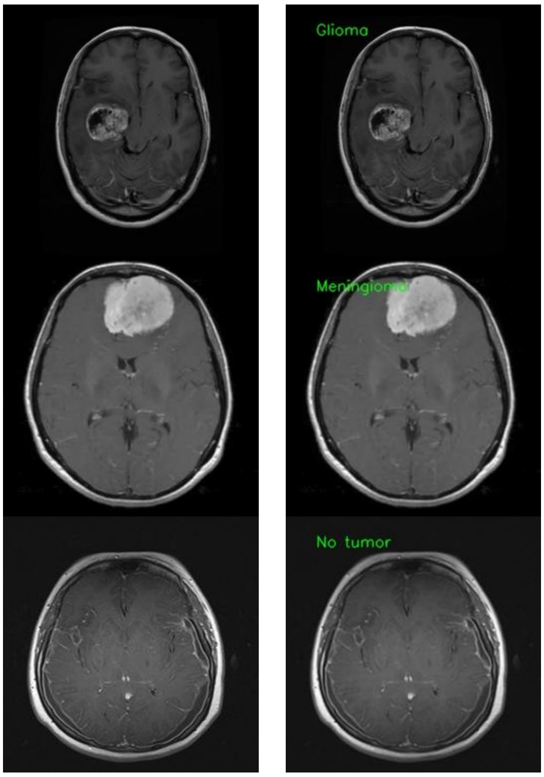


Fig. 14. Testing results of the proposed system on the Brats dataset.

The multiclass classification of brain MRI using the CNN, VGG19, and CNN-SVM algorithm yielded promising results and demonstrated the potential for accurate and reliable classification of brain tumors.

The results highlight the proposed approach's potential for accurate and reliable multiclass classification of brain MRI images. This holds substantial importance in aiding healthcare practitioners in identifying, planning treatments, and tracking brain tumors. Continued progress in deep learning methods, optimization approaches, and the accessibility of more extensive datasets has the potential to significantly improve the precision and utility of MRI-based brain tumor classification systems.

Diagnosing brain cancer types is at the heart of our methodology, and it is accomplished by applying a CNN, VGG19 and hybrid CNN-SVM technique. The hybrid CNN-SVM method improves the performance of classification tasks by combining the capabilities of these two types of networks. There are two prominent use cases for the model that have been developed. To begin, it may be educated and utilized for the autonomous classification of Brain MRI into different classes with minimal computing power.

The CNN-SVM algorithm combines the strengths of both CNNs and SVMs, resulting in improved classification performance. Unlike CNNs alone, which rely on SoftMax or sigmoid activation functions for classification, the hybrid approach uses SVMs, which are robust and effective classifiers. SVMs can handle high-dimensional feature spaces and create optimal decision boundaries, making them suitable for complex classification tasks. Moreover, the CNN-SVM algorithm takes advantage of the robust feature extraction abilities of CNNs, which autonomously acquire hierarchical and distinguishing characteristics from unprocessed data. The algorithm can capture relevant visual features using a pre-trained CNN, even with limited training data.

The CNN-SVM algorithm offers a more efficient solution than the VGG19 architecture, a deep and computationally expensive model. It reduces the computational burden by utilizing the CNN for feature extraction and then employing the SVM classifier, resulting in faster inference times while maintaining competitive accuracy. Overall, the CNN-SVM algorithm combines the best of both worlds, benefiting from the strong feature representation of CNNs and the powerful classification capabilities of SVMs, leading to improved classification performance and computational efficiency.

Table VIII compares the suggested system when pitted against the most advanced techniques on the Brats 2018 dataset.

TABLE VIII. COMPARATIVE ANALYSIS OF THE PROPOSED SYSTEM WITH STATE-OF-THE-ART METHODS ON THE BRATS DATASET

Author	Method	Dataset	Accuracy
Soltaninejad *et al.* [26]	Texture Features from Super voxels and Random Forest as the Classifier	Brats2018	80%
Melegy *et al.* [27]	Ten Statistical Features and Random Forest as the Classifier	Brats2018	80.85%
Xue *et al.* [28]	Dual-Path Residual Convolutional Neural Network	Brats2018	84.90%
Sajjad *et al.* [29]	Deep CNN with Extensive Data Augmentation	Brats2018	94.58%
Proposed (DL algorithm)	**CNN-SVM**	**Brats2018**	**98.01%**

Table VIII presents a comparative analysis of the proposed system, CNN-SVM, with state-of-the-art methods on the Brats dataset for brain tumor classification. Four existing methods by different authors are compared to the proposed system. Soltaninejad *et al.* [26] and El-Melegy *et al.* [27] achieved an accuracy of around 80% using texture features and random forests as classifiers. Xue *et al.* [28] achieved a higher accuracy of 84.90% using a Dual-Path Residual Convolutional Neural Network. Sajjad *et al.* [29] achieved an even higher accuracy of 94.58% by employing deep Convolutional Neural Networks (CNN) with extensive data augmentation techniques. In contrast, the proposed system, CNN-SVM, outperforms all these methods with an impressive accuracy of 98.01%, showcasing its superiority in brain tumor classification on the Brats dataset.

Table IX presents a comparative analysis of the proposed system, a deep learning (DL) algorithm with a CNN-SVM architecture, alongside state-of-the-art methods for the Sartaj dataset. Latif *et al*. [30] employed Support Vector Machines (SVM) and achieved an accuracy of 80%. Khan *et al*. [31] utilized the VGG19 architecture, achieving a slightly higher accuracy of 80.85%. Yahyaouni *et al*. [32] applied DenseNet and obtained an accuracy of 84.90%. Bhathele *et al.* [33] introduced a Hybrid Ensemble method, significantly improving accuracy to 94.58%. Murthly *et al.* [34] employed a CNN Ensemble approach, achieving an accuracy of 84.27%. Notably, the proposed DL algorithm with CNN-SVM achieved the highest accuracy among all methods, reaching an impressive accuracy of 95.16% on the Sartaj dataset, indicating its superior performance compared to the state-of-the-art methods.

TABLE IX. COMPARATIVE ANALYSIS OF THE PROPOSED SYSTEM WITH STATE-OF-THE-ART METHODS ON THE SARTAJ DATASET

Author	Method	Dataset	Accuracy
Latif *et al.* [30]	SVM	Sartaj	80%
Khan *et al*. [31]	VGG19	Sartaj	80.85%
Yahyaouni *et al.* [32]	DenseNet	Sartaj	84.90%
Bhathele *et al.* [33]	Hybrid Ensemble	Sartaj	94.58%
Murthly *et al.* [34]	CNN Ensemble	Sartaj	84.27%
Proposed (DL algorithm)	**CNN-SVM**	**Sartaj**	**95.16%**

Table X summarizes the results of one-way Analysis of Variance (ANOVA) tests, aiming to assess and compare the precision, recall, and F-measure of three distinct algorithms: SVM, VGG19, and CNN-SVM. These evaluations are conducted on two distinct datasets, namely the “Brats Dataset” and the “Sartaj Dataset.”

For each dataset, the “Parameters” column specifies the pairs of algorithms being compared, with entries like “CNN-CNN_SVM.” “CNN-VGG19.” and “VGG19-CNN_SVM.” The “f_statistic” and “p_value” columns display the outcomes of the ANOVA tests, with the “f_statistic” representing the ratio of variation between the groups (algorithms) to the variation within the groups. The “p_value” quantifies the likelihood of obtaining the observed or more extreme results if the null hypothesis (no significant differences) were true.

TABLE X. RESULTS OF ONE-WAY ANALYSIS OF VARIANCE (ANOVA) COMPARING PRECISION, RECALL, AND F-MEASURE OF SVM, VGG19, AND CNN-SVM ALGORITHMS

Dataset	Parameters	f_statistic	p_value	Decision
Brats Dataset	CNN-CNN_SVM	12,615,285	0.012045	Reject the null hypothesis
	CNN-VGG19	41,053,524	0.000681	Reject the null hypothesis
	VGG19-CNN_SVM	49,643,596	0.000408	Reject the null hypothesis
Sartaj Dataset	CNN-CNN_SVM	0.0903362	0.771412	Fail to reject the null hypothesis
	CNN-VGG19	146,487,284	0.0050367	Reject the null hypothesis
	VGG19-CNN_SVM	113,597,383	0.0097794	Reject the null hypothesis

The “Decision” column succinctly conveys the conclusion drawn from each ANOVA test. “Reject the null hypothesis” indicates substantial and statistically significant variations in precision, recall, or F-measure among the compared algorithms. Conversely, “Fail to reject the null hypothesis” implies that the observed differences can be attributed to random fluctuations and are not statistically significant.

In the case of the Brats Dataset, all three comparisons (CNN-CNN_SVM, CNN-VGG19, and VGG19-CNN_SVM) lead to the rejection of the null hypothesis, signifying meaningful distinctions in performance metrics among SVM, VGG19, and CNN-SVM on this dataset. Conversely, for the Sartaj Dataset, the “CNN-CNN_SVM” and “CNN-VGG19” comparisons do not yield p-values below the significance level, suggesting that there are no significant differences in precision, recall, or F-measure between these algorithm pairs on this dataset. However, the “VGG19-CNN_SVM” comparison does show a p-value below the significance level, indicating significant differences between VGG19 and CNN-SVM on this dataset. These results provide valuable insights into the comparative performance of these algorithms in different data contexts.

The following points provide a clear and thorough explanation of the innovative contribution made by this research in the specified field:

- A specially tailored Convolutional Neural Network (CNN) was created from scratch, featuring three convolutional layers and three pooling layers for effective feature extraction. Instead of the traditional final layer of a CNN, this model employs an SVM algorithm to automatically classify brain MRI images into multiple classes, distinguishing between benign and malignant cases and further categorizing them into glioma, meningioma, and no tumor. Regarding its architectural design, this CNN-SVM approach is notably less complex and less susceptible to overfitting than transfer learning models typically used for image classification tasks in this specific domain. Consequently, this CNN-SVM model is well-suited for portable automated brain MRI classification systems.
- The performance of this customized CNN-SVM algorithm for brain MRI classification was evaluated on previously unseen MRI data, resulting in a high level of accuracy in recognizing different brain conditions.
- The analysis of the results revealed that the custom CNN-SVM model achieved accuracy rates of up to 98.01% and 95.16% on the Brats and Sartaj datasets, respectively. When applied to the same dataset, these accuracy rates surpass those achieved by a standard CNN and the transfer learning model VGG 19. Consequently, the learned weights of the proposed CNN-SVM model can potentially be utilized for other image classification tasks based on the ImageNet dataset within this specific domain.

VI. Discussion on Limitations of the Proposed System

While holding great promise, the proposed system for brain tumor classification through a hybrid CNN-SVM approach in MRI presents several noteworthy limitations that warrant consideration in the context of this research. Firstly, it is crucial to acknowledge that the performance and generalizability of the model hinge significantly on the quality and quantity of available training data. Suppose the dataset used for training is limited in size or not adequately representative of the broader population. In that case, the model’s predictive accuracy may be compromised, potentially restricting its real-world applicability.

Another critical limitation pertains to interpretability. Deep learning models, including the hybrid CNN-SVM model proposed, can be inherently challenging to interpret. Understanding the rationale behind specific predictions or identifying the specific features that drive these predictions may prove challenging, particularly in medical applications where interpretability and transparency are paramount.

Additionally, the computational demands of the model must be considered. Training deep learning models, particularly Convolutional Neural Networks (CNNs), can be computationally intensive, posing constraints for researchers or practitioners with limited access to high-performance computing resources. Furthermore, the class imbalance in medical datasets, where certain tumor classes may have significantly fewer samples than others, can introduce bias and hinder model performance, necessitating specialized techniques for addressing this limitation.

Finally, like all medical diagnosis systems, the proposed model may still produce false positives and negatives, requiring careful assessment and quantification to understand their potential clinical impact fully. To mitigate these limitations, it is imperative to conduct comprehensive validation studies, engage closely with domain experts and clinicians, and continuously refine and update the system as more data becomes available and technology advances. Furthermore, addressing ethical and regulatory aspects should be an integral part of the overall development and deployment strategy to ensure the responsible and effective use of the system in clinical practice.

VII. Conclusion and Future Directions

This paper presents a comprehensive approach for multiclass classification of brain MRI images using a combination of CNN, VGG19, and the CNN-SVM algorithm. This method used the Brats 2018 dataset for HGG and LGG classification and the SARTAJ dataset for glioma, meningioma, and no tumor classification. The goal of the work was to correctly identify brain cancers in MRI images using the strength of deep learning for feature extraction and the adaptability of SVM for classification.

The results obtained from the experiments on the selected dataset demonstrate the effectiveness of the proposed approach. The combination of CNN and the SVM classifier achieved the accurate and reliable multiclass classification of brain tumors. The approach showed promising performance in differentiating between tumor types and provided valuable insights into the classification of brain MRI images.

In future, it is imperative to focus on advancing both the technical and practical aspects of this research. Firstly, consider further refining the model’s performance by exploring advanced deep learning techniques and architectures, such as attention mechanisms or capsule networks, to capture intricate features within MRI images, thereby potentially enhancing classification accuracy. In parallel, investigate the potential for multimodal analysis by incorporating complementary imaging data from sources like CT or PET scans. This could lead to a more comprehensive understanding of brain tumor characteristics. Furthermore, explore the dynamic aspect of tumor growth by delving into longitudinal analysis, enabling better treatment planning and monitoring.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Shweta Suryawanshi conceived and designed the research, conducted experiments, collected and analyzed the data, and wrote the initial draft of the paper. She was also responsible for the critical interpretation of the results and their implications; Sanjay B. Patil contributed to the literature review, assisted with data collection and analysis, and provided significant input on the organization and structure of the paper. He also revised the manuscript for clarity and coherence and played a crucial role in the final editing process. All authors had approved the final version.

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